Outlier Detection Approach for Discovering Anomalous Maritime Profiles

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***Abstract*—Maritime authorities play a key role in ensuring the safety and security of shipping lanes and ports. The port state control mechanism enables these authorities to physically verify suspect vessels (e.g., involved in smuggling or piracy events), but choosing the most relevant vessels to be inspected represents a challenging task. This decision can be enhanced by AI-powered systems that analyse large amounts of data, identify patterns and report all observed discrepancies. This paper presents a statistical analysis on the temporal durations of four types of naval statuses: sailing, docked in port, waiting at anchor and not transmitting AIS data. These durations were extracted from the historical activity of different classes of vessels that passed the Black Sea region (Romanian Exclusive Economic Zone) in 2022. Probability density functions were built for these vessels and all statuses' durations were fitted into known parametric distributions. Finally, the paper shows the results of multiple outlier detection algorithms that searched for anomalous data in a multivariate manner.**

Keywords—outlier detection, port state control, maritime anomaly detection, unsupervised learning, AIS

I. Introduction

The maritime transportation sector plays a vital role in facilitating international trade and the global economy, and its importance will continue to grow. Consequently, the increasing complexity of socio-economic activities in the maritime domain has made it the scenario of numerous activities with high impact on safety, security, economy and the environment. Nowadays, the shipping industry faces a wide range of risks, one threat being represented by smuggling events [1].

To combat smuggling in the maritime domain, countries and international organizations have implemented a range of measures, including maritime surveillance, intelligence-gathering, interdiction efforts, or the use of advanced technology such as satellite imagery [1]. Collaboration between countries and organizations is also important and it is present in the form of different regional Memorandums of Understanding (MoU) and international blacklists for vessels. For example, Paris MoU and Black Sea MoU are two examples of regional agreements that include provisions for inspecting vessels under the port state control (PSC) mechanism [2], [3]. Another example is given by the United States Office of Foreign Affairs (U.S. OFAC) list that reveals vessels under economic sanctions because of their involvement in the proliferation of weapons of mass destruction (WMD) [4].

To support the fair usage of maritime transportation, the research community has also studied the potential usage of artificial intelligence (AI) and machine learning (ML) for ensuring safety and security in shipping operations. Consequently, modern maritime surveillance systems have been upgraded with advanced and automated subsystems. Most of them can analyse data from multiple sources in real-time, and trigger alerts when anomalies are detected [5].

Most proposed methods imply the analysis of vessels' attributes and associated kinematic data. In their paper, Tu et al. provide a comprehensive survey regarding the early identification of anomalous activities. The authors reveal several relevant aspects in which maritime related data could be exploited in specific domain tasks such as: maritime traffic anomaly detection, route estimation, collision prediction and path planning. They classify anomalies into three types: related to position, time and speed; and provide a brief description for multiple identified methods, such as: Fuzzy ARTMAP, Holst Model, Potential Field Method, Trajectory Cluster Modelling, Gaussian Processes, Bayesian Networks, etc. [6]. Martineau et. al. also classifies maritime anomaly detection methods into three categories: statistical methods, neural networks and machine learning methods. Models' learning characteristics are classified into geographical (map-dependent) and parametrical data (map-independent) [5].

Most of the vessels' available data are unlabeled for the abnormality class. In consequence, the most common methods that had been studied are represented by statistical algorithms, such as: stochastic parametric methods (e.g., Gaussian Mixture Models), stochastic non-parametric methods (e.g., Kernel Density Estimation, Gaussian Processes) or clustering algorithms (e.g., K-means, Density-Based Spatial Clustering of Applications with Noise) [6]. For example, Wu et. al. investigated vessels' travel behavior in different hotspots and discovered that the speed distribution of these vessels had a Gaussian shape [7].

Even though multiple maritime agencies possess relevant data and information, accessing it represents a serious challenge. Restricted access to such informational resources is one of the biggest difficulties into conducting research for maritime anomaly detection. Konrad Wolsing et al. express that the lack of a common dataset heavily reduces transparency, hinders the replication of results, and makes it particularly impossible to evaluate and compare the effectiveness of different approaches in a sound and scientific manner [8]. The authors also notice that there is no established dataset to include labelled anomalies as ground truth and many researchers resort to simulating their own anomalies by virtually creating tracks or by simulating real vessels with rigid-hulled inflatable vehicles.

The following sections propose a different stochastic approach for detecting abnormal utilization profiles. This method is based on a stochastic temporal analysis of vessels' navigational statuses. Its scope is to find univariate and multivariate outliers by fitting data into multiple parametric distributions and by utilizing ensembles of known outlier detection algorithms. The main advantage of this method is that it relies on analyzing data from public web platforms.

II. Theory on Outlier Detection

In machine learning, outlier detection (OD) identifies anomalous records in various datasets. Based on context, these anomalies may refer to observations from samples that differ from the general distributions of a population, measurements error, population variability or execution error [9]. Since early implementation, OD algorithms have been utilized to detect inconsistent observations in applications, such as fraud detection, quality control, healthcare, finance or cybersecurity [10]. The following subsections briefly describe the most common types and settings for OD algorithms based on the supervision mode, input data and working principle.

A. Working principle

Based on their working principle, Xi divides OD algorithms into classical and spatial ones. The most common approaches are presented in Table I [11].

TABLE I. OD ALGORITHMS' CLASSIFICATION

Type	Derived from	Description and examples
Classical OD	Statistics	Identify data points that are significantly different from the expected distribution of the data.
	Distances	Use a distance measure to identify data points that are farther away from the other data points than expected.
	Deviations	Identify outliers by using statistical measures such as mean, median, and standard deviation.
	Densities	Considering the density of the points in the feature space and locate outliers in low-density regions.
Spatial OD	Space	Consider the spatial distribution of the points in the feature space and locate outliers farther away from other points.
	Graphs	Construct a graph from the data points and identify outliers that have unusual or abnormal relationships with other points in the dataset.

B. Supervision modes

Based on the availability of abnormality data labels, the OD algorithms can operate in three modes [12]:

1) Unsupervised models: often present a dataset with *n* samples $X = \{x_1, \ldots, x_n\} \in \mathbb{R}^{n \times d}$, where each sample x_i has *d* features. Given this setting, the goal is to train a model *M* to output an anomaly score $O = M(X) \in \mathbb{R}^{n \times 1}$, where higher values demote the highest abnormalities scores.

2) Supervised models: possess the binary ground truth labels of *X, i.e.,* $y \in \mathbb{R}^{n \times 1}$. These models M are first trained on $\{X, y\}$ and then return anomaly scores for $O_{test} = M(X_{test})$.

3) Semi-supervised models: only possess partial label information $y^l \in y$. These models are trained on the entire feature space *X* with partial labels y^l, *i.e.,* $\{X, y^l\}$, and then output $O_{test} = M(X_{test})$.

Also, based on the level of generalization, OD algorithm can operate in either inductive or transductive settings. In the first case, a model learns from a training dataset and use that model to identify outliers in new, unseen data. In the latter case, a model identifies outliers in a specific dataset without the scope of generalizing to new data.

C. Input data

Depending on dataset's dimensionality, two types of OD algorithms are present:

1) Univariate OD: identifies unusual observations in datasets by considering each feature independently. Some common algorithms and methods are represented by univariate statistical analysis, one class Support Vector Machine (SVM), Isolation Forest, calculus of Z-score, median absolute values (MAD) or interquartile range, etc.

2) Multivariate OD: identifies unusual observations in datasets by considering the relationship between multiple features. Some popular methods are represented by: clustering, Multivariate Local Outlier Factor (MLOF), Principal Component Analysis (PCA), calculus of Mahalanobis, Minkowski or Chebyshev distances, etc.

Additionally, local OD algorithms search for outliers within a specific subset or neighbourhood of the data, while global OD algorithms identifying data points that are unusual in the entire dataset.

III. Research Methodology

A. Data collection

The Automatic Identification System (AIS) represents a maritime navigation safety communications system that is utilized onboard naval platforms and by different maritime agencies. AIS allows exchanges of continuous data related to vessels' live location, course, speed, maritime mobile service identity (MMSI) code, International Maritime Organization (IMO) number, navigation statuses, etc. [13].

For the present study, data from multiple AIS transponders were collected over one year, in collaboration with local maritime authorities [14]. These transponders were utilized to monitor the maritime traffic in the Black Sea region, especially in Romania's Exclusive Economic Zone (EEZ). Next, by decoding these NMEA-0183 formatted messages, all MMSI codes were extracted for those vessels that transited the region in 2022. Subsequently, a web-scrapping module was implemented to extract additional data from multiple web platforms (e.g., Marine Traffic – Professional Plan, Fleet Mon, Vessel Finder). The extracted data included vessels' subclass, length, tonnage, total travelled distance and utilization profile. All utilization profiles data included annual durations of four different navigational statuses. These statuses referred to the following types of situations:

a) Sailing (underway): the total duration of transporting cargo or passengers over the sea.

b) Docked (in port): the total duration of being stationary in a harbor for activities such as: manipulating cargo onboard, maintenance or repair.

c) Waiting (at anchor): the total duration of being stationary outside harbors and held in place by an anchor.

d) Signal Lost (inactive AIS): the total duration in which vessels do not transmit data over AIS radio channels.

B. *Statistical analysis and distributions' fitting*

During 2022, approx. 4250 unique vessels' MMSI identities were recorded in Romania's EEZ. After utilizing a web-scraping module, the subclass field was available for approx. 3000 vessels. Of these, 700 vessels had been further investigated and classified as having low, medium or high-risk indexes. This task was done manually and was based on specialized operators' expertise. These operators applied internal procedures and classified vessels based on their insolvent in suspect activities, such as:

1) Unusual activities: MMSI manipulation, IMO code discrepancy, first-time visiting harbors, loitering, drifting, course deviations, turning off AIS, meeting at sea with other vessels, suspicious cargo, port calls in disputed areas, etc.

2) Managerial changes: identity change (MMSI code or call sign), ownership change, registering different flags of convenience (flag hopping).

3) International sanctions: vessels being mentioned in different blacklists, sanctioned vessel, company or country.

These 700 vessels represented the most frequent subclasses of observed vessels (e.g., bulk carriers, container vessels, tugs, oil product tankers) and their utilization profile durations was extracted from the available web platforms. After that, a statistical analysis and a distribution fitting application were built upon the following Python 3.9 libraries: NumPy, Pandas, Matplotlib, Seaborn and Fitter.

The median md_{ns}, mean values μ_{ns} (1) and standard deviations σ_{ns} (2) were calculated for each naval status (*ns*) that was recorded for all subclasses' datasets.

$$\mu_{ns} = \frac{\Sigma_{X_i}(x_{ns})}{n} \tag{1}$$

$$\sigma_{ns} = \sqrt{\frac{1}{n}\ \Sigma_{X_i}(x_{ns} - \mu_{ns})^2} \tag{2}$$

, where X_i represents the selected subclass dataset, x_{ns} represents all records of a naval status durations, and n is the number of records in X_i.

The next step involved plotting the probability density functions (PDF) for every combination of naval statuses and vessels' subclasses. The PDF representations of four different vessels' subclasses are presented in Figure 1. This step was done by applying a Kernel Density Estimation (KDE) function $f(x)$. It placed a kernel function ϕ on each observation x_i of the training set of size n (3). Each kernel was parameterized by the width of an adaptive window h. The ϕ chosen kernel was the Gaussian one (4).

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} \phi\left(\frac{x-x_i}{h}\right) \tag{3}$$

$$\phi\left(\frac{x-x_i}{h}\right) = \frac{1}{h\sqrt{2\pi}}\, e^{-\sqrt{(\frac{x-x_i}{h})^2}} \tag{4}$$

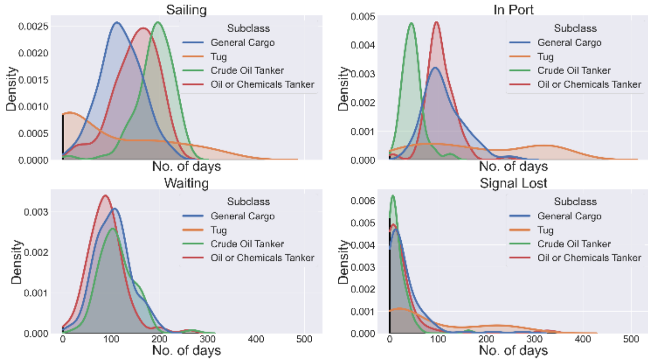

Fig. 1. PDF representations of four subclasses' utilization profiles

After visually inspecting the KDE distribution, it was observed that, excepting the tug vessels class, all other naval statuses' durations had the approximate shape of a known parametric distribution. It must be mentioned that there were no tug vessels to be recorded at anchor. Also, for all other tugs' statuses, the recorded datapoints were disposed evenly around the central tendency.

All other vessels' empirical data distributions were compared with multiple theoretical distributions (e.g., Gaussian, Log-normal, Gamma, Rayleigh, Weibull). The Summed Squared Error (SSE) (5) was utilized as a criterion for choosing the best-fitted parametrical distributions:

$$SSE = \sum_{i=1}^{n}(p_{x_i} - f_{x_i})^2 \tag{5}$$

, where n is the total number of captured records, p_{x_i} is the empirical probability density for all x_i records and f_{x_i} is the predicted density value that was extracted from the distribution fit.

The statistical methodology described above was inspired by a practical procedure used to identify anomalous maritime utilization profiles. Specifically, operators often utilize a univariate technique that involves selecting the top and bottom 5% of the available data (especially waiting status durations and AIS dark activities durations). The use of parametrical models could facilitate the development of a standardized methodology for understanding maritime patterns. For example, these models could aid in identifying anomalous data points that have a cumulative density function (CDF) below certain threshold.

C. *Multivariate OD implementations*

This study's last part consisted of comparing the performance of multiple OD algorithms (e.g., KNN, MCD, LOF, Isolation Forest, PCA). These algorithms analyzed all naval statuses in a multivariate manner for each category of vessels. For this, the open-source PyOD library was chosen. This library provides a wide range of unsupervised and supervised outlier detection algorithms, including both traditional and recent methods [15]. The experimental evaluation was conducted using standard implementations of all tested algorithms, and the sole hyperparameter that was varied was the contamination parameter *c*. It had values ranging from 0.01 to 0.5 with an increment step *s = 0.01*. K-nearest neighbors (KNN) and OCSVM samples are presented in Figure 2 and Figure 3 for comparison (*c = 0.1*).

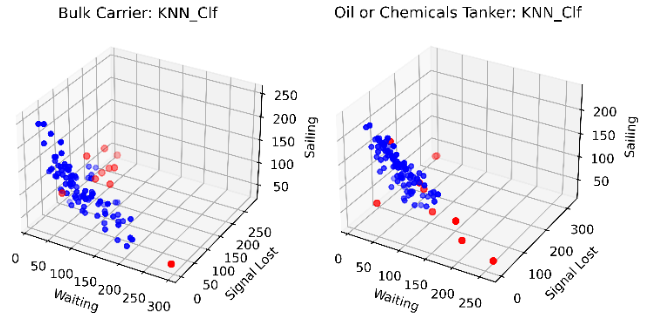

Fig. 2. KNN results for bulk carriers (left) and oil tankers (right)

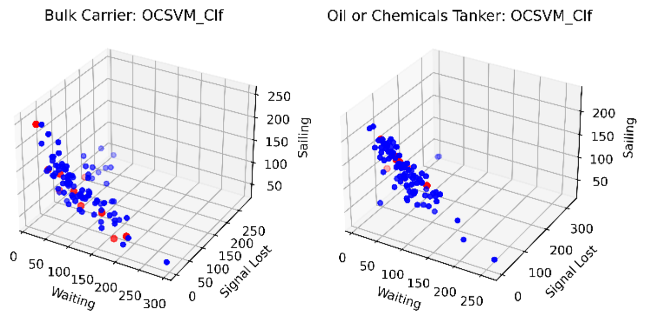

Fig. 3. OCSVM results for bulk carriers (left) and oil tankers (right)

A preliminary comparison was performed after Receiver Operating Characteristic (ROC) curves were built for all OD algorithms (see Figure 4). This was done under the naïve assumption that there is a correlation between the outlines score of all naval statuses' datasets and the vessels' associated risk (labeled data based on human expertise). The ROC curves plotted the true positive rates (TPR) against the false positive rates (FPR) at various *c* contamination levels (*0.01 ≤ c ≤ 0.50*). The TPR (6) represented the proportion of true positive cases correctly identified by the classifiers, while the FPR (7) represented the proportion of false positive cases incorrectly identified as true.

$$TPR = \frac{TP}{TP+FN} \tag{6}$$

$$FPR = \frac{FP}{FP+TN} \tag{7}$$

, where *TP, FN, FP, TN* represent the true positive, false negative, false positive and true negative rates between the OD algorithms results and the vessels' risk labels.

After that, the performances of all these binary classifiers were measured by calculating the Area Under the Curve (AUC) for each ROC. A higher AUC value indicated that the classifier was able to better distinguish between risk classes (normal and suspect vessels).

The next step involved selecting all ROC points that had a TPR score greater than 0.5. For those points, ratios between TPR and FPR were calculated. It was observed that a contamination level of *c = 0.35* represents a good setting where most algorithms recorded higher TPR/FPR ratios (average r ≈ *1.6*) and TPM scorers greater than 0.5.

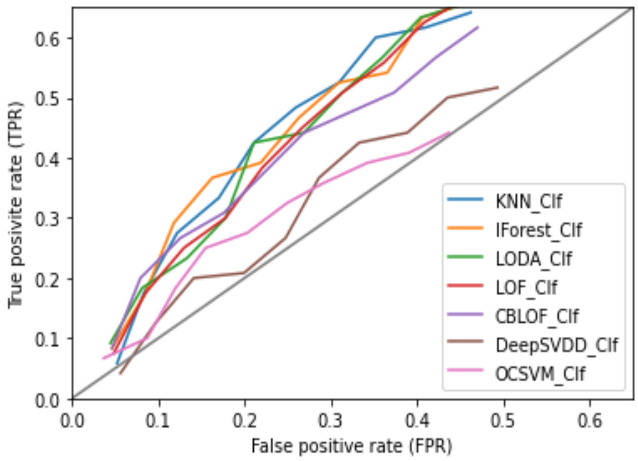

Fig. 4. ROC curve samples of multiple OD algorithms

After that, two ensemble classifiers were built. The first one combined the results of all individual OD algorithms ("*Ensemble_all_Clf*") while the second one utilized the top five algorithms ("*Ensemble_5_Clf*"), based on their AUC score. Ensemble learning uses combinations of various base estimators and creates more reliable and robust results than their individual counterparts [16], [17]. The built ensembles were composed of n_1 = *15* and n_2 = 5 different estimators and computed the final anomaly score A_s (8) for each category of vessels. This was done by averaging the binary scores s_i of all selected estimators. A threshold t = 0.5 was picked for selecting the vessels with the highest anomaly scores ($A_s > t$) for their class.

$$A_s = \frac{\sum_{i=1}^{n} s_i}{n} \tag{8}$$

In the next stage, all OD algorithms were tested by performing Monte Carlo simulations. This was done by random selecting anomalous vessels (the outliers in utilization profiles' datasets) and by counting how many of them were also classified by experts as suspect (TP - true positives). The selections were performed incrementally at various rates, between 1 and 200 vessels. Finally, the overall performance increase over random change was calculated for each OD algorithm.

IV. Results

All previous steps were applied to describe the behavioural profiles of multiple classes of vessels. This involved the temporal analysis of four complementary maritime behaviours in univariate (distributions fitting) and multivariate (ensemble OD) manners.

Table II highlights the results of fitting the durations of four types of maritime activities for the six main classes of observed vessels. Most activities obtained an SSE score lower than 10^{-2} and were fitted into a known parametric distribution. Figure 5 displays a graphical representation of fitting "*in port*" and "*at anchor*" activities for chemical tankers.

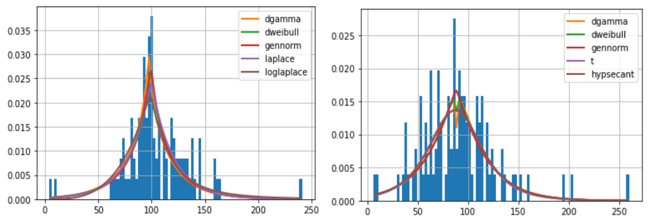

Fig. 5. Fittings "in port" (left) and "at anchor" (right) distributions for chemical tankers

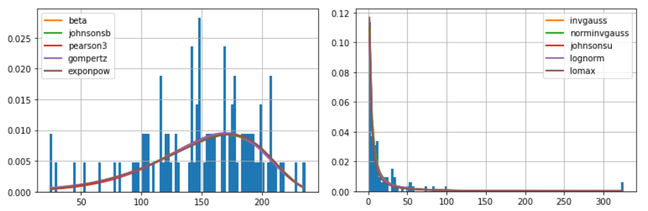

Fig. 6. Fittings "sailing" (left) and "signal lost" (right) distributions for chemical tankers

TABLE II. BEST FITTED DISTRIBUTIONS

Subclass (No. of records)	NS	*md* (≈)	*μ* (≈)	σ (≈)	Best fitted distribution	SSE score (≈)
Bulk Carriers (100)	Sailing	118	120	49	mielke	0.002
	In port	115	115	36	dgamma	0.003
	Waiting	87	96	50	exponnorm	0.002
	AIS off	10	34	57	lomax	0.001
Container Vessels (101)	Sailing	173	168	44	dgamma	0.003
	In port	121	126	32	dgamma	0.003
	Waiting	60	64	29	skewnorm	0.004
	AIS off	3	8	11	weibull_min	0.096
General Cargo (100)	Sailing	115	120	43	dgamma	0.003
	In port	104	111	41	exponnorm	0.003
	Waiting	104	104	37	burr	0.004
	AIS off	15	29	41	burr12	0.001
Crude Oil Tanker (78)	Sailing	194	190	39	dgamma	0.001
	In port	46	47	21	loglaplace	0.007
	Waiting	108	112	37	loglaplace	0.002
	AIS off	9	16	22	halfgennorm	0.003
Oil Products Tanker (82)	Sailing	122	118	47	dgamma	0.003
	In port	66	67	46	tukeylambda	0.001
	Waiting	135	134	48	dgamma	0.002
	AIS off	29	46	56	fatiguelife	0.001
Chemical tanker (100)	Sailing	155	151	45	beta	0.003
	In port	100	104	30	dgamma	0.002
	Waiting	88	90	38	dgamma	0.002
	AIS off	7	20	48	invgauss	0.001

Regarding the operator's analysis, after eliminating the tugs' class, 637 vessels were classified as follow: 120 suspicious (74 – high and 46 – moderate risk) and 517 – low risk vessels. These classifications were later used as labels for preliminary testing the performance of multiple OD classifiers. Table III highlights a preliminary ranking of all implemented OD algorithms, based on their AUC scores. Also, TPR and FPR scores are represented for a contamination levels $c = 0.35$.

TABLE III. OD ALGORITHMS RANKING BASED ON AUC SCORE

OD Algorithms	TPR score (c = 0.35)	FPR score (c = 0.35)	AUC score
KNN	0.525	0.309	0.185
IForest	0.525	0.309	0.182
ROD	0.525	0.309	0.178
PCA	0.533	0.307	0.178
COF	0.508	0.311	0.178
ABOD	0.525	0.321	0.178
MCD	0.508	0.313	0.175
LODA	0.508	0.313	0.173
LOF	0.508	0.313	0.173
CBLOF	0.475	0.321	0.172
ECOD	0.491	0.317	0.170
SOS	0.4	0.338	0.144
DeepSVDD	0.425	0.332	0.141
ALAD	0.291	0.357	0.128
OCSVM	0.358	0.292	0.117

KNN, IForest and ROD had the highest scores while DeepSVDD, ALAD and OCSVM registered the lowest performances.

After performing the Monte Carlo simulations, "*Ensemble_all_Clf*" was designated to be the best classifier in the naval statuses' datasets. When configured to a contamination level of $c = 0.35$, "*Ensemble_all_Clf*" registered the following results in detecting suspicious vessels: TP - 61, FP - 147, TN - 370, FN - 59, TPR – 0.5, FPR – 0.28 and FPR/FPR ratio – 1.78. The next best performances were obtained by LODA, PCA, KNN, ROD, ABOD and "*Ensemble_5_Clf*". Figure 6 and Figure 7 display the performances of several OD algorithms, at various pickup rates. These performances are represented by the total number of suspect vessels discoveries (true positives) and the overall performance over random chance pickup.

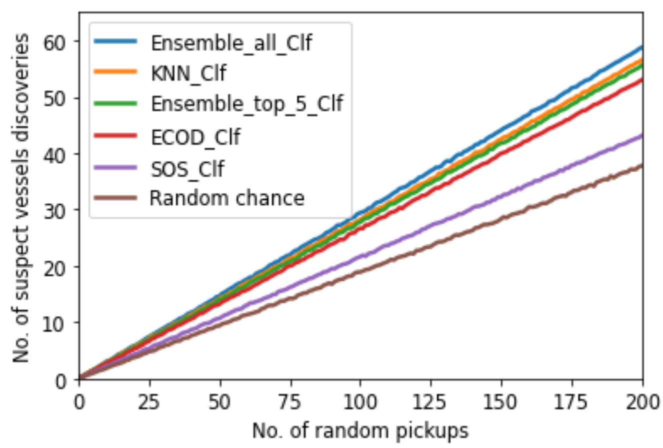

Fig. 7. Average number of suspect vessels being discovered

A public GitHub repository provides access to all datasets used in the project and its source code. The repository was created to enable other researchers and practitioners to replicate and investigate the research results. The link to the repository is provided below: https://github.com/Navy-APh/OD-for-anomalous-maritime-profiles.

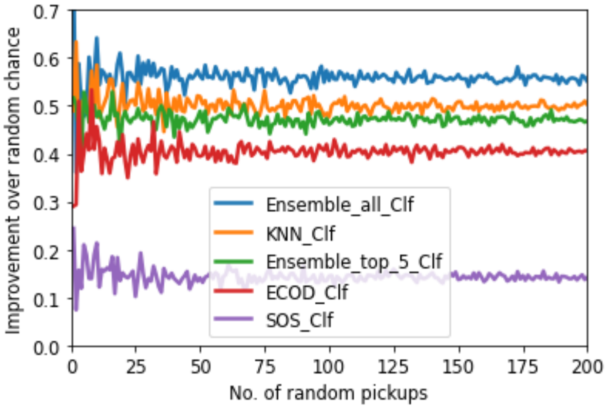

Fig. 8. OD algorithms' improvement over random chance pickup

At first glance, the OD algorithms showed a significant improvement over randomly selecting vessels (approximately 50% better on average). The results support the naïve assumption that there is a correlation between the calculated outlines score and the associated risk of vessels. However, it should be noted that the calculation of vessels' risk was based on specific internal procedures that may differ from those used by other maritime organizations. Furthermore, the statistical significance of this experiment is limited as it was conducted only once and in a specific region. To increase the robustness of the results, further similar experiments should be conducted in other regions with the application of different classification procedures.

V. Conclusion

Restricted access to information and a scarcity of data labels are two significant challenges in developing efficient maritime anomaly detection algorithms. However, this paper proposes a different approach that could help maritime authorities select more relevant vessels for investigation and inspection on board. The approach combines the results of multiple outlier detection algorithms that take four vessels' statuses as inputs. One advantage of this approach is its transparency, making it impossible to suspect discrimination against any vessels or operators. Additionally, it utilizes data from public web platforms, which could aid in data dissemination and algorithm testing if further analysis is conducted.

Overall, using AI models in port state control activities has shown potential to improve efficiency, accuracy, and safety by enabling authorities to identify and respond to potential issues more quickly and effectively.

References

[1] E. Papastavridis, "Intelligence Gathering in the Exclusive Economic Zone," U.S. Naval War College, vol. 93, 2017.

[2] "Black Sea MOU," [Online]. Available: http://www.bsmou.org/. [Accessed 27 12 2022].

[3] "On Port State Control," Paris MoU, [Online]. Available: https://www.parismou.org/. [Accessed 27 12 2022].

[4] "Sanctions List Search," Office for Foreign Assets Control, [Online]. Available: https://sanctionssearch.ofac.treas.gov/. [Accessed 27 12 2022].

[5] E. Martineau, J. Roy and D. Valcartier, "Maritime Anomaly Detection: Domain Introduction and Review of Selected Literature," Defence R&D Canada – Valcartie Technical Memorandum, 2011.

[6] E. Tu, G. Zhang, L. Rachmawati, E. Rajabally and G. B. Huang, "Exploiting AIS Data for Intelligent Maritime Navigation: A Comprehensive Survey," IEEE Transactions on Intelligent Transportation Systems, 2016.

[7] X. Wu, A. Rahman and V. A. Zaloom, "Study of travel behavior of vessels in narrow waterways using AIS data – A case study in Sabine-Neches Waterways," Ocean Engineering, vol. 147, pp. 399-413, 2018.

[8] K. Wolsing, L. Roepert, J. Bauer and K. Wehrle, "Anomaly Detection in Maritime AIS Tracks: A Review of Recent Approaches," Journal of Marine Science and Engineering, vol. 10, p. 112, 2022.

[9] M. Smith, S. Reece, S. Roberts and I. Rezek, "Online Maritime Abnormality Detection using Gaussian Processes and Extreme Value Theory," International Conference on Data Mining, vol. 12, 2012.

[10] F. Angiulli, S. Basta and C. Pizzuti, "Distance-Based Detection and Prediction of Outliers," Transactions on Knowledge and Data Engineering, vol. 18, no. 2, 2006.

[11] J. Xi, "Outlier Detection Algorithms in Data Mining," International Symposium on Intelligent Information Technology Application, vol. 2, 2008.

[12] S. Han, X. Hu, H. Huang, M. Jiang and Y. Zhao, "ADBench: Anomaly Detection Benchmark," Conference on Neural Information Processing Systems (NeurIPS), vol. 36, 2022.

[13] International Maritime Organization, "International Convention for the Safety of Life at Sea," United Nations, London, 1974.

[14] A. Pohontu, "AI models for automatic maritime surveillance: case study for Black Sea/Romania EEZ," The dynamics and complexity of Romania's maritime security, 2022.

[15] Y. Zhao, Z. Nasrullah and Z. Li, "PyOD: A Python Toolbox for Scalable Outlier Detection," Journal of Machine Learning Research, vol. 20, pp. 1-7, 2019.

[16] Y. Zhao and M. K. Hryniewicki, "XGBOD: Improving Supervised Outlier Detection with Unsupervised Representation Learning," International Joint Conference on Neural Networks, 2018.

[17] Y. Zhao and M. K. Hryniewicki, "DCSO: Dynamic Combination of Detector Scores for Outlier Ensembles," ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD), 2019.