International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

ASSESSING RECOVERABILITY OF CARGO THEFT: INSIGHTS FROM ANALYTICS AND MACHINE LEARNING

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Abstract

In today's rapidly evolving economic landscape, theft poses a significant challenge that affects businesses across various sectors. Cargo theft from warehouses can lead to substantial financial losses, operational disruptions, and shortages in the supply chain. These incidents not only jeopardize inventory but also impact customer trust and overall business performance.This researchleverages machine learning and analytics techniques to assess recoverable cargo losses. By examining a public dataset, we will identify patterns and factors influencing the likelihood of recovery for stolen cargo. This research will provide a clearer understanding of the potential for reclaiming stolen cargo and highlights how data-driven insights can inform better security practices. This research will provide valuable insightsto businesses on how to leverage proactive measures to protect their assets and enhance operational resilience in the face of theft.

Keywords: Warehouse security, theft, Machine Learning, supply chain security

I. INTRODUCTION

Criminal Justice Information Services (CJIS) Division [1] defines cargo theft [15]as the criminal taking of any cargo including, but not limited to, goods, chattels, money, or baggage that constitutes, in whole or in part, a commercial shipment of freight moving in commerce, from any pipeline system, railroad car, motor truck, or other vehicle, or from any tank or storage facility, station house, platform, or depot, or from any vessel or wharf, or from any aircraft, air terminal, airport, aircraft terminal or air navigation facility, or from any intermodal container, intermodal chassis, trailer, container freight station, warehouse, freight distribution facility, or freight consolidation facility.

In Q1 2024 CargoNet [2], a data-driven platform designed to help combat cargo theft and improve the recoverability of stolen goods reported that the logistics and transportation industry faced a significant rise in criminal activities. 925 incidents were reported in Q1 2024 which was up 46% from Q1 2023 and 10% from Q4 2023. The average value of stolen shipments was $281,757, leading to an estimated total loss of $154.6M in goods. Key states affected included California (+72%), Illinois (+126%), and Texas (+22%). Popular targets for thieves were small appliances, liquor, energy drinks, and copper. Thefts often involved complex fraud schemes, but simpler methods like stealing unattended trailers remained prevalent, especially in hotspots like Southern California, Dallas-Fort Worth, and Atlanta.

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

II. IMPACT OF CARGO THEFT

Cargo theft has significant and far-reaching impacts, including:

1. Economic Loss: Businesses face substantial losses from stolen goods, which can include the value of the cargo, shipping costs, potential insurance deductibles, and denied insurance claims [12]. Companies may see higher insurance costs because of theft incidents. National Insurance of Crime Bureau reports this as a $15 to $35 billion industry in the United States [5]
2. Increased Security Costs: Businesses often need to invest in additional security technologies, personnel, and protocols to mitigate future risks. Ekwall, D., and Lantz, B. discuss in their paper on cargo theft risk and security that it is noteworthy how goods owners insist on higher security measures for terminal areas and secure parking compared to what is generally deemed necessary for cargo theft risk [6]
3. Operational Disruption: Theft can lead to delays in delivery, affecting the entire supply chain and leading to customer dissatisfaction. Missing cargo can create stock shortages, impacting production and sales.
4. Reputation Damage: Frequent theft incidents can harm a company's reputation, leading to decreased customer trust and potential loss of business. Companies may struggle to maintain a strong brand image if they are perceived as vulnerable to theft.
5. Legal and Compliance Issues: Companies may face legal liabilities if they fail to adequately secure cargo, leading to lawsuits or regulatory penalties. Dealing with insurance claims can be time-consuming and complicated.
6. Impact on Law Enforcement: Increased cargo theft requires law enforcement to allocate more resources to investigate and recover stolen goods, potentially diverting attention from other criminal activities.
7. Economic Impact on Industry: Cargo theft can affect pricing and competition within industries, as companies facing higher theft rates may increase prices to compensate for losses.

Overall, the impact of cargo theft extends beyond immediate financial losses, influencing business operations, customer relationships, and broader economic conditions [10].

III. INSIGHTS FROM CARGO THEFT DATA

The purpose of this section is to explore the factors that affect the recoverability of cargo theft, with a specific focus on incidents involving goods stolen from warehouses or similar locations.

Recognizing the substantial economic repercussions of cargo theft and its potential use by terrorist organizations, Congress enacted H.R. 3199, the USA Patriot Improvement and Reauthorization Act of 2005, on March 9, 2006[4] [15]. This legislation mandated that the Attorney General take necessary steps to ensure cargo theft reports collected by federal, state, and local officials be categorized separately in the Uniform Crime Reporting System by December 31, 2006. In response, the Criminal Justice Information Services (CJIS) Advisory Policy Board established a definition for cargo theft in December 2006. The development of data specifications for capturing cargo theft information within the Uniform Crime Reporting (UCR) Summary Reporting System and the National Incident-Based Reporting System was completed in 2010, leading to the first publication of cargo theft data in 2013 [4] [15].

The FBI's UCR Program collects data [4] on cargo theft to inform law enforcement, federal and

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

state legislators, academic institutions, and the public about this specific crime. This data is instrumental in raising awareness and assessing the economic impact of cargo theft, as well as its potential threats to national security. Cargo theft is often linked to larger criminal activities and has been identified as a component of organized crime, drug trafficking, and terrorism financing. Although the UCR's collection of cargo theft data is relatively recent, the number of agencies reporting such incidents has increased annually. As participation grows, future cargo theft reports will provide a more comprehensive overview of these crimes in the United States.

For the purposes of this research, we utilize the cargo theft data published by the UCR, which includes approximately 41,000 reported theft incidents from 2012 to 2023. We will specifically focus on theft incidents from the five-year period between 2019 and 2023, concentrating on two locations that can be associated with warehouses locations [1], namely,

1. Parking/Drop Lot/Garage - this is defined in the Cargo Theft User Manual as areas primarily used for parking motorized vehicles that are commercial in nature
2. Dock/Wharf/Freight/Modal Terminal - this is defined in the Cargo Theft User Manual as separate facility with platforms at which trucks, ships, or trains load or unload cargo

1. Year over Year (YoY) theft trend

Figure 1 illustrates that from 2019 to 2023, there were between 4,307 and 8,435 reported thefts, with a total stolen value ranging from $44.09 million to $143.17 million. Notably, 2019 had the lowest theft reports but accounted for the highest total stolen value at $143.17 million. Additionally, 2019 recorded the highest average stolen value, which was $33.39 thousand, as depicted in Figure 2.

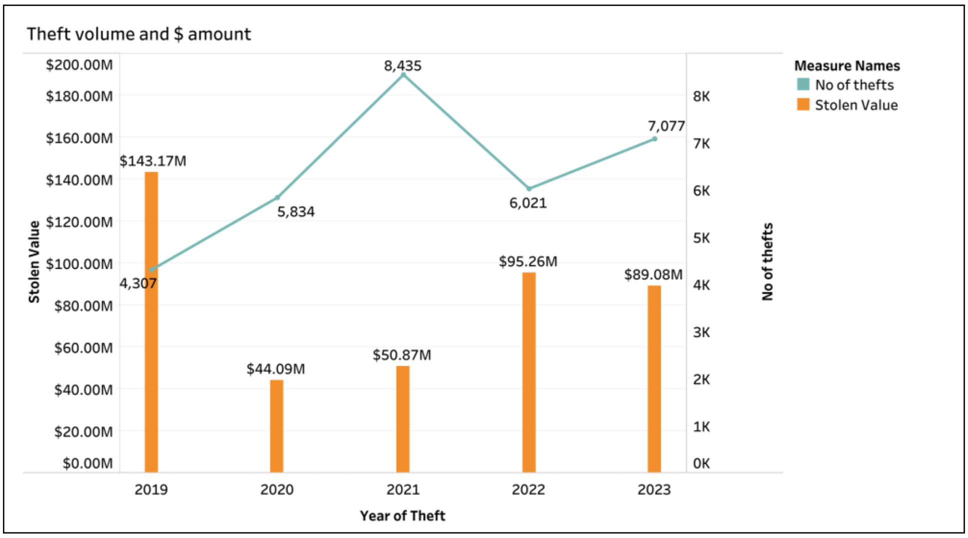

Figure 1: YoY trend in stolen volume and associated dollar value

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

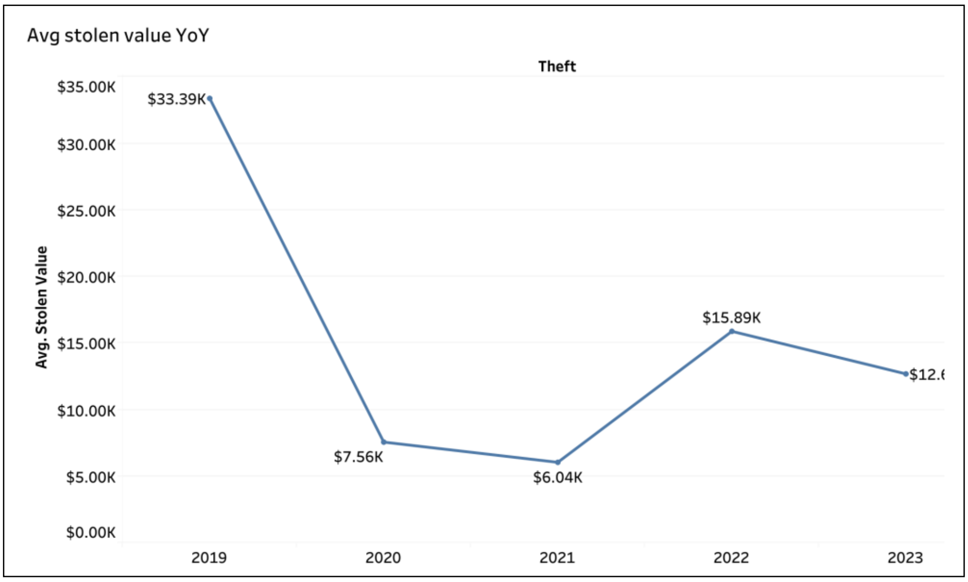

Figure 2: YoY trend in average stolen volume

2. **YoY theft recovery trend**

For this research, we will establish a metric for recovery rate, defined as the total value (in USD) of recovered cargo divided by the total value (in USD) of stolen cargo. Figure 3 illustrates that less than 50% of the stolen value was recovered year-over-year from 2019 to 2023. Notably, 2019 recorded the lowest recovery rate at 4.69%, while 2020 and 2022 both achieved recovery rates exceeding 40%.

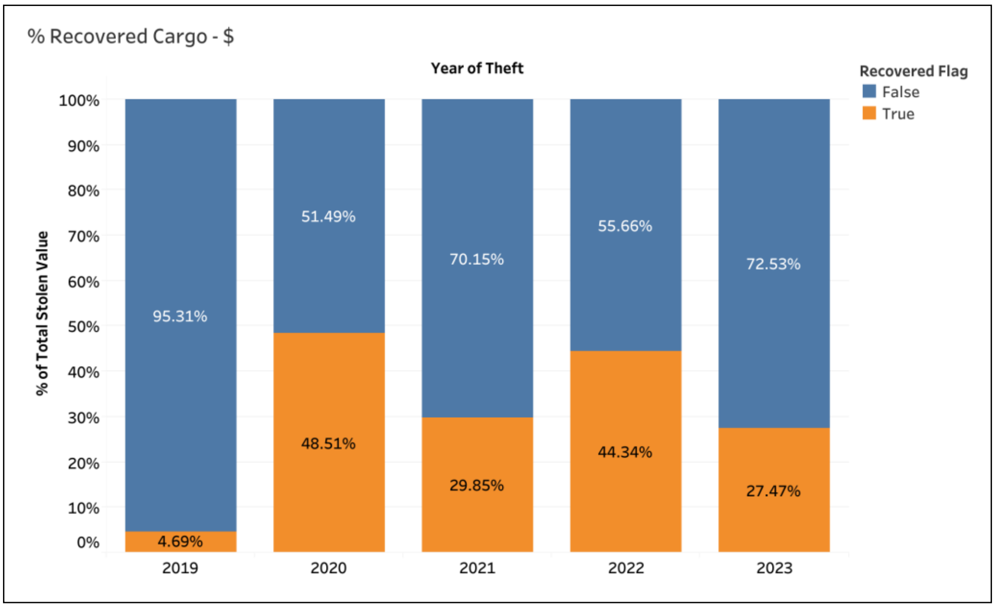

Figure 3: YoY recovery rate

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

Having gained insights into theft volumes, associated dollar amounts, and recovery rates year over year, we will now delve into potential factors that may influence the recovery of stolen cargo.

3. Impact of property type on recovery rate

TABLE I presents the types of property stolen, ranked by total stolen value from highest to lowest between 2019 and 2023. The top six categories include: [1] Recordings (phonograph records or various media such as CDs, DVDs, cassettes, and VHS tapes), Automobiles, Buses, Trucks and Vehicles, Consumable Goods (expendable items for nutrition, enjoyment, or hygiene like food and grooming products), and Trailers (transportation devices like truck trailers and utility trailers). All these categories have a recovery rate of less than 61.00%. Notably, Recordings had the highest stolen value at $120.29 million, but none of these items were recovered.

TABLE I. Recovery rate by property type (sorted by stolen value)

Property	No. of thefts	Stolen value (USD)	Recovered rate
Recordings	101	$120,286,891	0.00%
Automobile, Vehicles, Trucks, Buses	3,613	$85,282,291	60.86%
Other	4,888	$51,383,787	26.95%
Consumable Goods	1,287	$22,248,793	3.64%
Merchandise	697	$18,886,948	14.83%
Trailers	814	$18,387,568	39.49%

TABLE II highlights the top five property types with the highest recovery rates, which include Artistic Supplies/Accessories (items or equipment used for creating or maintaining art, such as frames, oil paints, and clay), Aircraft, Camping/Hunting/Fishing Equipment/Supplies (tools and objects for recreational activities like tents and fishing poles), and Gambling Equipment (devices used in gambling, including slot machines, card tables, and lottery tickets). Except for Automobiles, Trucks, and Buses, these other property types have fewer reported instances of theft. The stolen value for Automobiles, Buses, Trucks, and Vehicles totals $85.28 million, with a recovery rate of 60.86%. Automobiles, Buses, Trucks and Vehicles likely have higher odds of recovery [3] due to tracking systems such as a stolen vehicle tracking system which could include Global Positioning System (GPS) based, RFID (Radio Frequency Identification) based or Cellular based.

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

TABLE II. Recovery rate by property type (sorted by recovered rate)

Property	No. of thefts	Stolen value (USD)	Recovered rate
Artistic supplies/Accessories	30	$2,571,755	94.07%
Aircraft	6	$33,200	90.36%
Automobiles, buses, Trucks and Vehicles	3,613	$85,282,291	60.86%
Camping/Hunting/Fishing Equipment/Supplies	152	$328,522	53.30%
Gambling equipment	12	$4,058	49.29%

4. Impact of state on recovery rate

Table III presents the states ranked by total stolen value from 2019 to 2023, with Florida, Texas, California, Maryland, and Illinois among the top five. All these states have a recovery rate of less than 50.00%. Notably, recent CargoNet studies [2] also identify Texas, California, and Illinois as the most affected states by theft.

TABLE III. Recovery rate by State (sorted by stolen value)

State	No. of thefts	Stolen value (USD)	Recovered rate
Florida	1,102	$141,113,278	2.97%
Texas	2,768	$81,822,573	23.96%
California	1,477	$29,298,174	22.86%
Maryland	1,817	$16,064,777	53.75%
Illinois	701	$16,056,600	12.18%

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

Table IV highlights the top five states with the highest recovery rates. Guam, Vermont, the Federal District, Kentucky, and New Hampshire each have recovery rates over 60.00%.

TABLE IV. Recovery rate by State (sorted by recovery rate)

State	No. of thefts	Stolen value (USD)	Recovered rate
Guam	16	$53,860	92.87%
Vermont	8	$6,284	80.84%
Federal	44	$12,005,150	74.97%
Kentucky	182	$5,281,475	59.97%
New Hampshire	33	$50,616	59.66%

5. Impact of property value on recovery rate

Table V indicates that most stolen items are valued at less than $50,000. We observe a slight negative correlation between stolen value and recovery rate; as the value of stolen items increases, the recovery rate tends to decrease. Interestingly, items in the $550,000 to $600,000 range still exhibit a recovery rate of about 35%. This suggests that there could be other factors that influence recovery rates within that property value range.

TABLE V. Recovery rate by stolen value

Stolen Value	No of thefts	Recovered %
<=50K	26,822	34.69%
>50K-100K	630	28.85%
>100K-150K	173	27.94%
>150K-200K	127	26.49%
>200K-250K	71	34.92%
>250K-300K	42	16.14%
>300K-350K	23	30.01%

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International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

>350K-400K	27	41.49%
>400K-450K	7	3.31%
>450K-500K	13	0.00%
>500K-550K	6	0.90%
>550K-600K	23	34.65%
>650K-700K	2	0.00%
>700K-750K	3	0.00%
>750K-800K	3	0.00%
>800K	23	7.26%

Table VI shows stolen cargo valued over $300,000, categorized by property type. Here, a clear correlation between property type and recovery rate emerges. Despite the high value, items that are easier to track, such as Trucks, Automobiles, and Trailers, demonstrate recovery rates exceeding 50%, in contrast to other property types.

TABLE VI. Recovery rate by stolen value and property type

Stolen Value	Property	No. of thefts	Stolen Value (USD)	Recovered Value (USD)	Recovered %
300K+	Trucks	14	$5,885,000	$4,455,000	75.70%
	Automobile	8	$3,127,859	$2,280,000	72.89%
	Trailers	2	$650,000	$360,000	55.38%
	Other	20	$24,773,119	$9,369,000	37.82%
	Computer Hard/ Software	12	$11,179,620	$2,248,958	20.12%
	Merchandise	24	$12,849,768	$2,362,920	18.39%
	Industrial Equipment	4	$6,146,000	$1,128,000	18.35%
	Vehicle Parts	4	$1,530,000	$100,000	6.54%
	Consumable Goods	18	$8,641,892	$400,000	4.63%
	Tools	2	$1,314,290	$0	0.00%
	Recreational/ Sports Equipment	2	$800,000	$0	0.00%

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

	Recordings	1	$120,029,400	$0	0.00%
	Radio/ TV/ VCR	3	$1,607,730	$0	0.00%
	Portable Electronic Communications	2	$1,111,640	$0	0.00%
	Photographic/ Optical Equipment	1	$1,000,000	$0	0.00%
	Office Equipment	1	$700,000	$0	0.00%
	Money	1	$490,000	$0	0.00%
	Medical/ Medical Lab Equipment	1	$1,088,949	$0	0.00%
	Jewelry/ Precious Metals	1	$1,600,000	$0	0.00%
	Household Goods	3	$1,712,647	$0	0.00%
	Clothes/ Furs	1	$600,000	$0	0.00%
	Alcohol	5	$1,997,040	$0	0.00%

IV. MACHINE LEARNING TO INTERPRET FACTORS INFLUENCING RECOVERY RATE

Having explored the descriptive statistics related to factors influencing the recovery of stolen property, we will now examine how machine learning [9] can quantitatively interpret these factors. We will take a step-by-step approach to developing and testing the model, and we will conclude with an intuitive interpretation of the model results. Figure 4 shows the model training and validation process. The steps are outlined below

1. **Data Preprocessing**: The first step in our analysis involves preprocessing the data to extract relevant features from the dataset. Since categorical variables cannot be directly utilized in machine learning models, we convert them into a suitable format through encoding. The following features are identified as predictors and target for training the model.

2. **Predictors**
   - stolen_value: Total monetary value of the stolen item in USD.
   - offender_info_available: A flag indicating whether details about the offender's age, sex, and race are known. For this model we do not use the demographics directly, instead we create a feature to indicate if the offender demographics was available
   - prop_desc_name: The type of property, such as Automobile, Merchandise, or Consumable Goods, etc.
   - region_name: Geographic region classification, including Northeast, West, South, and U.S. Territories, etc.
   - victim_type: The category of victim, such as Individual, Business, or Government.
   - offense_name: The specific type of offense, including Theft from Motor Vehicle, Theft of Motor Vehicle, and Theft from Building, etc.

3. **Target Variable**:
    1. Recovery Rate: This is defined as the total value (in USD) of recovered cargo divided by the total value (in USD) of stolen cargo.

4. **Model Training**: The objective of this analysis is to identify which selected factors influence the recovery rate of stolen cargo. The target variable—recovery rate—has two possible outcomes: True (cargo is recoverable) or False (cargo is not recoverable). Consequently, this becomes a classification problem. For this analysis, we selected Extreme Gradient Boosting (XGBoost) as the model to classify cargo as recoverable or not. Data from 2019 to 2022 is used for training, while data from 2023 is reserved for testing model performance. To enhance the model's efficacy, we employ GridSearch with cross-validation to determine the optimal combination of parameters that yields the best performance. Given the imbalanced nature of the target variable where the proportion of recovered cargo is lower than that of unrecovered cargo, we implement a positive weight scaling. Positive weight scaling approach gives more importance to the minority class (recovered cargo) during training. Adjusting the loss function in this way ensures that misclassifying instances of the minority class (recovered cargo) incurs a higher penalty compared to misclassifying instances of the majority class(not recovered).

5. **Model Validation**: Since the target variable is imbalanced, using accuracy as a performance metric would be misleading, as it could skew results. Since failing to recover stolen cargo can lead to financial loss, we opt for a more balanced metric, specifically the recall score, to evaluate model performance. The recall score provides a clearer picture of the model's ability to correctly identify recoverable cargo, ensuring that we prioritize the detection of stolen items that can potentially be recovered.

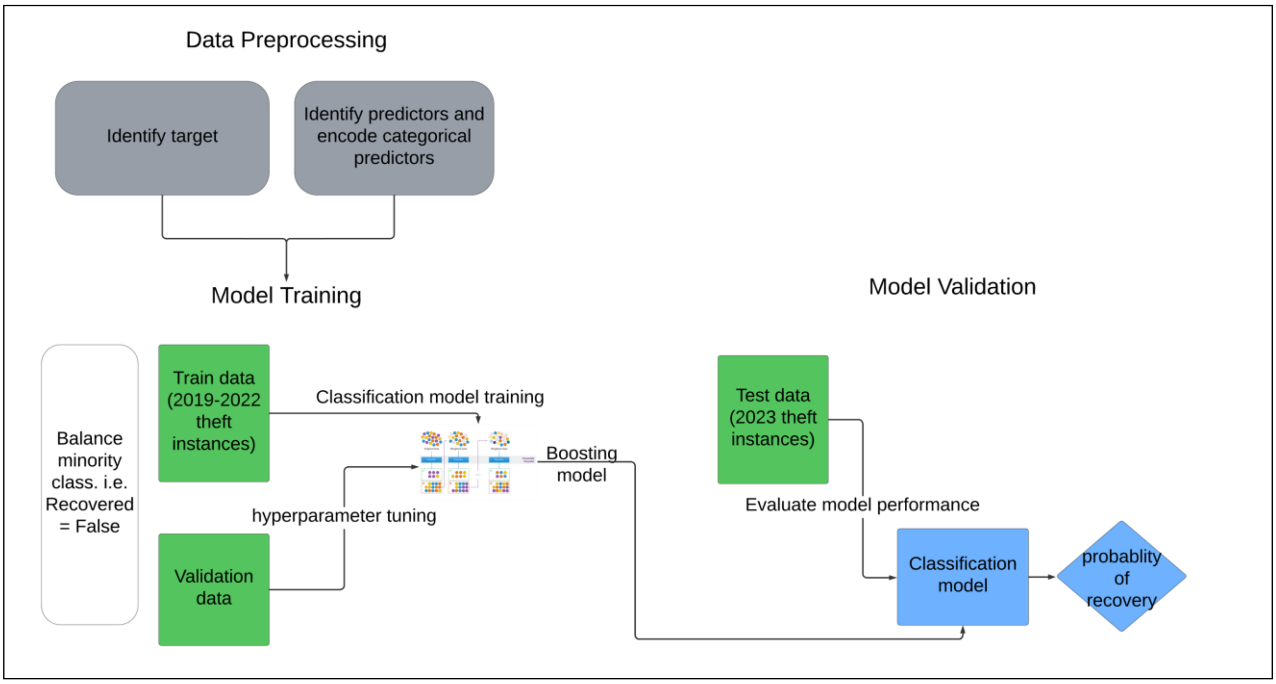

Figure 4. Model training and validation

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

V. RESULTS AND DISCUSSION

1. Model performance metrics

From the Classification reports in Table VII and TableVIII, we can see that the train and test datasets had a recall of 84% and 73% respectively on the minority class, that is, the recovered theft instances. The recall score, also known as sensitivity or true positive rate, measures the proportion of actual positive cases [13] that were correctly identified by the model. It is particularly important in scenarios where the cost of missing a positive instance (false negative) is high. The recall score is calculated using Equation (1):

$$Recall = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Negative(FN)} \qquad (1)$$

Recall is a critical metric for assessing a model's performance, especially in scenarios where identifying all positive instances is vital. Having high recall score is essentialfor capturing positive cases, whereas a low recall score suggests model should be tuned to avoid missing important instances.

TABLE VII. Confusion matrix on Train dataset (2019-2022 theft instances)

Classification Report:

	precision	recall	f1-score	support
0	0.97	0.85	0.90	21023
1	0.48	0.84	0.61	3574
accuracy			0.85	24597
macro avg	0.73	0.84	0.76	24597
weighted avg	0.90	0.85	0.86	24597

TABLE VIII. Confusion matrix on Test dataset (2023 theft instances)

Classification Report:

	precision	recall	f1-score	support
0	0.93	0.78	0.85	5847
1	0.42	0.73	0.53	1230
accuracy			0.77	7077
macro avg	0.67	0.76	0.69	7077
weighted avg	0.84	0.77	0.80	7077

2. Interpreting impact of predictors in recovering stolen cargo

SHAP, or SHapley Additive exPlanations, is a method used to interpret the predictions of machine learning models [7] [14]. SHAP aims to explain how each feature contributes to a model prediction by using underlying concepts of game theory. We will leverage SHAP to interpret predictions of the XGBoost classifier model for cargo recovery.

Figure 5 shows a SHAP summary plot, this plot provides insights into the contributions of each feature to model predictions. The y-axis lists the features used in the model, typically ranked by their importance. Features higher up the list have a greater impact on the model's predictions. The x-axis represents how each feature impacts a model's output. Positive SHAP values increase the likelihood of the positive class (recovered cargo in this instance), while negative SHAP values decrease it. The color of the points often represents the feature value (e.g., red for high values and blue for low values).

From Figure 5, we see that

1. Knowing the offender's demographics, the value of cargo, cargo type being automobile, theft from motor vehicle and property type being money are top five predictors that are most influential in driving predictions.
2. If most points for a feature are on the right side of the plot (positive SHAP values), it suggests that higher values of that feature are associated with the positive class. In this case, knowing offender's demographics, property type being Automobile, Trucks, Trailers and Other Motor Vehicles are associated with cargo being recovered.
3. Conversely, if most points are on the left side (negative SHAP values), it suggests that higher values of that feature are associated with the negative class. In this case, not knowing the offender's demographics, property type being Money, Tools, Credit/Debit cards, Portable Electronic Communication, Clothes and Consumable goods are associated with cargo not being recovered.
4. Knowing the offender's demographics, property type being Automobile, Truck, Trailer, Other Motor Vehicle increase the likelihood of recovery.
5. Not knowing the offender'sdemographics, theft from motor vehicles, property type being Money, Tools, Credit/Debit cards, Portable Electronic Communication, Clothes and Consumable goods decrease the likelihood of recovery.
6. Stolen value shows up high on the list but has a mix of positive and negative SHAP values (blue and red points), it may have a complex relationship with the prediction, suggesting that its impact depends on the values of other features. As we saw earlier in Section III Table VI of this research, a combination of stolen value and property type may influence the recovery rate

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

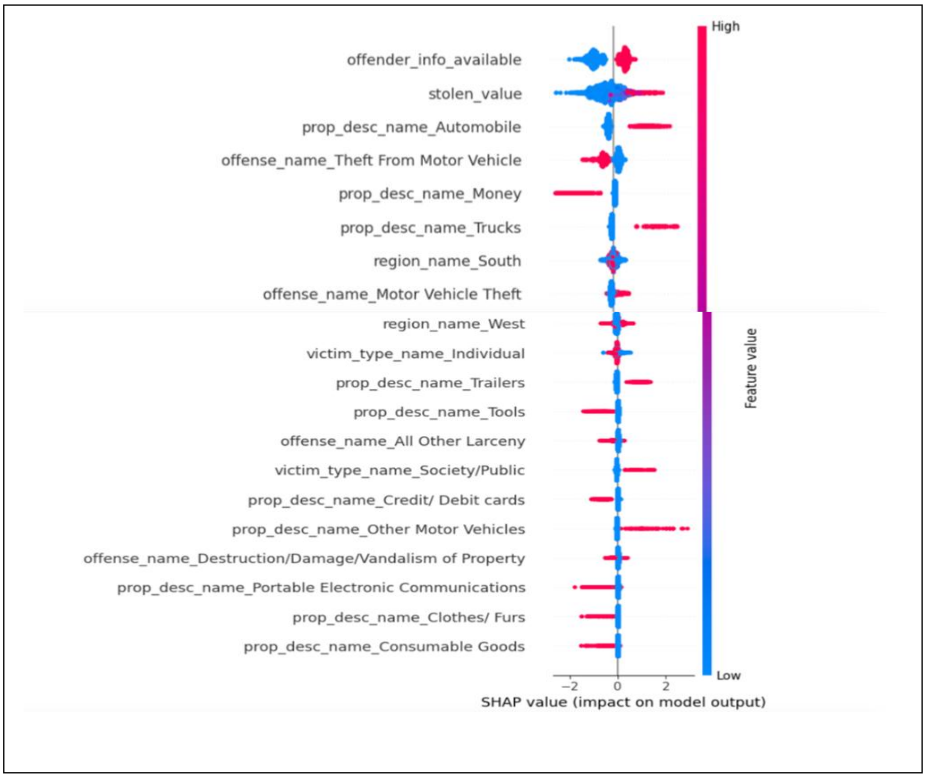

Figure 5. SHAP Summary plot

We can use SHAP's force plot to understand why a particular instance was classified as recoverable or not recoverable. Each feature'scontribution provides insights into the model's output. The plot clearly shows which features had the most significant impact on the prediction. Features with longer arrows (either positive or negative) are more influential. Rightward arrows indicate features that increase the likelihood of recovery. Leftward arrows indicate features that decrease the likelihood of recovery. Figure 6and Figure 7 show a force plot for a recovered cargo. From Figure 6 we see stolen value, property type being Automobiles and knowing the offender's demographics are influential factors for this cargo being recovered. On the other hand,in Figure 7 we see offense type being All Other Larceny and region being South are likely decreasing the likelihood of recovering this cargo.

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

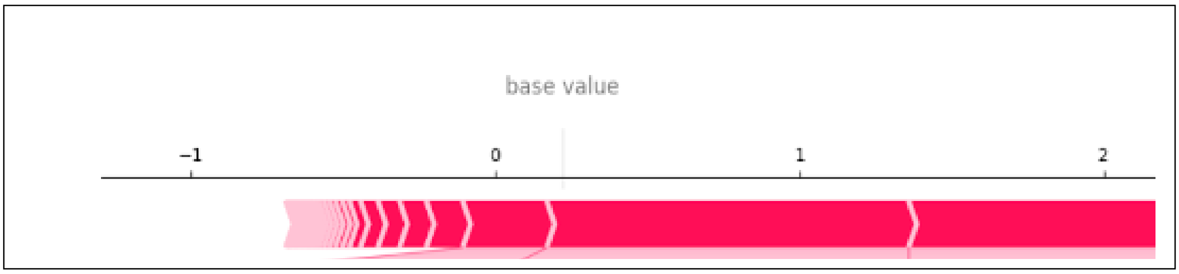

Figure 6. Force plot showsfactors increasing the likelihood of recovery

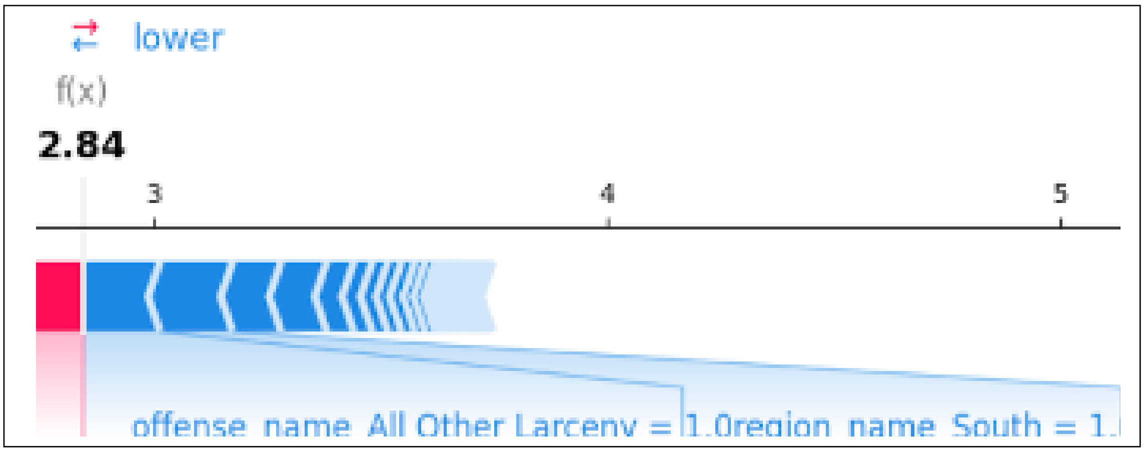

Figure 7. Force plot showsfactors decreasing the likelihood of recovery

VI. CONCLUSION

1. This research indicates that stolen trucks, motor vehicles, and automobiles are generally more recoverable than other types of stolen property.
2. Key demographic information about offenders significantly increases the likelihood of recovery; notably, property value alone does not determine this likelihood.
3. Analysis of cargo theft data revealed interactions between property type and stolen value that affect recovery rates.
4. It is crucial to implement security measures and access controls to mitigate theft risks for property types that lack inherent tracking systems, unlike vehicles.
5. The use of economical sensors [11] can help protect valuable inventory and consumable goods.
6. Enhanced surveillance, particularly in high-risk locations, is vital for capturing offender information during theft incidents.
7. The model developed in this research can serve as a tool to assess overall cargo recovery risk, enabling law enforcement to strategize and prioritize recovery efforts effectively.

International Journal Of Core Engineering & Management
Volume-7, Issue-11, 2024 ISSN No: 2348-9510

VII. FUTURE WORK

Future research should focus on optimizing model training to improve performance metrics. While this research prioritized increasing the recall rate, there is an opportunity to balance it with precision to reduce false positives. Exploring additional classification models, such as Neural Networks [9], Naive Bayes, Random Forests, and Support Vector Machines, may reveal improved fit and predictive accuracy. Furthermore, future work should aim to compile a more comprehensive dataset that includes detailed temporal data—such as the exact date and time of theft, as well as information on surveillance systems, access control measures, inventory management practices, weather conditions, transportation routes, and other economic factors that could influence cargo theft [8] and recovery dynamics.

REFERENCES

1. Cargo Theft User Manual, Uniform Crime Reporting (2023), Retrieved from https://www.fbi.gov/
2. First Quarter Supply Chain Risk Trends Analysis, CargoNet (2024), Retrieved from https://www.cargonet.com/
3. Roberts, A. (2012). Motor Vehicle Recovery: A Multilevel Event History Analysis of NIBRS Data. Journal of Research in Crime and Delinquency, 49(3), 444-467. https://doi.org/10.1177/0022427810397953
4. Crime in the United States, Additional Data Collections, Cargo Theft, Criminal Justice Information Services Division (2018). Retrieved from https://www.fbi.gov/
5. On the Rise: Cargo Theft, a Billion Dollar Industry, National Insurance Crime Bureau (NICB), (2020). Retrieved from https://www.nicb.org/
6. Ekwall, D., & Lantz, B. (2017). Cargo theft risk and security: Product and location. In D. Hellsröm, J. Kembro, & H. Bodnar (Eds.), NOFOMA 2017 The 29th NOFOMA Conference: Taking On Grand Challenges (pp. 140-155). Lund University.
7. Lundberg, Scott & Lee, Su-In. (2017). A Unified Approach to Interpreting Model Predictions. 10.48550/arXiv.1705.07874.
8. Liang, Xinrui & Fan, Shiqi& Lucy, John & Yang, Zaili. (2022). Risk analysis of cargo theft from freight supply chains using a data-driven Bayesian network. Reliability Engineering & System Safety. 226. 108702. 10.1016/j.ress.2022.108702.
9. Lorenc, A., Kuźnar, M., Lerher, T., &Szkoda, M. (2020). Predicting the Probability of Cargo Theft for Individual Cases in Railway Transport. Tehnickivjesnik - Technical Gazette.
10. The full cost of cargo losses, Inbound Logistics, 2004, Retrieved from https://www.inboundlogistics.com/
11. Gupta, Prasang& Young, Antoinette & Rao, Anand. (2022). Investigating Cargo Loss in Logistics Systems using Low-Cost Impact Sensors. 197-206. 10.5121/csit.2022.120618.
12. J. Paul Dittman, Will you be ready when a loss happens to you? 2015, Retrieved from https://www.campusship.ups.com/
13. Alyoubi, Esraa H., Kawthar M. Moria, Jamaan S. Alghamdi, and Haythum O. Tayeb. 2023. "An Optimized Deep Learning Model for Predicting Mild Cognitive Impairment Using Structural MRI" Sensors 23, no. 12: 5648. https://doi.org/10.3390/s23125648

14. Mishra, Akshansh&Jatti, Vijaykumar. (2023). Employing Explainable Artificial Intelligence (XAI) Methodologies to Analyze the Correlation between Input Variables and Tensile Strength in Additively Manufactured Samples. 10.48550/arXiv.2305.18426.
15. FBI – Cargo Theft,Retrieved from https://ucr.fbi.gov/crime-in-the-u.s/2018/crime-in-the-u.s.-2018/additional-data-collections/cargo-theft