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Investigation of Deficiencies Originating from Ballast Water Management in Port State Controls: A Research on Container Ships

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INTRODUCTION

Port state controls in maritime transportation are the process of inspecting foreign-flagged ships in order to ensure the safety of life and property at sea, prevent marine pollution caused by ships, and improve living and working conditions on ships.

INTRODUCTION

Currently, there are ten PSC regimes (IMO, 2023):

- Europe and the north Atlantic (Paris MoU)
- Asia and the Pacific (Tokyo MoU)
- Latin America (Acuerdo de Viña del Mar)
- Caribbean region (Caribbean MoU)
- West and Central Africa (Abuja MoU)
- Black Sea (Black Sea MoU)
- Mediterranean Sea (Mediterranean MoU)
- Indian Ocean (Indian Ocean MoU)
- Persian Gulf (Riyadh MoU))
- the United States Coast Guard

Some member countries belong to more than one PSC regime.

Source: *IMO (International Maritime Organization) (2023). Port State Control. https://www.imo.org/en*

INTRODUCTION

The basis of port state controls is to ensure that ships comply with international maritime conventions and the standards determined by these conventions.

One of these conventions, the "Ballast Water Management Convention", is a convention that is taken into consideration during port state controls and its compliance is checked by ships.

A serious (major) deficiency detected within the scope of this convention may be among the deficiencies that cause the ships to be detained.

AIM OF THE STUDY

In this study, an analysis was made on the deficiencies arising from the Ballast Water Management Convention in port state controls of container ships, and a model was proposed for the detention risk assessment of ships.

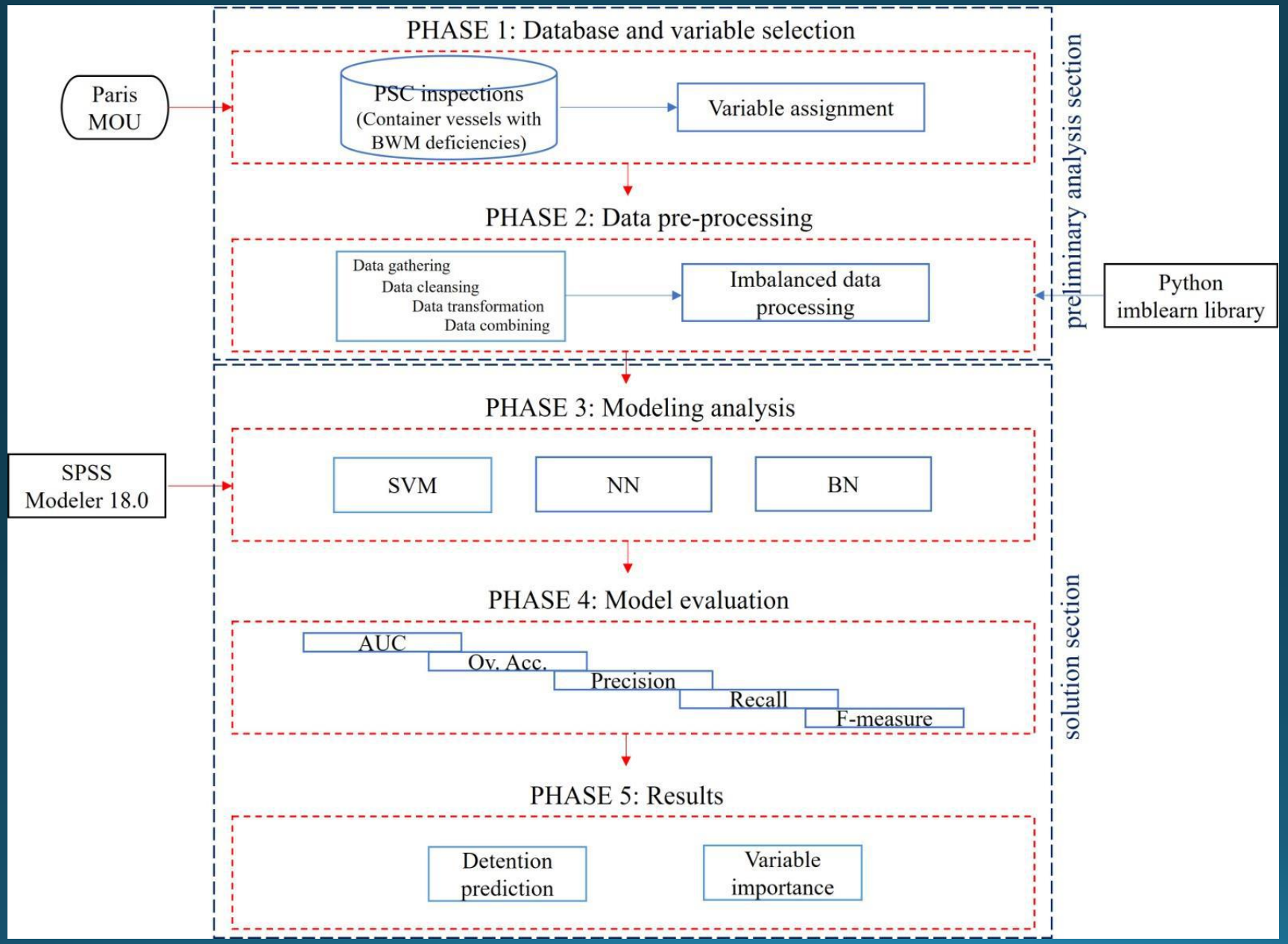
METHODOLOGY

A data set was created by examining the reports sharing the results of the controls carried out by the Paris Memorandum (Paris MoU) in the last three years (10.10.2020 – 10.10.2023).

Based on this data set, contributing factors in the detention of container ships, including deficiencies arising from the Ballast Water Management Convention, were determined.

A model was generated to predict the risk of ships being detained using machine learning algorithms.

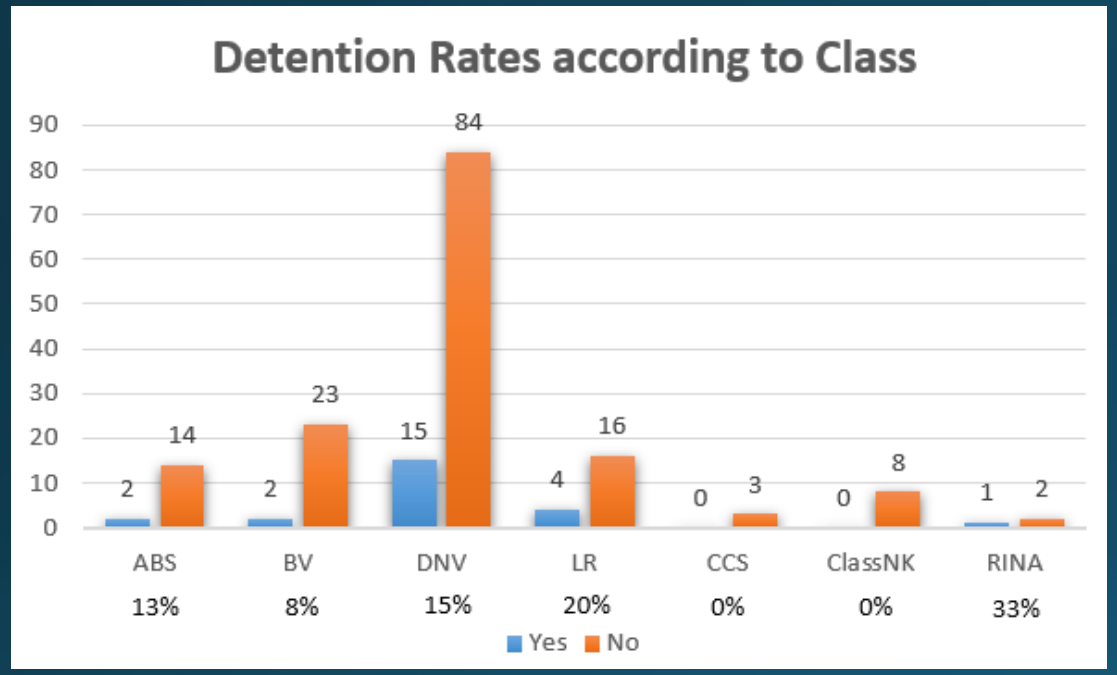
Methodological Flowchart

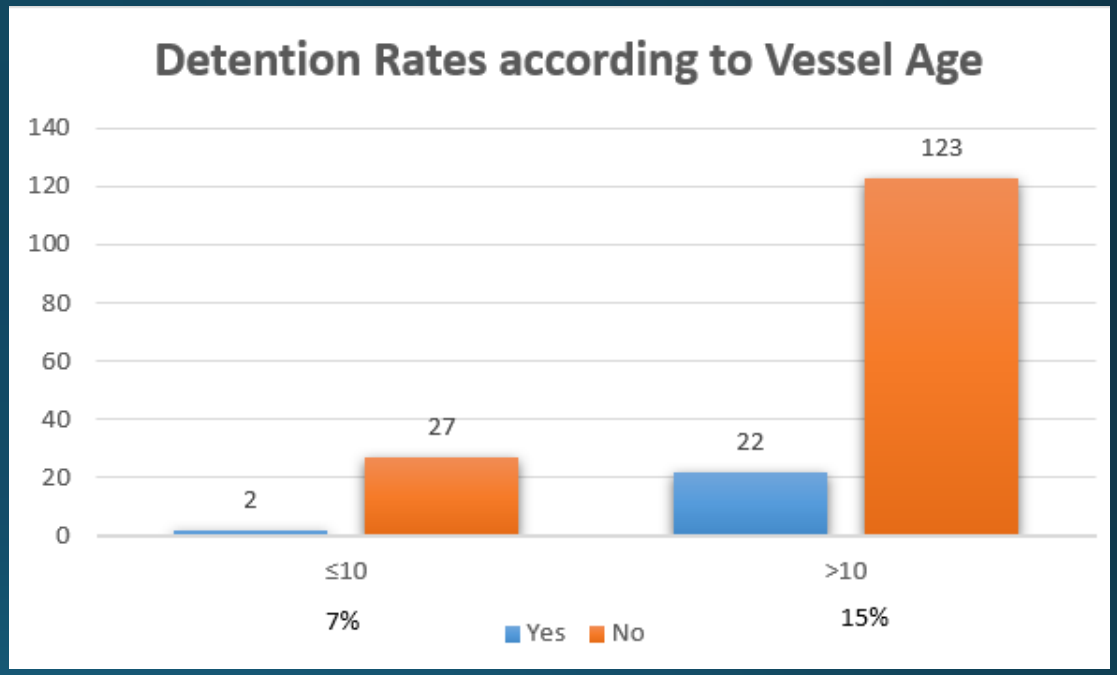


Variables

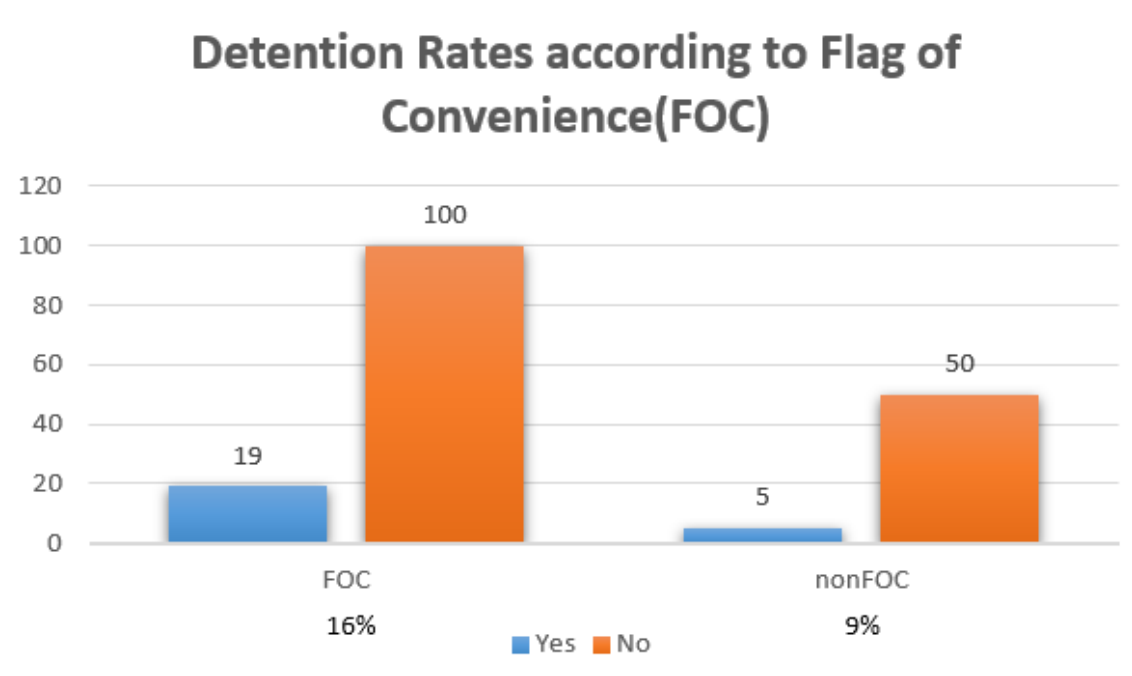
Variable	Description	Node name	Value	Imbalanced data					Balanced data				
				No. of data	Statistic				No. of data	Statistic			
					min	max	mean	SD		min	max	mean	SD
Target													
Detention	Result of detention or not	Detention (yes/no)	yes; no	174	1	2	1.862	0.345	300	1	2	1.500	0.500
Attributes													
Vessel class	Classification society of the vessel	Class	ABS; BV; DNV; RINA; CCS; ClassNK; LR	174	1	7	4.270	1.595	300	1	7	4.456	1.528
Vessel class performance	Performance of the classification society	Class_Performance	very low; low; medium	174	1	3	1.379	0.612	300	1	3	1.276	0.530
Vessel age	Age of the vessel	Age	(≤10); (>10)	174	1	2	1.833	0.374	300	1	2	1.876	0.329
Vessel size	Classification by GT	Size	(<15k); (15k-20k); (20k-50k); (50k-100k); (>100k)	174	1	5	3.012	1.329	300	1	5	3.136	1.255
Vessel flag	Flag flown by the vessel	Flag	FOC; nonFOC	174	1	2	1.316	0.466	300	1	2	1.283	0.451
Vessel flag performance	Performance of the flag	Flag_Performance	very low; low; medium	174	1	3	1.247	0.539	300	1	3	1.143	0.428
Owner performance	Performance of the owner	Owner_Performance	very low; low; medium	174	1	3	1.764	0.780	300	1	3	1.463	0.719
Type of inspection	Inspection type applied to the vessel	Type_of_Inspection	initial; more detailed	174	1	2	1.695	0.461	300	1	2	1.823	0.382
Number of deficiencies	Deficiency number recorded	Number_of_Deficiencies	(<3); (3-5); (6-10); (>10)	174	1	4	2.339	1.039	300	1	4	2.896	1.084
Defective item	The item regarding the deficiency	Defective_Item	BWM certificate; BWM plan; BW record book; crew training and familiarization; other	174	1	5	3.339	1.180	300	1	5	3.386	1.265

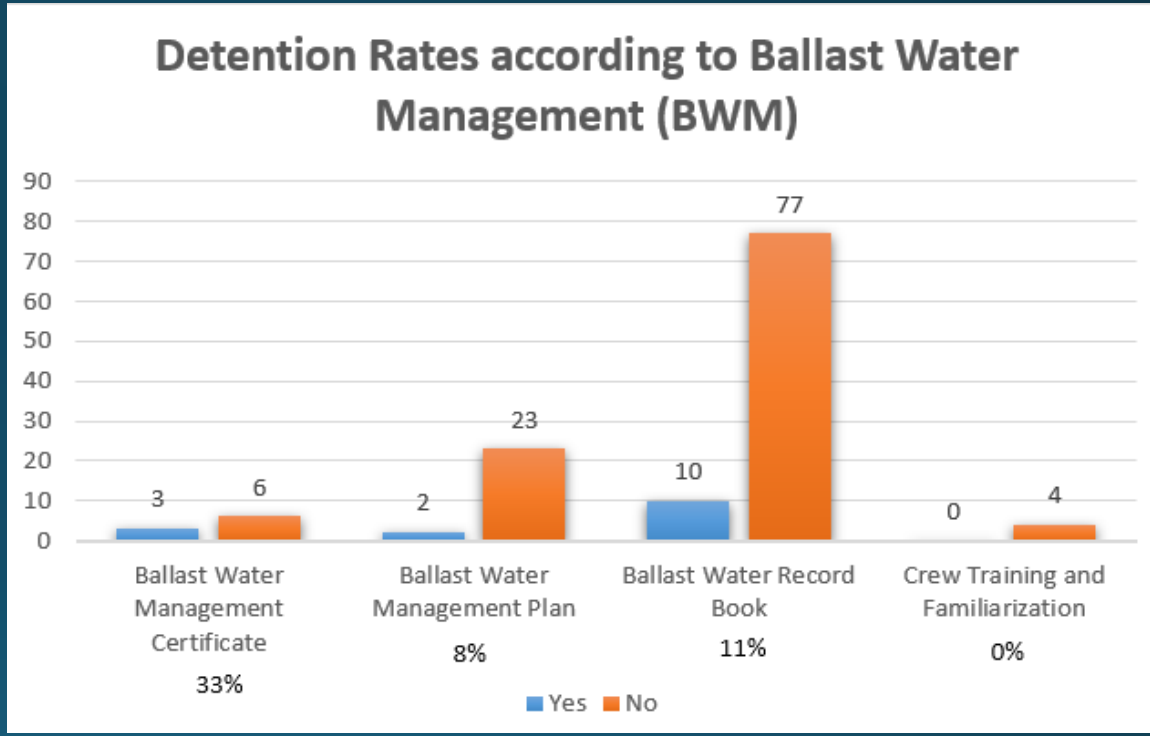
Descriptive Statistics



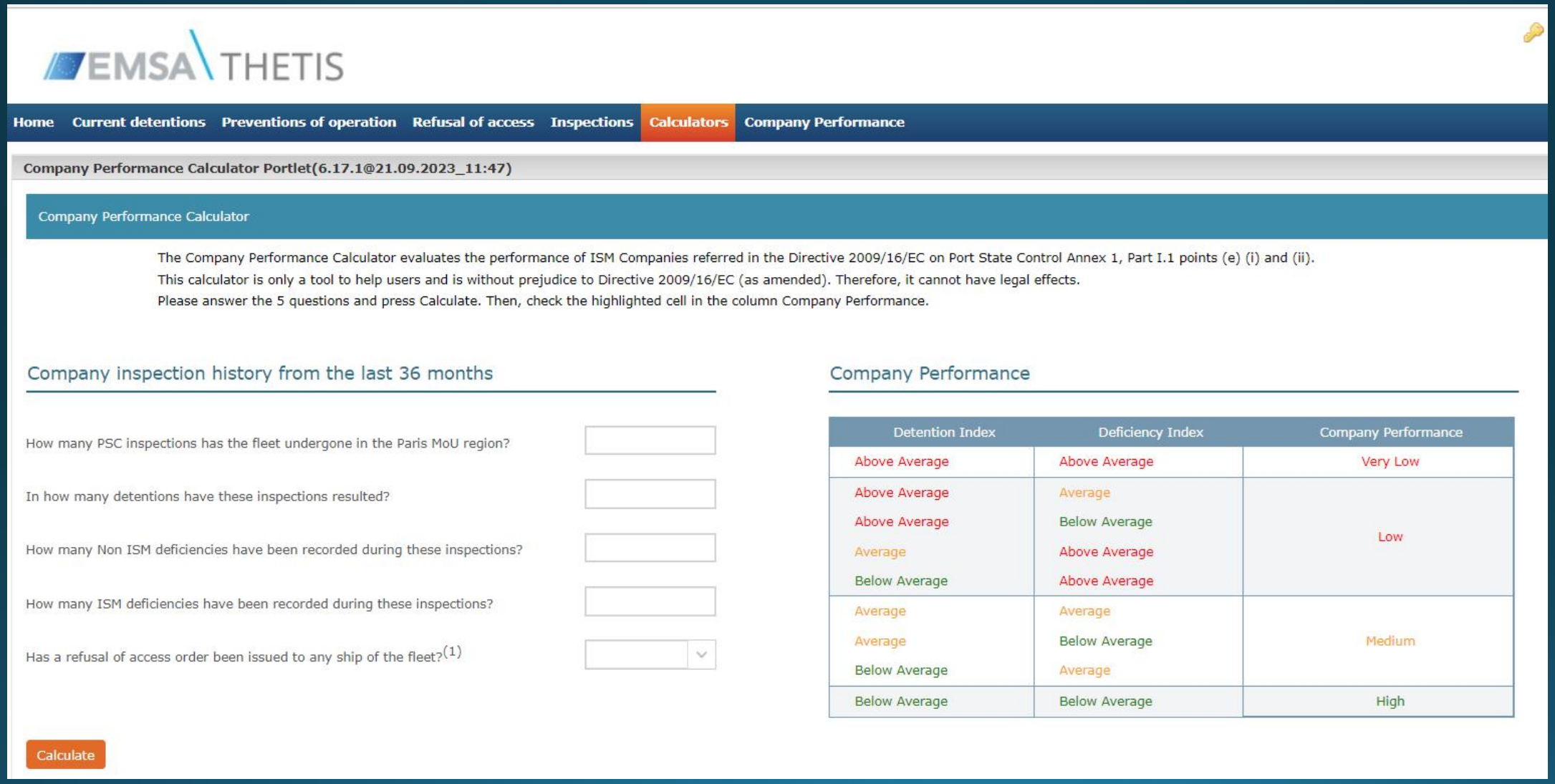


Descriptive Statistics

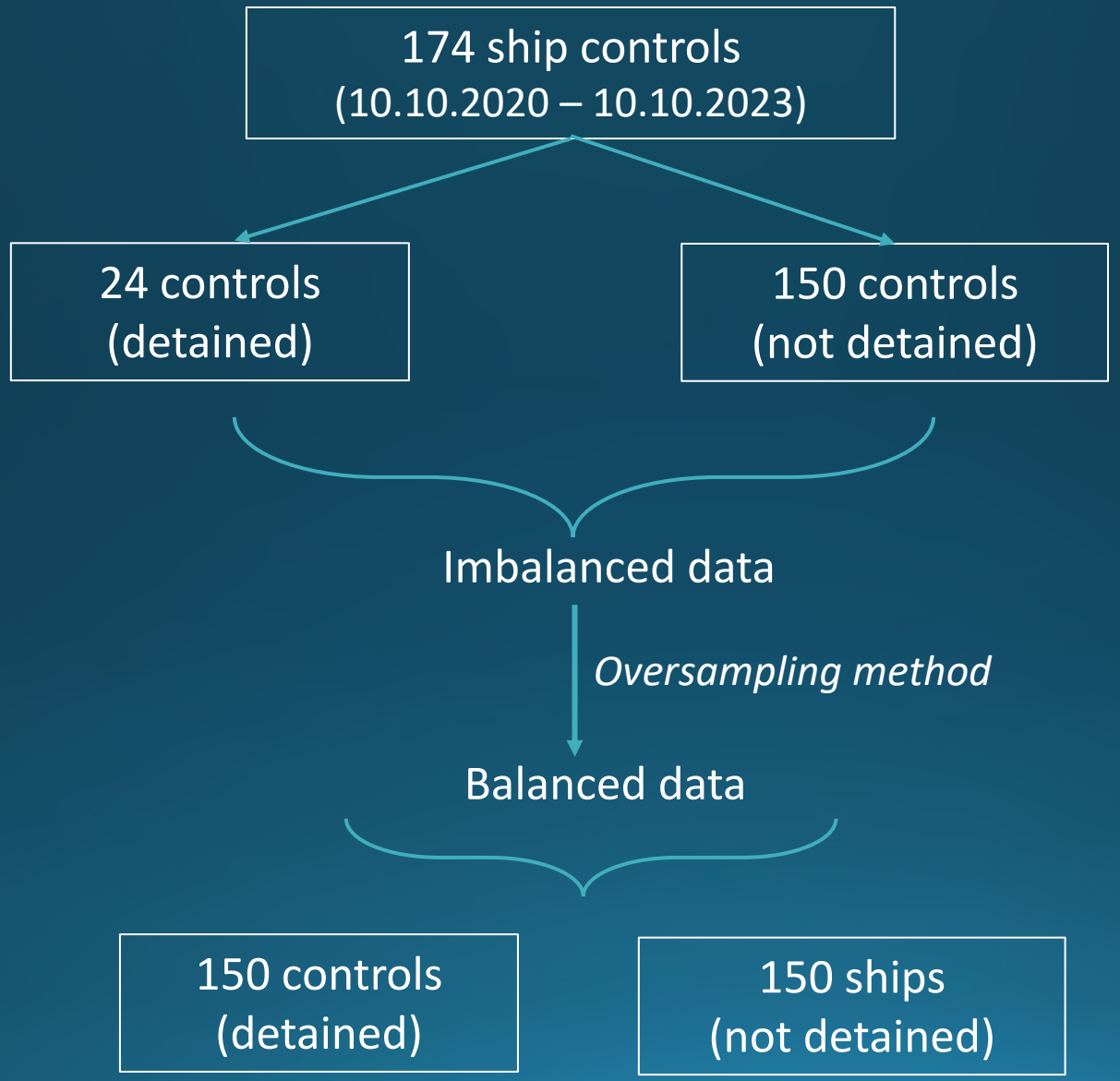




Performance Calculator
(Owner performance, Flag performance, Class performance)



Imbalanced data processing



Imbalanced data processing

```
[4] from google.colab import files
    uploaded = files.upload()
```

```
Dosyaları Seç veri_BWM_...YSIS2.xlsx
• veri_BWM_konteyner_FORANALYSIS2.xlsx(application/vnd.openxmlformats-officedocument.spreadsheetml.sheet) - 20482 bytes, last modified: 14.11.2023 - 100% done
Saving veri_BWM_konteyner_FORANALYSIS2.xlsx to veri_BWM_konteyner_FORANALYSIS2.xlsx
```

```
[5] import pandas as pd
    df = pd.read_excel('veri_BWM_konteyner_FORANALYSIS2.xlsx')
```

```
print(df.head())
```

```
  Class Class_Performance    Age        Size    Flag Flag_Performance  \
0   ABS               Low  (>10)   (15k-20k)     FOC          Very Low
1  RINA          Very Low  (>10)      (<15k)  nonFOC          Very Low
2   DNV          Very Low  (>10)      (<15k)     FOC            Medium
3  RINA          Very Low  (>10)   (15k-20k)  nonFOC          Very Low
4   DNV          Very Low  (>10)  (50k-100k)     FOC          Very Low

  Owner_Performance Type of Inspection Number_of_Deficiencies  \
0            Medium            Initial                   (<3)
1               Low      More detailed                 (6-10)
2            Medium      More detailed                   (<3)
3          Very Low      More detailed                 (6-10)
4            Medium      More detailed                 (6-10)

                     Defective_item Detention (Yes/No)
0         Ballast Water Record Book                 No
1         Ballast Water Record Book                 No
2         Ballast Water Record Book                 No
3         Ballast Water Record Book                Yes
4  Crew Training and familiarization                No
```

```
[7] df["Detention (Yes/No)"].value_counts()
```

```
No     150
Yes     24
Name: Detention (Yes/No), dtype: int64
```

```
[13] import imblearn
     from collections import Counter
     X = df.drop(["Detention (Yes/No)"],axis=1)
     y = df["Detention (Yes/No)"]
```

```
[14] from imblearn.over_sampling import RandomOverSampler
     ROS = RandomOverSampler()
```

```
[15] print('Original dataset shape %s' % Counter(y))
```

```
Original dataset shape Counter({'No': 150, 'Yes': 24})
```

```
[16] X_res, y_res = ROS.fit_resample(X, y)
```

Imbalanced data processing

```
[16] X_res, y_res = ROS.fit_resample(X, y)
```

```
[21] print(X_res)
```

```
    Class Class_Performance    Age        Size    Flag Flag_Performance  \
0     ABS              Low  (>10)   (15k-20k)     FOC         Very Low
1    RINA         Very Low  (>10)      (<15k)  nonFOC         Very Low
2     DNV         Very Low  (>10)      (<15k)     FOC           Medium
3    RINA         Very Low  (>10)   (15k-20k)  nonFOC         Very Low
4     DNV         Very Low  (>10)  (50k-100k)     FOC         Very Low
..    ...              ...    ...         ...     ...              ...
295   DNV         Very Low  (>10)   (20k-50k)     FOC         Very Low
296   DNV         Very Low  (>10)  (50k-100k)     FOC         Very Low
297   DNV         Very Low  (>10)      (<15k)  nonFOC         Very Low
298   DNV         Very Low  (>10)   (20k-50k)     FOC         Very Low
299    LR         Very Low  (>10)   (20k-50k)     FOC         Very Low

    Owner_Performance Type of Inspection Number_of_Deficiencies  \
0              Medium           Initial                  (<3)
1                 Low     More detailed                (6-10)
2              Medium     More detailed                  (<3)
3           Very Low      More detailed                (6-10)
4             Medium     More detailed                (6-10)
..               ...               ...                   ...
295         Very Low      More detailed                 (>10)
296         Very Low      More detailed                 (>10)
297         Very Low      More detailed                 (>10)
298         Very Low      More detailed                 (>10)
299         Very Low      More detailed                 (>10)

                    Defective_item
0          Ballast Water Record Book
1          Ballast Water Record Book
2          Ballast Water Record Book
3          Ballast Water Record Book
4   Crew Training and familiarization
..                                ...
295        Ballast Water Record Book
296                            Other
297                            Other
298                            Other
299                            Other

[300 rows x 10 columns]
```

```
from google.colab import data_table
data_table.DataTable(X_res)
```

1 to 10 of 300 entries Filter

index	Class	Class_Performance	Age	Size	Flag	Flag_Performance	Owner_Performance	Type of Inspection	Number_of_Deficiencies	Defective_item
0	ABS	Low	(>10)	(15k-20k)	FOC	Very Low	Medium	Initial	(<3)	Ballast Water Record Book
1	RINA	Very Low	(>10)	(<15k)	nonFOC	Very Low	Low	More detailed	(6-10)	Ballast Water Record Book
2	DNV	Very Low	(>10)	(<15k)	FOC	Medium	Medium	More detailed	(<3)	Ballast Water Record Book
3	RINA	Very Low	(>10)	(15k-20k)	nonFOC	Very Low	Very Low	More detailed	(6-10)	Ballast Water Record Book
4	DNV	Very Low	(>10)	(50k-100k)	FOC	Very Low	Medium	More detailed	(6-10)	Crew Training and familiarization
5	DNV	Very Low	(≤10)	(>100k)	nonFOC	Low	Low	Initial	(3-5)	Other
6	DNV	Very Low	(≤10)	(15k-20k)	FOC	Very Low	Low	More detailed	(6-10)	Ballast Water Record Book

Model Evaluation

SPSS Modeler 18.0

	SVM with balanced data	NN with balanced data	BN with balanced data
Accuracy	0.973	0.972	0.916
Precision	0.972	0.944	0.888
Recall	1.000	1.000	0.941
F1-score	0.986	0.971	0.914

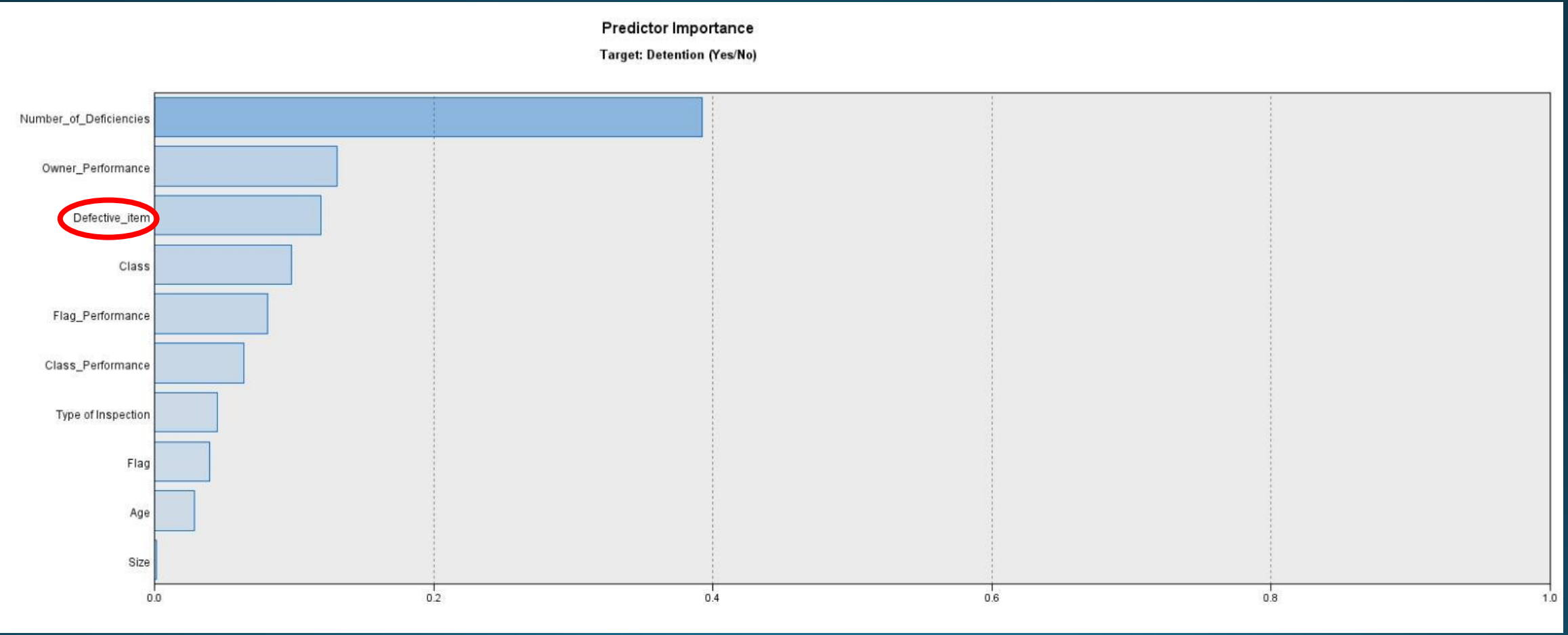
(SVM: Support vector machine; NN: Neural network; BN: Bayesian network)

- ✓ The algorithm that gives the best prediction was determined as SVM (Support vector machine) algorithm.

Model Evaluation

	SVM with imbalanced data	SVM with balanced data
Accuracy	0.952	0.973
Precision	0.972	0.972
Recall	0.972	1.000
F1-score	0.972	0.986

Predictor importance



Factor	State	Probability
Class	ABS	0.080
	BV	0.060
	CCS	0.000
	ClassNK	0.000
	DNV	0.680
	LR	0.153
	RINA	0.027
Class Performance	Very Low	0.860
	Low	0.140
	Medium	0.000
Age	(>10)	0.933
	(≤10)	0.067
Size	(<15k)	0.100
	(15k-20k)	0.087
	(20k-50k)	0.360
	(50k-100k)	0.327
	(>100k)	0.127
Flag	FOC	0.767
	nonFOC	0.233
Flag Performance	Very Low	1.000
	Low	0.000
	Medium	0.000
Owner Performance	Very Low	0.973
	Low	0.027
	Medium	0.000
Type of Inspection	Initial	0.000
	More detailed	1.000
Number of Deficiencies	(<3)	0.000
	(3-5)	0.033
	(6-10)	0.273
	(>10)	0.693
Defective Item	BWM Certificate	0.107
	BWM Plan	0.113
	BW Record Book	0.393
	Crew Training and Familiarization	0.000
	Other	0.387

CONCLUSION

- ✓ It was determined that deficiencies within the scope of Ballast Water Management (BWM) were ranked as the 3rd in terms of their impact on the detention of container ships, after the total number of deficiencies and owner performance.

- ✓ This result shows how important BWM is in port state controls of container ships.

CONCLUSION

- ✓ The most common deficiency we encounter within the scope of BWM in container ships is related to BW Record Book.
- ✓ Apart from BW Record Book, there are BWM Plan, BWM Certificate, and other deficiencies (loading/ballast condition, ballast tanks, ballast water exchange, ballast water discharge violation in port, construction dates applicable for BWM, etc.)
- ✓ Among the deficiencies that caused the detention of container ships, it was observed that there was no deficiency related to "Crew training and familiarization" within the scope of BWM.

CONCLUSION

- In this study, port state controls, carried out for container ships within the scope of the Paris MoU, were examined.
- Future studies may focus on different ship types and different PSC regimes.
- Additionally, an analysis can be made with more data, taking into account a wider date range.

THANK YOU