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Utilizing Machine Learning, Predicting Shipping Costs on a Freight Brokerage Platform

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Description

Setting shipping costs on a freight brokerage platform can be difficult if there isn't a precise cost standard. It can also be challenging to establish rates when transport brokers take advantage of their position in the market by charging excessive commissions. Additionally, fares are undervalued in relation to the labor input because there is no quantified fare policy in place. As a result, car owners are working for less money than they are worth. This study presents the recommended shipping cost provided by a machine learning-based price prediction model and the main variables that influence its setting. Four algorithms were used to construct the cost prediction model: XGBoost regression, LightGBM regression, multiple linear regression, and deep neural network regression. The performance evaluation index was R-squared. LightGBM was selected as the model with the highest explanatory power and the quickest processing speed in light of this study's findings. In addition, realistic usage patterns were taken into consideration when determining the range of the anticipated shipping costs. The range of the predicted shipping costs was calculated using the confidence interval, and the dataset was classified using the K-fold cross-validation method for this purpose. This paper could be used to raise utilization rates and set shipping costs on freight brokerage platforms. Internet transactions are on the rise, and the logistics market is also being developed. The parcel forwarding service has expanded and numerous logistics centers have been constructed. The volume of general freight has been steadily rising. Even with the COVID-19 outbreak, domestic freight transportation via roads has been emphasized. After the COVID-19 outbreak, the traffic volume of small and medium-sized vehicles used for freight transportation increased between and As a result, domestic road freight transportation is crucial to boosting the logistics market. However, there is no precise standard for the domestic freight industry's shipping costs. Currently, only distance and vehicle tonnage are taken into account when determining shipping costs. Because it does not take into account a variety of freight characteristics and is difficult to implement in practice, this is only intended as a guide for new market entrants. The shipper's expertise is used to determine shipping costs. The shipping costs are set by shippers based on the current market price and the shipping costs of similar freights in the past. Shipping costs are undervalued in comparison to labor and unreasonable from the point of view of vehicle owners; additionally, some transportation agents take advantage of their superior market position to charge excessive commissions. Current vehicle owners are extremely dissatisfied as a result of this circumstance, which is made up of intense disagreements between shippers and the owners of the vehicles [1,2].

Using data from a freight brokerage platform, a machine learning-based method for predicting shipping costs for domestic freight transportation is proposed in this paper. In addition, it compares predictive power to identify the best predictive model and demonstrates that predictive models are able to appropriately set shipping costs. For six months, we used data from the freight brokerage platform that related to transportation. New factors were added and various preprocessing techniques were used to identify the major factors. The major factors were determined using a step selection method and correlational analysis. After that, we used the derived factors and a machine learning algorithm to create a fare prediction model. Multiple linear regression (MLR), deep neural networks (DNNs), extreme gradient boosting (XGBoost) regression, and light gradient boosting machine (LightGBM) regression were the machine learning algorithms that we utilized. Compared to the XGBoost model, LightGBM's learning time is shorter [3]. We demonstrate a method for determining the range of predicted fares in light of actual usage patterns; The user should be able to see the fares as a range rather than as a single value. k-fold cross-validation was used to generate thirty training sets in total. For each iteration, we trained the sets and predicted the test set. A confidence interval was calculated and an appropriate fare range was presented, assuming that the 30 derived predicted values have a normal distribution. The predictive model's performance evaluation index was R-squared [4.5].

Conclusion

This paper's structure is as follows: Section 4 discusses the derivation of the major factors, while Section 5 provides an explanation of the theoretical background and previous research. The model's construction and outcomes are explained, and then the conclusions and directions for future research are presented. The main factors that affect the setting of shipping costs were derived in this study, and a price prediction model was constructed using machine learning, in order to address the issue of fare setting on a freight transportation brokerage platform where there is no standardized shipping cost. From a total of 73 factors, correlational analysis and the stepwise method were used to select factors that affect shipping costs. These factors include factors obtained from the freight brokerage process and environmental factors like precipitation. Cargo characteristics, vehicle owner characteristics, and environmental factors were the ones chosen. A shipping cost prediction model was constructed using these elements, and the results of each model were compared. The "freight weight," "loading/unloading location," and "loading/unloading time" were all cargo characteristic factors. The owner's "vehicle type" and "vehicle tonnage" were included as characteristics. An element of the environment was the precipitation. The analysis showed that machine learning models like the DNN, XGBoost, and LightGBM performed better than traditional analysis methods like linear regression. Among the models used, the LightGBM model had the highest predictive power.

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Conflict of interest

No potential conflict of interest was reported by the authors.

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