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Shipment delay prediction and feature importance analysis using random forest

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Abstract

The logistics sector plays a very important role in the functioning of the modern supply chain market by delivering goods in less time. With the advancement of globalisation, e commerce companies in the modern era have gained a very significant role in contributing to any economy. Therefore, any delays in the delivery of goods will have an adverse impact on the companies. This study deals with the factors that are usually responsible for the delays of any shipments. The data used in this study contains several logistics features like delay time, weather conditions like temperature, humidity, and other factors like waiting time, latitude and longitude. Initially, an Exploratory Data Analysis (EDA) was done on the dataset to understand the distributions of the variables and to understand which variables impact the logistics delay. The heatmap showed that all the variables used in this dataset have very little correlation with each other. Most of the variables were uniformly distributed. Hence, the random forest algorithm was used in this study to predict the logistics delay of the shipment. After optimisation, the random forest achieved an overall classification accuracy of about 73 percent. The model showed high precision for delay predictions and strong recall for non delay cases, although recall for delay cases remained moderate. Feature importance analysis identified heavy traffic and operational variables such as inventory level and asset utilisation as the most influential predictors, while weather related factors showed limited influence. This type of study will help the logistics firm to make decisions based on data, which could ultimately reduce the waiting time of the shipments and increase the efficiency of the firm. The findings support the shift from reactive problem solving to proactive, data driven logistics management.

Keywords: Shipment Delay Prediction, Random Forest, Supply Chain Logistics, Exploratory Data Analysis, Feature Importance

JEL Classification: C53, C55, L91

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1. Introduction

The progress seen in logistics and supply chain management over the years has changed the way companies plan and manage their operations. Previously, logistics was mainly treated as a support activity. The main aim was to transport, store, and deliver products at cost as low as possible cost. More attention was given to completing these day-to-day activities rather than to using logistics to create long-term value for the business. With the growth of industries came the expansion of markets and a rise in expectations of customers as far as service is concerned. However, the limitations of this strategy became more noticeable. Merely delivering a product was no longer enough. Companies also had to make sure that products reached customers on time and in a reliable manner. As a result, activities such as inventory control, order processing, packaging, and information management began to be handled in a more coordinated way. Logistics slowly emerged as an integrated network of previously individual activities to enhance efficiency, reduce response time and satisfy consumer demands (Christopher, 1998). These changes occurred in the 1980s and 1990s as international trade expanded. Companies started purchasing raw materials from different countries and selling their products in distant markets. This increased the connections between different parts of the supply chain. However, at the same time, it also increased the chances of delays and other problems affecting one part of the chain being passed on to other parts. The competition also increased, making companies maintain low inventories and maintain reliable deliveries. Logistics therefore became more important to the overall business performance. Christopher (1998) reasoned that effective logistics and supply chain management can help companies improve customer service while also reducing costs. Logistical stability was crucial in ensuring deliveries are timely, smooth operations, and competitiveness. With more sophisticated supply chains, transportation was no longer sufficient. Companies required improved coordination among various departments and improved monitoring of their performance. The logistics role thus broadened to include coordination of activities amongst various departments, business relationship management and business process control, starting with the goods movement through final delivery. Delays and uncertainty in transportation can affect different parts of a supply chain. A delay at an early stage can lead to missed deadlines, slower operations, shortages of products, and dissatisfied customers. Noland and Small (1995) observed that unreliable travel time can lead to high financial and operational costs for companies that work with tight schedules. Supply chain management was also changed with the development of new technologies. Warehouse management systems, GPS tracking and enterprise systems, as well as improved communication technologies, enabled companies to much more easily track shipments, manage inventory, and address problems. Simultaneously, logistics systems started to encounter several new challenges. Delivery networks are subjected to increased pressure due to rapid urban development, growing customer demands, increasing environmental issues and the increase in e-commerce. These problems are particularly important in cities, where traffic, limited space, and inadequate infrastructure can make deliveries more difficult. Allen (2012) established that freight

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transport is not only influenced by company-level decisions, such as inventory management, but also by factors such as the location of warehouses and the way cities are planned. Off late, the availability of data has further changed supply chain management. Current supply chain models produce large amounts of information through tracking systems and routine operational records. This information can be used not only to understand what has already happened but also to identify possible problems in advance. Companies now have to maintain efficiency while also preparing for issues such as traffic, bad weather, and sudden changes in demand. This has increased the use of machine learning and artificial intelligence in logistics (Tsolaki, 2023; Oğuz & Yalçıntaş, 2024; Rane, 2024).

This has slowly transformed logistics from a problem-solving process into an attempt to predict problems. Conventional approaches are usually perceived in conventional ways, but machine learning can be utilized to predict possible outcomes in different conditions (Wang, 2016). Machine learning is of great use when it comes to transportation, because it can consider several factors at the same time. For example, Random Forest has been used to predict travel times and deal with uncertainty caused by traffic. Machine learning has also been used to predict arrival times in ocean shipping, intermodal transport, and other freight operations (Balster, 2020; Hathikal, 2020; Steinberg, 2023). Even with these improvements, shipment delays continue to be a major problem. A delay is often not caused by a single factor. Traffic conditions, waiting time at facilities, limited resources, and weather conditions such as temperature and humidity may all contribute to delays. This chapter looks at shipment delays using exploratory data analysis methods and machine learning. It considers both operational factors, such as traffic and waiting time, and environmental factors, such as temperature and humidity. A supply chain's performance depends on both internal management choices and outside conditions that are often unpredictable. The analysis of these aspects, along with machine learning and exploratory data analysis algorithms, can assist in explaining the reasons shipment delays occur, and the (potentially) data-driven approach can be utilised to improve logistics decision-making.

2. Review of Literature

The way logistics performance is understood has changed considerably over time. Logistics was once considered an operational support activity primarily, but it later evolved to be a significant organisational strategic capability (Christopher, 1998; McKinnon, 2015). Previously dominant strategies in supply chain management were more oriented towards operational effectiveness, especially in inventory management and delivery scheduling (Simchi-Levi, Kaminsky & Simchi-Levi, 2004). Some of the most commonly used measures of logistics performance included cost efficiency, order completion time, inventory levels and order handling (Beamon, 1999; Gunasekaran et al., 2001).

In this previous method, logistics performance was primarily determined by the ability of firms to manage their costs efficiently, fulfil orders, maintain stocks and make their deliveries on time.

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Internal weaknesses often included ineffective coordination among functions, ineffective warehouse operations and inappropriate routing decisions, which were often related to problems (Bowersox, Closs, & Cooper, 2013). These problems may result in delays in shipments, higher transportation costs, unreliable services and weaker supply chain performance. The effectiveness of internal processes in a firm was thus a major contributor to logistics performance. With the complexity of the supply chain, this perspective was extended to responsiveness, integration, and adaptability as well as management of uncertainty over longer networks. The development of supply chains and urban freight flow also made researchers take into account the situational factors beyond the firm. Reliable delivery depends not only on internal efficiency but also on external conditions. Road congestion, travel-time variation, infrastructure and the complexity of city logistics can directly affect timely delivery (Noland & Small, 1995; Allen et al., 2012). Logistics delays were consequently no longer understood only as outcomes of poor coordination or weak internal management. They could also arise from the condition and performance of the wider transportation system. Logistics delays therefore began to be examined at the system level, taking both firm-level practices and transport network conditions into account (McKinnon, 2015). The greater availability of logistics information, traffic data and real-time tracking systems has supported the use of predictive models in transportation and logistics. Hagenauer and Helbich (2017) provide relevant methodological evidence through their use of machine learning for transportation prediction problems. They compared different machine learning classifiers and examined their ability to model behavioural and transportation patterns using travel diary data. Their study did not directly examine shipment delays. Its relevance to logistics research comes from its demonstration that machine learning can handle non-linear relationships and improve prediction when outcomes are affected by several interacting variables. Shipment delay has a similar characteristic because it may depend on a combination of operational and contextual conditions that are difficult to represent through conventional linear models.

Wang (2016) provides a more direct connection to delay analysis through the use of Random Forest for travel-time prediction. The study demonstrates the usefulness of Random Forest in transport forecasting, particularly because it can handle large datasets and account for interactions among variables under uncertain traffic conditions. Since travel time is an important component of delivery delay, this work is relevant to the use of Random Forest for predicting logistics delays. Estimating the effect of traffic conditions on travel time can provide information that helps anticipate possible shipment delays. Wang (2016) therefore provides an analytical basis for using machine learning to convert transport data into information useful for transport planning and operational decisions. These studies indicate two important developments in the literature. One is the movement from describing transport and logistics performance to predicting it. The other is the increasing use of machine learning to deal with complex, non-linear and changing relationships in operational data. This is particularly relevant to logistics delays because they are rarely the result of one factor alone. Traffic, waiting time, operational inefficiencies and environmental conditions

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may operate together. The growing use of predictive methods is part of the wider shift towards data-based and proactive logistics and supply chain management. Reliability in delivery is still a significant aspect of supply chain performance. Responsiveness in time assists in keeping up with product availability, diminishing uncertainty and leading to customer satisfaction (Christopher, 1998). Delays may raise operating expenses since companies might have to maintain more inventory, production might be interrupted, and penalties could be imposed due to late deliveries (McKinnon, 2015). Similar results were also established by Stank, Goldsby and Vickery (1999), who concluded that both operational factors, such as timely delivery, and relational factors, such as communication with customers, have a common effect on customer satisfaction and supply chain performance. Chaudhari et al. (2025) discussed the increased application of Artificial Intelligence (AI) and Machine Learning (ML) in supply chain management and logistics. Their research states the ability of such technologies to manage large volumes of operational information and to assist in decision-making in complicated logistics environments. Artificial intelligence can assist companies in solving operational issues, predicting demand and making improved use of existing resources, contributing to the efficiency of supply chains. Milan Kumar (2025) also examined learning-based shipment tracking systems and their contribution to logistics efficiency. Such systems provide real-time visibility and can support improvements in the delivery process. Machine learning models can identify patterns from historical and real-time data and use them to support operational planning, scheduling and routing decisions (Maksym Alieksieiev & Nebava, 2024; V. G. Kotenko, 2022). Studies on AI use in logistics indicate a broader scope of applications. Oguz and Yalcintas (2024) reviewed the use of applications in demand forecasting, inventory management, and transport planning. Rane (2024) discussed how AI-based systems can enhance the capability of supply chains to respond to uncertainty. Specialised areas have also utilised machine learning and automation. Zevallos (2025) discussed such applications in ports and maritime logistics to enhance efficiency. These studies are indicative of the increased contribution of technology and data to logistics operations. Numerous studies have concentrated particularly on machine learning-based shipment-delay prediction. Balster (2020) developed an ETA prediction model, which is based on a machine learning model in international transport networks. The model generated predictions by considering individual transport legs together with historical transport information and external information. Hathikal (2020) used milestone-based shipment information from different logistics stakeholders to predict ocean import shipment lead time through machine learning. These studies show a movement away from examining delays only after they occur towards predicting potential delays before they affect logistics operations.

The broader literature on logistics analytics also points to the increasing role of AI and ML in transportation. Tsolaki (2023) identified delay prediction as part of the wider shift towards data-based logistics decision-making. Firms are using predictive models not only for performance monitoring but also to anticipate operational problems and respond earlier. The literature indicates that logistics delay is a multi-causal problem. A delivery may be late because of a combination of

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operational, temporal and contextual factors rather than a single variable. According to Muller (2025), machine learning is the appropriate approach to this type of problem since delays in delivery can be determined by heterogeneous and interacting predictors that are challenging to measure using simple analytical techniques. A systematic review conducted by Muller (2025) also emphasizes the necessity of studying delivery disruptions in relation to multiple independent variables, such as traffic, time-related factors and environmental conditions. It has been found that traffic conditions are a significant factor in logistics delays. Traffic congestion is especially correlated with the relationship between travel-time variability and delivery inefficiency, particularly in dense urban and inter-urban transport systems (Noland & Small, 1995; Allen, 2012). Transport conditions must thus be taken into account when interpreting the logistics performance as well as when developing anticipatory models. Another significant component of logistics delay is the waiting time. Time is wasted not only when shipments are in transit through the transport network but also when they remain in warehouses, terminals or customer locations. Traffic and waiting time are other components of the delay process. Together, these considerations provide a comprehensive view of the circumstances that delay shipment movement. The previous studies on logistics delays emphasized more strongly on the internal operational problems. The recent research has been more concerned with extraneous variables and their importance in prediction. Gabellini (2024) identified that the estimation of supply chain delays can be enhanced when external inputs are included in the modelling process. Internal operations decisions are applicable to the performance of deliveries, yet environmental factors can also impact transportation and handling. Factors like temperature and humidity are thus taken into account in the research on logistics delays, especially where external factors may affect movement or handling of the shipments. Another aspect emphasized by Steinberg (2023) is the need to determine variables reflecting real conditions of operations. The quality of prediction is not only dependent on the technique used to model but also on how the relevant variables are identified, interpreted and organized in the model.

Generally, the literature demonstrates that there is a gradual shift of traditional logistics management towards predictive and data-driven logistics systems. Recent studies have considered machine learning to predict ETA, predict supplier delays, predict delivery delays, and delay-risk assessment, whereas previous studies have focused on delivery reliability and operational coordination. The sources indicate that an approach based on studying traffic conditions, waiting time and the environment, as well as exploratory analysis and machine learning, is supported by the literature. Such an approach can help identify the factors most closely associated with logistics disruptions and shipment delays. This approach is relevant to the present study because its purpose is not only to understand the factors associated with delays but also to predict them. The study of operational and environmental factors, using exploratory data analysis and machine learning, can provide useful information when planning delivery and decision-making. Early detection of

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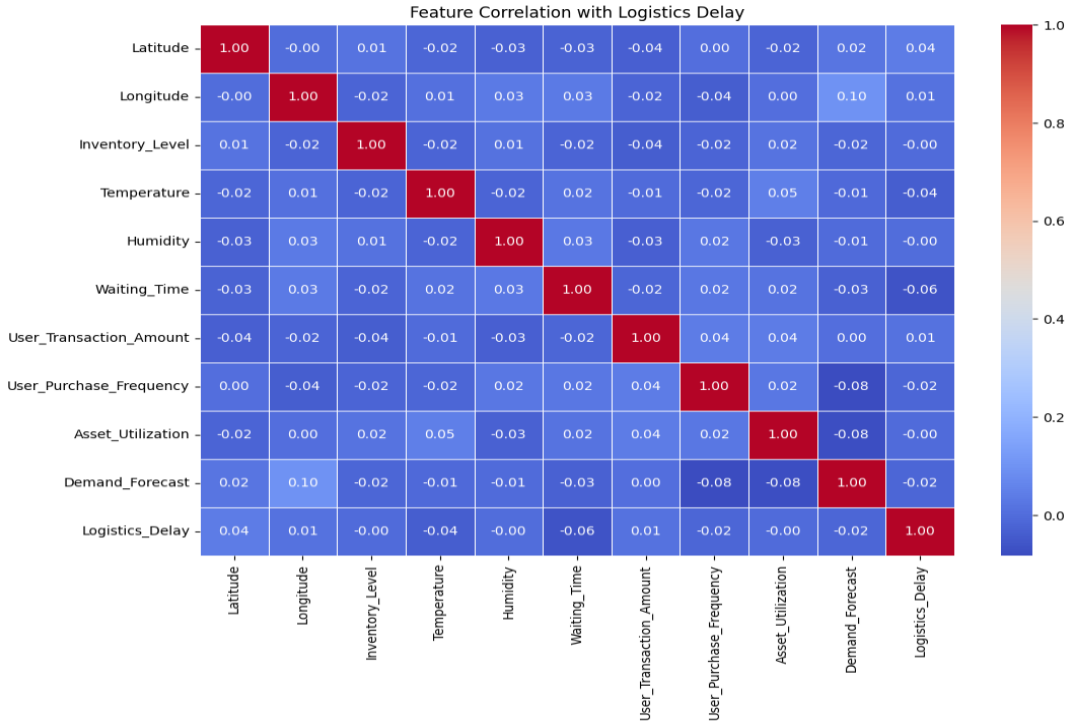
potential delays would assist logistics companies in making more informed decisions about deliveries and mitigate operational risks.

3. Methodology

The dataset on which the study was carried out comprises about 1000 observations of logistics activities. The major variable is binary in nature; it is called Logistics_Delay, and it states whether there was a delay or not. The independent variables were latitude and longitude; the operational variables, which included the inventory level, asset usage and time until next use (waiting time); and environmental-related variables, which were humidity and temperature. To transform the categorical variables into numbers, one-hot encoding of variables such as traffic conditions and delay reasons was performed. These diverse factors imply that logistic delays are multifaceted, with geographical, environmental, operational, and demand factors contributing to the delays.

Figure 1. Correlation Matrix



The heatmap, i.e., the correlation matrix of all variables used in this study, is shown in Figure 1. It can be seen that almost all variables' correlation values are near zero, which means that there is no strong relationship between most of the variables and hence there is no chance of multicollinearity between the variables. Moreover, the correlation is weak, and it can therefore be assumed that the delay in the logistics supply is not due to the influence of a single variable but to various variables in the model. The delays are influenced by the non-linear relation between the variables, which

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could be modelled using different machine learning algorithms like Random Forest or XGBoost regressor because these algorithms handle non-linear relations in a better manner when compared to multiple linear regression.

Figure 2. Distribution of Traffic Conditions

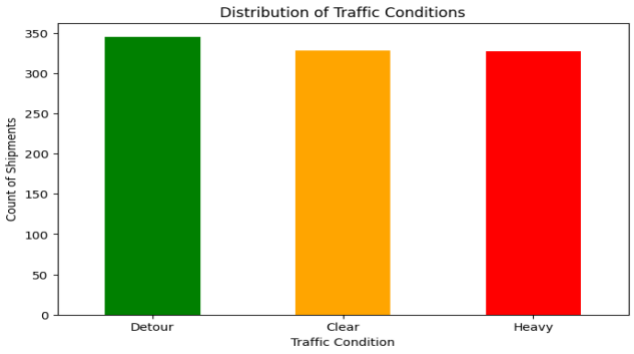

Figure 2 shows the distribution of traffic under three different conditions, and the distribution was almost uniform. Hence, it can be inferred that in almost all the traffic conditions, the number of shipments is uniform; that is, about 345 shipments are distributed under detour, clear and heavy traffic conditions. Although under detour-type traffic conditions, the distribution is slightly higher compared to the other two, it can still be considered almost uniform for all three conditions. However, no single factor was the most significant, and the delay in logistics may be attributed to various combinations of these factors.

Figure 3. Average Waiting Time by Traffic Condition

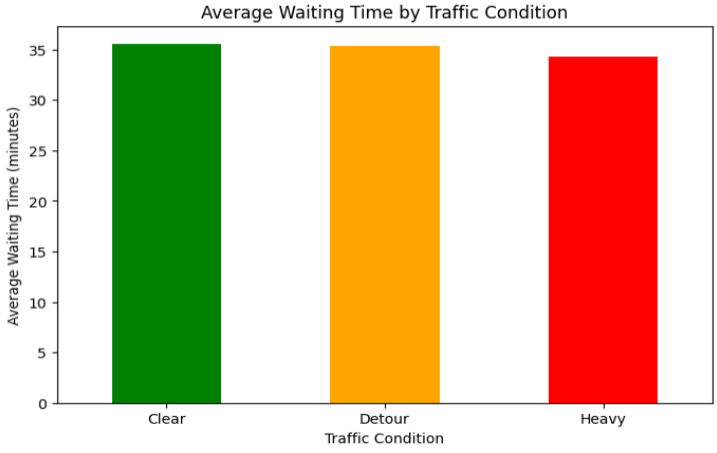

Figure 3 shows the average waiting time by traffic condition under clear, detour, and heavy traffic conditions. Average waiting time was about 35.4 minutes, which was almost constant under the three different traffic conditions, which suggests that average waiting time was not the main reason for the delays in the logistics shipment. It implies that problems within the internal logistics processes of the site, which include operational delays or scheduling issues, might have a greater

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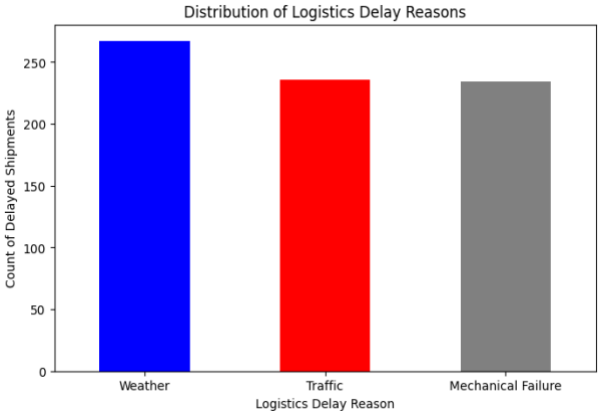
impact on waiting time. The delay for the shipment might not be because of an external issue but could be internal.

Figure 4. Distribution of Logistics Delay Reasons



The distribution of logistics delays and their reasons is shown in Figure 4. It was observed that due to weather conditions, there were the maximum delays, which were 267, and traffic and machine failure reasons stood next to it, which were about 235 delays. Since most of the delays are primarily caused by weather conditions such as rain, storms, etc., it may be beneficial to formulate policies that could be weather-based and then used for different weather forecasting models, which may be different depending on the season. Applying technology such as real-time navigation, as well as informing people about the congestion, can also inform them about the time they can expect to deliver based on the real-time weather forecast.

Figure 5. Average Waiting Time by Logistics Delay Reason

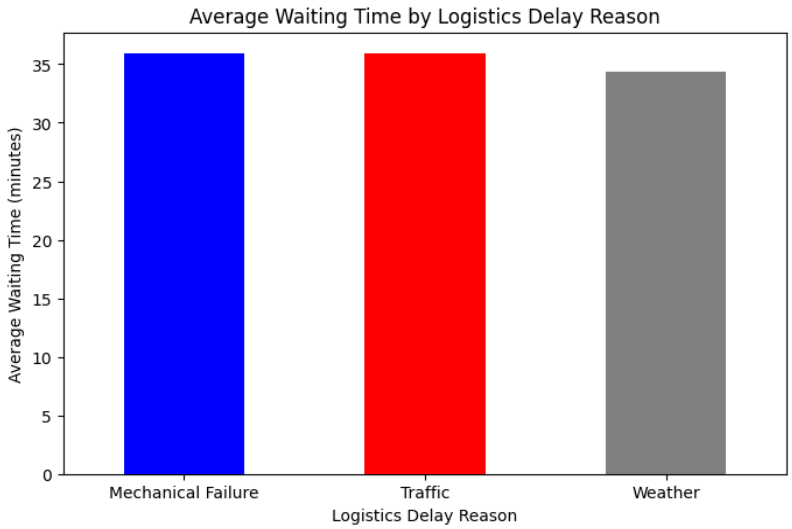


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Figure 5 shows the average waiting time (in minutes) for mechanical failure, traffic and weather. The waiting times were approximately 36 minutes, were uniformly distributed and were not very different between the three variables. Therefore, waiting time is almost independent of the dependent variable, i.e., delay in logistics shipping. This means logistics delays are not necessarily caused by waiting time and, therefore, waiting time alone is not a critical factor to minimise logistics delay.

4. Results

The dependent variable, i.e., logistics delay, was coded as class 1 if there was a delay and class 0 for no delay, and then it was regressed on the independent variables using the random forest algorithm. Before running the regression, the whole dataset was divided into training and testing datasets. 80% of the dataset was used for training purposes, while 20% of the dataset was used for testing purposes. Initially, a moderate accuracy was obtained for the Random Forest model, with an overall classification accuracy of about 71.5%. The model has a relatively high recall of 85% for non-delay cases, whereas the model's recall for delay cases was relatively lower at about 61%, indicating that a large portion of cases were not identified as delay cases. The high precision (82%) for delay predictions, however, showed that if the model forecasts a delay, there is a high likelihood that this would be the case. The model can be improved to account for delay cases, particularly to support real-time logistical decisions, but this trade-off indicates that the model is fairly reliable.

Figure 6. Feature Importance in Logistics Delay Prediction



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The influence of all the independent variables on logistics delay is shown in Figure 6. The Random Forest model shows that heavy traffic is the most important variable affecting logistics delays, with operational variables like inventory level and asset usage being the next most important variables for predicting the logistics delay. Complex non-linear relations between features were included in the model, which were not reflected in the correlation analysis. The optimized model gave an overall classification accuracy of approximately 73%, which is an average score. The model achieves high accuracy in recalling non-delay cases, but its performance is not as good in recalling delay cases, meaning there are some cases of actual delay that are not recalled. The predictions of delay, however, indicate that if a delay is predicted, then it will likely be correct, due to the high precision in the predictions. The prediction for a new shipment forecast suggests that there is no indication of any delay, with a probability of delay being 38%, which means a moderate level of risk with a need for monitoring.

5. Conclusion

The study reveals that the traffic conditions and fleet utilisation were among the most important factors that affect the logistics delays, while the weather has limited influence. After optimisation, the random forest model achieved an overall classification accuracy of about 73%, and the accuracy can be increased provided we use more relevant variables which have an impact on logistics delays. There are some limitations to this study, as there is no real-time traffic data, which could enhance the accuracy of the model. If the total number of observations is increased and if we work with big datasets, then the chances of increasing the accuracy become high. Also, our future work will include working with hybrid models, which will be useful to help the logistics business make decisions and minimise delays, thereby increasing the overall efficiency of the company.

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