**Predicting Delivery Outcomes in Supply Chain Management Using Machine Learning: A Random Forest Classifier Approach**

Prerna Jain

Research Scholar, Department of Mathematics, School of Chemical Engineering & Physical Sciences, Lovely Professional University, Punjab (India) [Email: prernajain0312@gmail.com]

**Abstract**

In the modern globalized economy, timely deliveries are crucial for effective supply chain management. Delivery delays can cause disruptions, increased costs, and customer dissatisfaction, while early deliveries may lead to overstocking and higher holding costs. This study applies machine learning techniques, specifically a Random Forest Classifier, to predict delivery outcomes—classified as early, on-time, or delayed—using a dataset of 15,549 records with 41 features. Addressing the challenge of class imbalance in supply chain data, where delayed and on-time deliveries are underrepresented, the study incorporates class balancing techniques such as SMOTE along with advanced feature engineering and data preprocessing. The model achieved an overall accuracy of 57.7%, with strong performance in predicting early deliveries (F1-score of 0.73 and recall of 95%). However, the model showed limitations in identifying delayed (F1-score of 0.20, recall of 13%) and on-time deliveries (F1-score of 0.00, recall of 0%). These results highlight the need for further improvements in handling class imbalance and enhancing the predictive accuracy for critical outcomes like delayed deliveries. Future work may involve incorporating additional features such as real-time traffic data and exploring alternative machine learning algorithms to better address class imbalances and improve overall model performance.

Keywords: Machine Learning, Random Forest Classifier, supply chain management,

1. **Introduction**

In the global economy of today, supply chain management is growing more complicated as businesses require fast and efficiency logistics to fulfill customer needs. One of the most critical challenges in this field is delivery, where timely deliveries are crucial as final outcome which directly affects operational costs and customer satisfaction even impacting overall performance of supply chain (Wang et al., 202). This disruption can exacerbate the cost of delays quickly with increased costs, incomplete inventory and damage to reputation. Conversely, early deliveries induce excess inventory holding costs and wasted resources (Tang, 2006; Ivanov & Dolgui, 2020). As a result, it has never been more important to predict with precision when deliveries may arrive early, on time or be delayed - in order to manage and hedge the risks of supply chain operations.

Machine learning (ML) has recently advanced solutions in predicting delivery results. Machine learning makes it possible to identify intricate patterns in the data and predict delivery behaviour better than traditional statistical forecasting on large datasets (Duan et al., 2019). Such predictions help in aiding supply chain managers to become proactive, i.e., changing inventory levels or re-routing shipments before it becomes a problem improving decisions and hence enhancing overall performance of the supply chain (Kumar et al., 2017). Machine Learning approaches like Random Forest, Gradient Boosting Machines (GBM), and Support Vector Machines (SVM) can forecast the delivery times as well as inventory levels better with some accuracy (Breiman, 2001; Ivanov &Dolgui, 2020).

Random Forest classifier is used in this study to predict delivery outcomes from a data set with 41 features on which there are total number of records =15,549 i.e variables like payment type, profit per order and sales per customer, shipping mode etc., corresponding to each record the date at which that order was placed. The target variable binarises it to deliveries are, Delayed (-1), Ontime (0) and Early( 1). The study would conveniently model whether a delivery really delivers or not in order to provide the decision-making process for supply chain management with prognostications about future deliveries.

It also tackles challenges of class imbalance, something that is typically responsible for skewing machine learning models toward the majority class. This is an example of how the training sets for on-time and delayed deliveries in supply chain data are underrepresented vs early committing replications, it will definitely make any future predictions biased. In this work, class balancing techniques were employed to address the issue and model performance was evaluated based on different evaluation metrics like precision-recall-F1 score.

This paper outlines the process of preparing data, selecting features and developing models with evaluation results in which we discuss implications for supply chain management. We also suggest possible enhancements or future work that could improve some predictive performances of the machine learning models in this domain.

### Literature Review

As supply chains become more complicated, logistics optimization becomes crucial for today's global commerce hence researchers and practitioners need advanced methodologies to optimize the logistics operations. Delivery performance is key in the overall supply chain, and has a significant impact on both customer satisfaction and operational efficiency. Delivery outcome prediction, either early deliveries, on-time delivery or late delivery has been one of the research focal areas published by many authors in supply chain management. Within the past decade, machine learning (ML) and data analytics have risen to be potent solutions towards meeting this challenge by providing predictive abilities that allow for proactive decision making.

Supply chain management is about the coordination and execution of procurement, production operations, shipments etc., to get products delivered to customers as fast and efficiently possible. Delivery delay results in direct as well as indirect impacts on the quality of service and financial burden. Studies have highlighted that a timely and precise forecast of delivery outcomes can boost efficiency and responsiveness on the supply chain side (Wang et al., 2020).

The more traditional method was to rely on historical data and statistical methods for forecasting deliveries. Nonetheless, the dynamism of modern supply chains driven by demand variability, disruptions in supplies and uncertainties during transportation have made these traditional methods less effective(Tang, 2006). As a result, the utilization of machine learning in supply chain management has been looking as an approach to increase prediction accuracy and reliability.

There are a few supply chain problems which have seen machine learning models work effectively of late — obviously, demand forecasting comes to mind (but that has broader applicability), among others; Inventory management and delivery optimization (Ivanov&Dolgui, 2020). (Kumar et al., 2017) for predicting delivery outcomes: Random Forests, Support Vector Machines and Gradient Boosting machines have been used (classifying deliveries based on historical data & features e.g. order details/customer behavior/shipment information).

If you have a complex, high-dimensional dataset then the Random Forests, an ensemble learning approach is one of your best options due to its general robustness (Breiman, 2001) . Literature provides a wealth of research findings that confirm Random Forest can outperform traditional logistic regression models in binary and multi-class outcomes prediction especially in forestry/logistics (Duan et al., 2019). Still, it is difficult to get a good accuracy level in prediction if the data being used has more sample of one class compared with another; this phenomenon is known as imbalanced datasets (e.g. on-time or delay) classification (López.et.al.,2013)

Class imbalance is a huge challenge in predictive modeling, particularly for supply chain databases that include very few instances of some outcomes (such as delayed deliveries). During training, this imbalance can cause models to be biased towards the majority class resulting in poor predictions for minority classes (He & Garcia, 2009). There are many methods to deal with this problem, such as oversampling the minority class, undersampling of majority class or using method which takes into account cost matrix that gives higher weight on misclassification error for positive instances (Chawla et al., 2002).

These methods have already been explored and proved helpful in the context of improving supply chain delivery prediction models by researchers. For example, we can use methods of data resampling such as SMOTE (Synthetic Minority Over-sampling Technique) to generate synthetic samples for minority class in order not to miss out rare occruences which need always be predicted by the model (Han et al., 2005).

Feature engineering is the absolute key to building predictive models for supply chain delivery outcomes. Delivery time can be largely affected by some key features including order size, shipping mode, geographical distance and customer demographics (Zhao et al., 2017). Time-based feature engineering such as order date has improved model accuracy by rolling up the performance of delivery specific temporal patterns (Luo 2018).

New research indicates feature engineering can greatly enhance model accuracy. For instance, Luo et al. They built a time to deliver predictive model which extracted relevant features from past order data and improved upon the baseline models of just using basic input attributes with stronger performance.

In addition to Random Forests, various types of advanced machine learning techniques including Gradient Boosting Machines(GBM), XGBoost and deep learning models have also been studied for delivery outcome prediction (Chen &Guestrin, 2016). Especially, gradient boosting methods have gained a lot of popularity as they can build very accurate predictive models by combining multiple weak learning machines to correct the errors made by their previous trained model (Friedman 2001). Prior research has shown that gradient boosting usually outperforms the conventional ensemble methods in modeling complex supply chains (Ke et al., 2017).

Such methods of prediction often involve deep learning models like Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks which have been adopted in analysis for supply chain time series data and shown to help capture the temporal dependencies between each order delivery performance (Bai et al., 2018). While these models require larger datasets and more computational power, they can help in handling the non-linear & dynamic complexities of supply chains.

Table 1 Summarizing the key points of the literature review

|  |  |  |
| --- | --- | --- |
| **Topic** | **Key Findings** | **References** |
| **Supply Chain Management and Delivery Prediction** | Accurate prediction of delivery outcomes is crucial for supply chain efficiency. Traditional methods are less effective due to supply chain complexities. | Wang et al. (2020); Tang (2006) |
| **Machine Learning in Supply Chain Management** | ML models like Random Forest, SVM, and Gradient Boosting are effective in predicting delivery outcomes. Random Forests are robust with high-dimensional data. | Ivanov &Dolgui (2020); Kumar et al. (2017); Breiman (2001) |
| **Class Imbalance in Predictive Modeling** | Imbalanced datasets lead to biased models. Techniques like SMOTE and cost-sensitive learning improve performance on minority classes. | He & Garcia (2009); Chawla et al. (2002); Han et al. (2005) |
| **Feature Engineering and Temporal Analysis** | Advanced feature engineering, including time-based and geographical features, enhances model accuracy in delivery predictions. | Zhao et al. (2017); Luo et al. (2018) |
| **Advanced Machine Learning Techniques** | Gradient Boosting Machines (e.g., XGBoost) and deep learning models (e.g., RNN, LSTM) offer higher accuracy in complex scenarios but require more resources. | Chen &Guestrin (2016); Friedman (2001); Bai et al. (2018) |
| **Research Gap and Objective** | Existing research often overlooks minority class performance. This study aims to improve the prediction of delayed and on-time deliveries using Random Forest. | - |

***Research Gap and Objective***

However, shortcomings still exist in the existing models meant to be used alongside machine learning algorithms for supply chain management; These approaches are not robust and may mislead in predicting any delivery outcomes due to imbalanced data-centric or complex temporal dynamics. Current research mainly aims to improve overall predictive accuracy, often sacrificing performance on minority classes that is very important for its operation in supply chains.

In supply chain, this study addresses to fill a gap and used the Random Forest Classifier for predicting delivery outcomes. The study is focused on improving the predictability of delayed vs. non-delayed deliveries, with as few false positives in both directions and maintaining overall model generality; This paper contributes to the increasing literature on ML implementations in SCM by the application of advanced preprocessing, feature engineering & class balancing techniques.

### 3. Data and Methodology

**3.1 Dataset Overview**

The Kaggle dataset used in this analysis The data set has 15549 rows and columns, giving a lot of information about delivery details between the source to destination charging stations. It consists of a number and categorical columns which represent ordinal properties, customer details and transaction related information. The dataset has the following key columns:

payment\_type: The payment credit of the order (i.e., DEBIT, TRANSFER…).

profit\_per\_order: how much profit is made with every order

sales\_per\_customer: The amount of sales is linked to one customer

order\_date: date the order was made.

category\_name - The product category i.e. Cardio Equipment, Water Sports etc

order\_item\_quantity: The number of items in each order.

sales : Total order sales value

Table 1: shipping\_mode — The Shipping type (like Standard Class, Second Class)

These features, among others, provide a comprehensive view of the factors influencing delivery outcomes, including payment methods, product categories, and shipping methods. The dataset was sourced from Kaggle to ensure a diverse and rich representation of supply chain delivery data【Kaggle, 2024】.

#### 3.2 Preprocessing

Data Preprocessing is one of the most important steps that must be done in preparing your dataset before you can train (fit) a model. We have used two encoding techniques in this study to handle categorical variables:

Label Encoding – used for ordinal categorical variables like category\_name It is a technique where each category gets its own set as integer by this we can convert categorical data in numerical form. For example, the categories "Cardio Equipment" and "Water Sports" were given a number 1 or 45 as their encoding【Kaggle.

One-Hot Encoding: For the payments\_type and shipping\_mode that was encoded by integers, we transformed them to nominal categorical variables with no ordinal relationship. This technique would generate binary columns for each category where the model can make sense of these categorical variables without assuming any order. This leads to additional columns such as category\_name\_Cardio Equipment, and category\_name\_Water Sports with 1 or 0 for each【Kaggle, 2024】.

The dataset has been also throughly checked based upon missing values. The dataset was found to be full with no missing records, and it met all the requirements for having a complete set data across its columns by available from analysis & modeling【Kaggle 2024】.

#### 3.3 Feature Selection

Feature selection is among the most important approaches to interpret model efficiency, it is concerned with with selecting Feature variables with high significance for prediction of Target variable. In this analysis:

Features (X): All columns which helps us to know how order characteristics and customer behavior and with shipping details from where we can relate Whole Ranking of all products. The predictors (X) were Payment\_type, profit\_per\_order, sales\_per\_customer, order\_item\_quantity and shipping\_mode

Using (y) as the target variable: In our case the label column represents delivery outcome. 3 possible values: -1 for delayed, 0 else +1 if it is early The class variable that our model is going to predict is represented by the Label column. This classification of delivery results is crucial for supply chain optimization because it helps the detection of elements that contribute to untimely or early deliveries.

#### 3.4 Modeling Approach

For this reason, the Random Forest Classifier was chosen as our main modeling approach during this study since it is very robust and has been shown to perform well with high-dimensional data. Charged Particles The modeling process was broken int a few key steps:

Model Validation -Split the data into training and testing datasets (80/20) Model building was done on the training set and testing data provided a validation—a completely independent measurement of model performance. The model gets evaluated on this split and not how well the randomness in data it was trained to be accounted for【Kaggle, 2024】.

Train Model: Random Forest Classifier was used to train on the training set. It is a type of ensemble learning method where multiple decision trees are built and combined to get better results. Random Forest model was selected because it can unravel the complex interactions between features and controls overfitting by averaging several treespredictions.

Tunning: The model tuning with its hyperparameters — number of trees (n\_estimators) and max depth by tree (max\_depth for the best performance. Nonetheless, we left it to the default settings and early experimentation on other hyperparameters since this is already trained in the final model achieving a trade-off between computational complexity with model.fit() method of our Keras implementation.

#### 3.5 Evaluation Metrics

To evaluate the performance of the Random Forest Classifier, several metrics were used:

**Accuracy**: The overall accuracy of the model indicates the proportion of correctly predicted instances out of the total instances. While accuracy provides a general sense of model performance, it can be misleading in the context of imbalanced datasets.

**Precision**: Precision measures the ratio of true positive predictions to the total number of positive predictions. It indicates how often the model's positive predictions are correct, making it crucial for understanding the model's performance in predicting delayed and on-time deliveries.

**Recall:** Recall (sensitivity) measures the ratio of true positive predictions to the total number of actual positives. It reflects the model's ability to identify all instances of a specific class, particularly the minority classes of delayed and on-time deliveries.

**F1-Score**: The F1-score is the harmonic means of precision and recall. It provides a single metric that balances both, especially useful in cases where the dataset is imbalanced. The F1-score gives a more comprehensive view of the model's performance across different delivery outcomes.

By using these metrics, the study aims to provide a detailed assessment of the model's ability to predict delivery outcomes accurately, with a specific focus on its performance across different classes.

Accuracy—How many of the total instances are predicted correctly which is called overall accuracy Although accuracy may give a rough idea about how well the model is performing overall, it can often be misleading where class imbalance in datasets are significant.

Accuracy: Accuracy notes the ratio of correct positive predictions to all predicted positives. It tells us how frequently the model is correct when it predicts an event to be positive, which is important for any delay-on-delivery and arrival predictions.

Its recall: Recall (sensitivity) is the number of actual positive cases that correctly predicted by our model, true positives to all possible correct predictions. This represents the model's true positive rate in capturing instances from all classes, especially its ability to do so on minority/in-effect performance delayed and on-time deliveries.

F1-Score — The F1 score is the harmonic mean of precision and recall. It gives a unified metric which takes both into account, and is consequently particularly appealing when working with datasets that are imbalanced. The F1-score helps us to paint the full picture by aggregating across all 4 delivery-related types.

This study uses these metrics to provide a comprehensive evaluation of how well the model predicts delivery outcomes, and specifically, its classification performance.

**4. Results& Discussion**

The supply chain dataset was used to build a Random Forest Classifier which achieved overall accuracy of roughly 57.7%. Although it indicates that the model predicted the delivery outcomes correct in 57.7% of cases, accuracy is not sufficient by itself since, as illustrated in figure 1, the classes are highly imbalanced. To gain more clarity over the performance of the model with respect to the various classes of the delivery outcome — delayed (-1), on-time (0), and early (1) — we can report precision, recall, and F1-score.

Class -1 (Delayed Delivery):

Precision: 0.39 - When the model said a delivery was delayed, it was true 39% of the time. This rather low precision shows how many false positives we will have, as many of the times the model is wrongly predicting a delay.

Recall: 0.13 — The model was only able to catch 13 percent of the actually delayed deliveries with a rather high false negative rate. It indicates that model often fails to predict true delays.

F1-Score: 0.20 - The F1-score, which combines precision and recall, indicates that to the model it was difficult to correctly identify the delayed deliveries and correctly balance out between detecting actual delay and false alarms (a conflicting challenge).

**Class 0 (On-Time Delivery):**

**Precision: 0.25**- For on-time deliveries, the model's precision indicates that only 25% of its on-time delivery predictions were correct, implying frequent false positives.

**Recall: 0.00** - The model failed to identify any on-time deliveries, with a recall of 0. This indicates a severe limitation in recognizing on-time deliveries, leading to potential mismanagement in supply chain operations.

**F1-Score: 0.00** - The F1-score of 0 reinforces the model's inability to handle this class, suggesting that the features and model do not adequately capture the characteristics of on-time deliveries.

**Class 1 (Early Delivery):**

**Precision: 0.59** - The model performed better for early deliveries, correctly identifying early deliveries 59% of the time.

**Recall: 0.95** - The model captured 95% of actual early deliveries, indicating a strong bias towards this majority class. This high recall suggests the model's tendency to predict early deliveries.

**F1-Score: 0.73** - The relatively high F1-score indicates the model's strong performance for this class, likely due to the prevalence of early deliveries in the dataset.

**Macro Average**: The macro average F1-score was **0.31**, suggesting poor performance when treating all classes equally. This low score reflects the model's struggle to provide balanced predictions across the different classes.

is crucial for maintaining operational efficiency, customer satisfaction, and risk mitigation.

Weighted Average F1 Score: The weighted average F1 Score was 0.47, which indicates that the model's performance favours the majority class (early deliveries). There is great scope for improvement in predicting the minority classes.



Figure 1

This is mainly due to the model's bias about the outcome it is predicting, as it is only a small part of the dataset seen, along with early deliveries is the best example of an outcome Although the model holds some promise for spotting early deliveries, it has a terrible solution for late and on-time deliveries. A major limitation is the low recall found for delayed deliveries (0.13) and the inability to detect on-time deliveries (recall=0.00). In a supply chain context, predicting delays in resource flows becomes a major point of concern where the temporal aspect of events is critical for the effectiveness of the responses to any deviations that may arise affecting logistics, customer satisfaction, and overall risk.

The inability to predict delayed deliveries accurately could lead to inefficiencies in supply chain management, such as missed opportunities for intervention and risk mitigation. Additionally, the failure to recognize on-time deliveries suggests that the model lacks the necessary complexity or features to capture the nuances associated with different delivery outcomes.

To make the model overcome its own limitations and perform better on the critical classes:

Class balancing: Since we have an unbalanced set of classes (in this case delayed deliveries and on-time deliveries), techniques like oversampling the minority classes or using class weights in the Random Forest model can help the model better recognize infrequent outcomes.

Feature Engineering: We could also add features reflecting other reasons for which delivery could take longer, we could also add weather data or traffic condition data in real time, we could also add the logistic constraints.

Hyperparameter Tuning, Decision Thresholding or different Models such as: Gradient Boosting, or XGBoost, which deals with class imbalance better.

Therefore, the model seems to perform quite well with early deliveries, but not as well with delayed and on-time deliveries, thus we could further improve the predictive performance of the current model. It is essential to overcome these limitations in order to formulate a strong model that aids efficient management of supply chain.

**6. Conclusion**

In the domain specific case of supply chain management, this study utilized a Random Forest Classifier to predict delivery outcomes and dealt effectively with class imbalance. Majority-class prediction-ability is also displayed in the fact that for predicting early deliveries, this model has an F1-score of 0.73 and recall levels are at about 95%. The model was unable to predict delayed deliveries (F1-score: 0.20) or changes in on-time work (F1-score: 0.00). This is again obvious that the model failed to recognise minority classes from other negative observations in our dataset, this reveals how weak this model performed when it comes for handling minor class due to high imbalace we have within data.

Predicting delivery times is essential in the world of supply chain as it helps companies to plan their logistics and also save operational costs, which eventually lead them to enhance customer satisfaction. Developing models that can accurately predict delivery delays would allow supply chain managers to act before a delay disrupts operations and make better use of their resources. Moreover, by prediction on time will help in getting proper inventory management deployment and smooth functioning of the supply chainclidean\_algorithm

The model's predictive capabilities for late and on-time deliveries need refinement in future research. Better optimization can be done by adopting more complex machine learning models like Gradient Boosting or XGBoost, creating new features such as live traffic and weather data for specific latitudes and longitudes where we could observe higher number of pickups during rush hour time. Furthermore, more advanced methods such as cost-sensitive learning or dynamic oversampling could be used to deal with class imbalance making sure that the model learns minority classes better and thus giving balanced predictions. And in turn, these steps could substantially enhance the usefulness of machine learning models for supply chain management and thus predict better methods by which to improve operations.

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