Machine Learning Models for Cost-Effective Shipping Line Selection: A Comparative Analysis for Freight Forwarders

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Abstract

The effectiveness of machine learning models in making cost-effective shipping line selections is investigated in this study from the perspective of freight forwarders. We had access to a dataset encompassing 983 shipment records from 37 different Egyptian freight forwarding companies. We then tested three different machine learning algorithms to see which one best predicted cost-effective shipping selections. The three algorithms were: Decision Trees, K-Nearest Neighbors (KNN), and Naive Bayes. After thoroughly testing these three algorithms, we determined that the best algorithm for use with our dataset, and

the best one for use broadly within the market, was the Decision Tree method.

Keywords: Freight Forwarding, Machine Learning, Decision Trees, Shipping Line Selection, Logistics Optimization, Cost-Effectiveness, Predictive Analytics

1. Introduction

1.1 Background

Freight forwarding plays a key role in the global logistics network. It connects the bridge, the shipper, and the carrier, ensuring that international cross-border shipments arrive at their destinations in an effective and efficient manner—in other words, that they get there in good time and at a good cost (Dzakah Fanam et al., 2018; Ho et al., 2017). In this complex international environment, with so many paths from point A to point B, choosing the right shipping line is a key strategic decision that forwarders must make for each shipment to ensure good operational efficiency and competitive advantage. Freight forwarders must consider a several factors—such as service costs, transit times, and carrier reliability—when making such a critical decision (Dzakah Fanam et al., 2018; Ergin & Alkan, 2023; Ho et al., 2017).

The logistics and supply chain management field are now reaping the benefits of machine learning (ML), a key emerging technology with the potential to reveal complex patterns within large datasets and forecast the best logistical choices. It has a variety of models, and the field hasn't yet settled on which one or ones work best for predicting cost-effective shipping routes. This research examines five prominent models—Random Forest, Decision Trees, K-Nearest Neighbor, Naive Bayes, and Support Vector Machines—and pits them against one another by measuring their forecasting accuracy and precision, among other performance metrics.

1.2 Problem Statement

The current literature on shipping line selection has lack the predictive capability needed for real-time decision-making. Despite the proven success of machine learning models in other logistics applications, few studies have comprehensively evaluated the performance of multiple ML algorithms in identifying cost-effective shipping lines specifically from a freight forwarder’s perspective.

Freight forwarders require, from a practical standpoint, a solid, data-centric foundation that elucidates the influence of service costs on the selection of shipping lines. More importantly, they need this foundation to predict with a high degree of accuracy the most favorable options. My research endeavors to close that gap. It does so by marrying several machine-learning models together to get at the heart of the matter—that is, to decode not only the key service cost factors that sway the decisions of freight forwarders but also the main features of those decisions.

1.3 Research Objectives

This research pursues several objectives:

First, it wants to see how well different machine learning models work in making predictions. These predictions have to do with placing cost-effective choices of shipping lines, from the perspective of a freight forwarder, into the framework of a logistics decision-support system.

Second, it investigates which features of the data fed into the models have the most influence on the models' making these predictions.

Finally, it develops a framework that can be integrated into similar decision-support systems.

1.4 Research Questions

The study is guided by the following research questions: What are the leading machine learning models for forecasting cost-effective shipping lines? What are the principal features of cost-effectiveness in selecting a shipping line? How can freight forwarders apply these models to better effect in making their shipping line choices?

2. Literature Review

2.1 Freight Forwarding

Freight forwarding service has an important role in the international setup of trade and commerce, which allows for movement of goods from one place to another with exactness, effectiveness, and cost efficiency. Freight forwarding services According to the International Federation of Freight Forwarders Associations (FIATA):

"Freight Forwarding Services means services of any kind relating to the carriage, consolidation, storage, handling, packing or distribution of the Goods as well as ancillary and advisory services in connection therewith, including but not limited to customs and fiscal matters, declaring the Goods for official purposes, procuring insurance of the Goods and collecting or procuring payment or documents relating to the Goods." (FIATA, 2019)

The services of a freight forwarder include the following: the management of shipping routes, customs operations, documentation, storage, and distribution of goods. These intermediaries facilitate the link between shippers and carriers, promoting a seamless and timely movement of products across international borders (Ding et al., 2017; Huang et al., 2019).

Freight forwarding requires a deep understanding of global trade complexities, including navigating various international regulations and procedures. Research indicates that freight forwarders significantly contribute to optimizing supply chains by selecting the most efficient shipping routes and facilitating smooth cross-border trade (Rajasekar & Prabhakar, 2015).

Their role is important in the liner shipping industry because they represent the most frequent customer of the shipping lines.

Hence, their criteria for carrier selection are paramount in defining winners and losers in the marketplace. Typically, forwarders would pay special attention to various elements when picking shipping lines: freight rates, adherence to schedules, reliability in service, door-to-door services, and environmental performance (Dzakah Fanam et al., 2018).

2.2 Machine Learning in Freight Forwarding

Machine learning enables systems to improve performance by learning from past data. This added sophistication in data analytics is through the kind of algorithms that learn from patterns, adjust with new data, and keep perfecting their predictions. This is very beneficial for handling large datasets or situations in which the data is too complex for conventional statistical methods (Rao et al., 2017).

The use of machine learning in logistics and freight forwarding has greatly transformed these sectors. Machine learning empowers systems to learn from data, thus improving predictive accuracy over time. This combination is very effective at solving complex logistic problems; among them, there are predicting demand (Ermagun et al., 2020), optimizing shipping routes (Cao, 2022), and reducing operational costs (Gkerekos et al., 2019).

The studies (Cao, 2022) and (Sert et al., 2020) also found that the combination of data analytics and machine learning in logistics for task automation, even in such simple tasks as tracking of shipment and route planning. This does not only increase efficiency but also raises the satisfaction level among the clients. It was found that companies implementing machine learning models can reduce delivery time and operational costs by real-time insights into automation of decision-making and freight forwarder performance

The table delineates global machine learning applications in freight forwarding. It highlights both established research domains and notable knowledge deficiencies. Predominantly, studies originate from developed economies like the USA, Netherlands, and Portugal, with scant contributions from emerging markets, including Indonesia and Poland. Notably, there exists a substantial gap in research from critical logistics hubs and developing economies, such as China, India, North Africa, and the Middle East. In Table 1, different machine learning techniques are presented, encompassing options like Naive Bayes and linear regression, together with Bayesian Nonparametric structures. The research covers various aspects of freight forwarding activities, including risk assessment, fraud detection, personnel performance forecasting, traffic management, and cost and time evaluations.

Table 1. Machine Learning Applications in Freight Forwarding

#	PAPER	COUNTRY OF APPLICATION	ML TECHNIQUE	PREDICTION AREA
1	(Shang et al., 2017)	Global	Bayesian Nonparametric (Probit Stick-Breaking Process mixture model)	Risk Assessment in Air Cargo Transport
2	(Cyperski, Okulewicz and Domański, 2024)	Poland	Hybrid Approach: DBSCAN, k-NN, XGBoost	Cost Estimation for Full Truckload (FTL) Shipping
3	(Triepels et al., 2015)	Netherlands	Probabilistic Classification: Naive Bayes (NB), Tree-Augmented Naive Bayes (TAN)	Document Fraud Detection in Maritime Freight

4	(Calixto & Ferreira, 2020)	Portugal	Naive Bayes Classifier	Salespeople Performance
5	(Hathikal, Chung and Karczewski, 2020)	USA	Multinomial Logistic Regression, Decision Tree, KNN, SVM	Shipment Lead Time for Ocean Freight
6	(Wahyudi & Septya Arroufu, 2022)	Indonesia	Linear Regression	Delivery Time Prediction
7	(Bridgelall, 2024)	USA	Data Mining and GIS-based Analysis	Freight Traffic Reduction
8	(Birkel et al., 2020)	Germany	NA	Capacity forecasting, resource allocation
9	(Jang, Chang and Kim, 2023)	Republic of Korea	LightGBM, XGBoost, DNN, MLR	Cost prediction for freight shipping

Considering the research that have been presented within the table 1, it becomes evident that a multitude of conclusions can be drawn, which will be systematically analyzed and examined in a sequential manner for clarity and depth of understanding.

2.3 Shipping Line Selection

To achieve the best possible results, freight forwarders must perform a careful evaluation of the shipping lines they utilize. They consider many aspects of a shipping company over which that company has direct control. First, and most important, is the aspect of price. The freight rates a shipping line offers directly impact both the forwarder and the forwarder's customer. The second major aspect, service reliability, is equally crucial. Price advantages can mean little to a forwarder and its customer if the service that the forwarder is paying for is unreliable. Service reliability encompasses both the ship's performance (arriving on time and in good condition) and the performance of the shipping line's staff on both ends of the journey. After price and service reliability comes the matter of transit time. These factors significantly affect forwarder efficiency and client satisfaction

(Dzakah Fanam et al., 2018; Ergin & Alkan, 2023; Ho et al., 2017; Lukinskiy & Lukinskiy, 2015).

3. Methodology

3.1 Data Description

The dataset used in this study consists of 983 shipment records collected from 37 freight forwarding companies operating in Egypt, covering a variety of shipments features such as service cost, cargo type, port of loading, port of discharge, importer country, and shipping line. The data spans the year 2022 and includes key variables relevant to the decision-making process for selecting shipping lines.

Table 2 lists these features and describes them.

Table 2. Summary of Dataset Features and Descriptions

Feature	Description	Type
Cargo	**TYPE OF CARGO BEING TRANSPORTED**	**QUALITATIVE**
Industry	**INDUSTRY ASSOCIATED WITH THE CARGO**	**QUALITATIVE**
Port of Loading	**DEPARTURE PORT FOR THE CARGO**	**QUALITATIVE**
Port of Discharging	**ARRIVAL PORT FOR THE CARGO**	**QUALITATIVE**
Importers Countries	**COUNTRIES WHERE THE IMPORTERS ARE LOCATED**	**QUALITATIVE**
Service Cost (USD)	**COST OF SERVICE PER TONNAGE IN USD**	**QUANTITATIVE**
Shipping Line	**NAME OF THE SHIPPING COMPANY**	**QUALITATIVE**

The data cleaning process involved handling missing values, removing outliers, and standardizing the service cost to a common currency using the Central Bank of Egypt's exchange rates. Additionally, new features such as Service Cost per Tonnage were engineered to improve model accuracy.

3.2 Model Training and Evaluation

three machine learning models— Decision Trees, K-Nearest Neighbors (KNN), and Naive Bayes—were trained and validated using an 80-20 train-test split. The following evaluation metrics were used to compare model performance:

- Accuracy: The express the ratio of correctly predicted observations to total observations (Tohka & van Gils, 2021).
- Precision: The the ratio between true positive predictions and the total amount of positive predictions (Hicks et al., 2022).
- Recall: The ratio between correctly classified positive samples and all samples assigned to the positive class (Hicks et al., 2022; Tohka & van Gils, 2021).
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of model performance (Hicks et al., 2022; Tohka & van Gils, 2021).

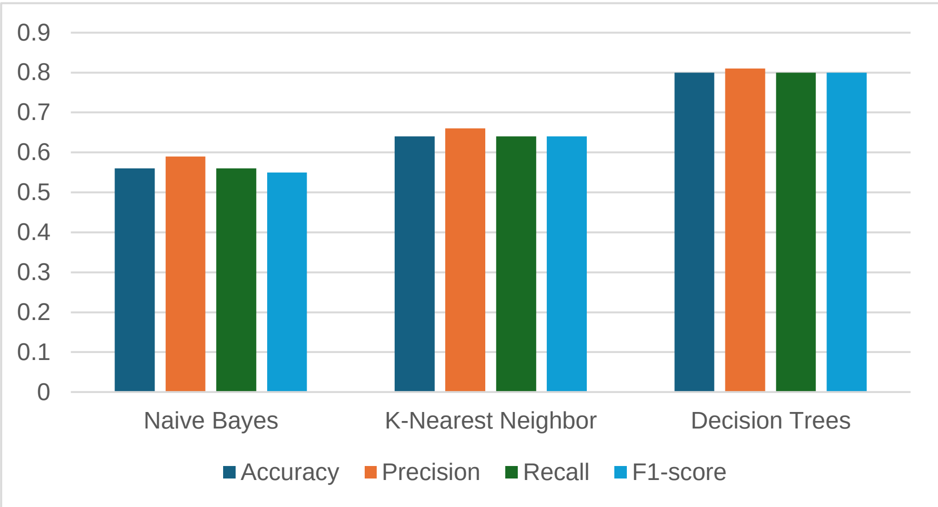
4. Results

4.1 Model Performance Analysis

This study's main goal is to assess how well various machine learning models perform when it comes time to predict shipping selections—from a cost perspective—for a freight forwarder. The

models used were Decision Trees, K-Nearest Neighbors (KNN), and Naive Bayes. They were trained on a dataset of 983 shipment records, and then their performances were compared using four key metrics: accuracy, precision, recall, and F1-score.
The figure below shows the performance metrics of each model:

Figure 1: Performance metrics for Cost-Effective Shipping Line Prediction



4.1.1 Naive Bayes Performance

The Naive Bayes model has significant problems in predicting shipping lines that are cost-effective. Its accuracy is just 0.56, which amounts to a correct prediction in only 56% of cases. Naive Bayes does not make a clear enough distinction between the two classes—cost-effective and non-cost-effective. Its precision score of 0.59 indicates that it's not the class of cost-effective shipping lines that has been identified that's cost-effective; rather, it's nearly 41% of the time that we've encountered false positives. Finally, when we look at recall, with an F1 score of 0.55, we get a very weak result. In summary, Naive Bayes ranks as the least effective model within the ensemble, rendering it unsuitable for maintaining high-quality logistics decision-making.

4.1.2 K-Nearest Neighbor (KNN) Performance

In our assessment of economical shipping lines, the K-Nearest Neighbor (KNN) algorithm surpassed Naive Bayes. With an accuracy of 64%, KNN uses a distance-based approach that is more suitable for this dataset, but it also shows potential for enhancements. KNN's precision is 0.66, which means that we can have a certain level of trust in about two-thirds of the identified cost-effective shipping lines—certainly an improvement over Naive Bayes, but still risky in terms of false positives. KNN's recall is 0.64; it recognized nearly two-thirds of the true cost-effective shipping lines, which I suspect also represents a slight improvement over the recall of our previous model.

The KNN algorithm is very good at identifying the correct class for positive instances, albeit it does include some false positives in the result. Its F1-score of 0.64 indicates that the KNN algorithm has a moderate balance of precision and recall. It is a good algorithm to use in contexts where we are slightly okay with identifying some negative instances as positive (false positives) and identifying some positive instances as negative (false negatives). It has an intermediate performance across all the metrics we considered in our analysis, making it a reasonable choice for solving uncomplicated, low to medium complexity logistics decisions. On the other hand, KNN is sensitive to data scaling and not the best algorithm if you put priority on computational requirements.

4.1.3 Decision Trees Performance

The model used for decision trees showed great effectiveness when it came to predicting the selection of a cost-effective shipping line. It achieved a gratifying 80% accuracy level and classified nearly all our shipping line choices in the test dataset just right. Overall, this model would be a good tool for a freight forwarder who wants to maximize selection of a low-cost line.

The model achieved a precision of 0.81, meaning that 81% of the shipping lines classified as cost-effective were indeed correct. This small false positive rate instills confidence in the model's ability to identify true cost-effective alternatives—in other words, it mostly doesn’t mistake mediocre shipping lines for outstanding ones.

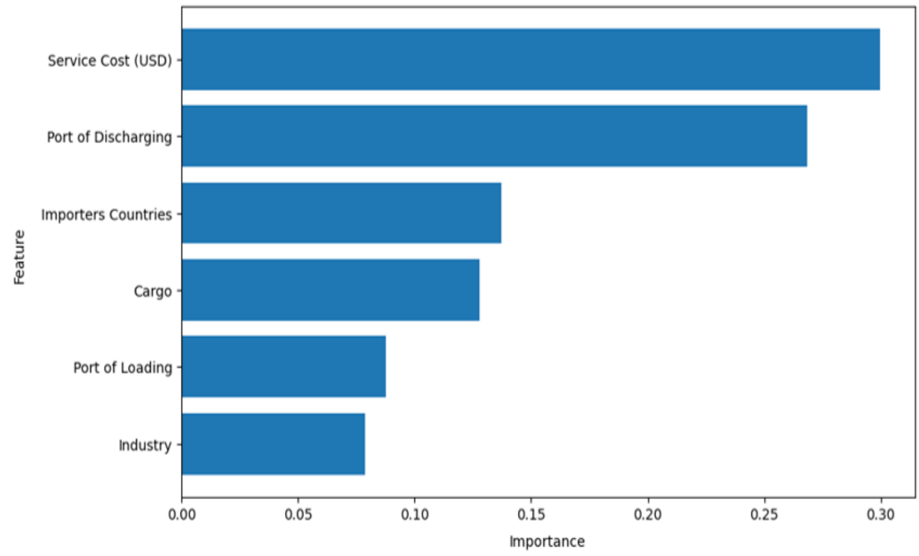
The model also attained a recall score of 0.80. This means that it identified 80% of the actual cost-effective shipping lines and did so without many missed opportunities. Grasping the meanings behind these two scores gives a solid sense of how competent this model is at performing its designated task.

The F1-score of 0.80 exhibits a nearly perfect balance between precision and recall, making Decision Trees a robust second-choice model for identifying cost-effective alternatives to standard treatments. The algorithm not only identifies the standard-cost-effective options but also finds a good number of both standard and nonstandard cost-effective alternatives.

To sum up, the preeminent model that emerged was the Decision Tree. It surpassed its competitors in all the metrics we used for evaluation. It not only predicted effectively but also furnished us with a usable model that contained understandable "decision rules." These rules made sense and, when following them, you would arrive at the same decisions that you would if you were following the model's more algorithmic path. This combination of performance and good use-model makes the Decision Tree the best choice for anyone wanting to pick a model for this kind of problem.

Decision Tree Model delineated the important features including service cost, port of discharge, importer countries, port of loading, cargo, and industry as illustrated in Figure 2. Service Cost is considered a principal predictor of the shipping line with a score of 0.3, Port of discharge attained a score of 0.27, while importer countries and cargo received scores of 0.137 and 0.128, respectively. The port of loading was assigned a score of 0.087, and the final feature, industry, exhibited the lowest significance with a score of 0.078.

Figure 2: Decision Trees Features Importance for Cost-Effective Shipping Line Prediction



5. Discussion

5.1 Interpretation of Results

When we stacked up the models, we found that Decision Trees was the standout. It was the best machine learning model overall for making good predictions about which shipping line choices would be the best ones in terms of cost. On four key metrics, it notched the highest scores, accuracy was 0.80, and precision, recall, and F1 were all at 0.81. What makes Decision Trees a champion among models? It's their ability to see complex interactions between service cost, transit time, port characteristics, and so forth—factors that render logistics decision-making a kind of multifactorial nature problem.

The K-Nearest Neighbor algorithm (KNN) achieved satisfactory results, with an accuracy of 0.64 and an F1-score of 0.64. But it is sensitive to how data are scaled and uses a lot of resources when it is run. So, if it were to be used on a large scale, say for large-scale logistics operations, or with datasets having many dimensions (which is often the case with logistics data), KNN might tend toward ineffectiveness. The Naive Bayes algorithm performed the weakest of all the alternative algorithms under consideration. It attained an accuracy of only 0.56 and an F1-score of 0.55. The reason for this poor performance seems to be Naive Bayes very simplistic assumptions that the algorithm makes, which don't hold in the context of logistics data.

5.2 Practical Implications for Freight Forwarders

The findings from this study provide valuable insights for freight forwarders seeking to optimize their shipping line selection processes:

- Understanding how to use and integrating Decision Tree models into their decision-support systems can greatly benefit freight forwarders. Doing so will help them predict with high accuracy the most cost-effective shipping lines and, in turn, will help them create additional decision rules that make digesting their complex data into complex yet simple enough insights that's actionable.

- Using machine learning models enables freight forwarders to make important decisions based on more than just tradition and experience. They allow for the analysis of vast quantities of data and can improve decision-making. They provide for the kind of operational excellence that can lead to cost savings and improved efficiency.

5.3 Comparison with Existing Literature

The current research investigates the application of machine learning in the decision-making process, particularly concerning selecting a shipping line that is cost-effective. It offers a summary of how freight forwarders can arrive at palatable choices, affirming some theories while introducing new concepts to the field. The work is based on prior studies regarding data analytics and decision-making within the realm of logistics.

The results from the machine learning analysis confirm that cost-effective shipping line predictions can be made quite accurately using decision trees. This is consistent with a handful of studies (Cheng et al., 2019; Jian, 2017; Mariappan et al., 2023), that have found decision trees to be a good bet for predictions involving logistics outcomes.

In contrast, naive Bayes was not a good performer in this regard, a finding that directly supports several previous studies, including (Hathikal et al., 2020b; Hossain et al., 2023), that have called naive Bayes less effective in making accurate predictions. Nonetheless, the study’s findings do suggest that if one is going to predict something related to logistics, one should probably opt for decision trees rather than either of the two algorithms mentioned before.

6. Conclusion

The shipping line selection problem of freight forwarders appears to have a solid solution pathway through the usage of machine learning models. This study's primary focus was on determining the models' capabilities of identifying a cost-efficient shipping line choice. From a pool of three model candidates, the work uncovered the Decision Tree as the best performer and most reliable solution predictor. With an 81% accuracy score, the model cleanly passes through a freight forwarders' dataset of 983 shipments records.

To enhance the model's generalizability, the researchers recommend expanding the dataset to encompass a broader array of geographical regions and time periods. They also suggest using different machine learning techniques—such as random forests and gradient boosting for yield improvement. Because the current approach frames the predictive problem with a negligible consideration for either environmental or delivery sustainability, providing a more nuanced and practical tool for decision-making in complex logistics scenarios.

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