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Exploring maritime movement information: an explainable AI approach using Hi-DBSCAN and SHAP analysis

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Abstract

Maritime movement information is pivotal for several applications, including monitoring and examining vessel activities, ensuring efficient and secure navigation, logistics optimisation, and enhancing safety and environmental protection. The maritime industry relies on Automatic Identification System (AIS) data, which provides information on movement of vessels at sea. Determining meaningful and useful insights from this data is a challenge. The complexity and volume of the information make it difficult for traditional methods to provide in-depth insights and explanations. This paper presents an innovative Explainable AI (XAI) approach to explore maritime movement information using AIS data by leveraging high dimensional Density-Based Spatial Clustering of Applications with Noise (Hi-DBSCAN) algorithm and SHAP (SHapley Additive exPlanations) values in a novel way. Through experiments using real AIS datasets, the study reveals the efficacy of SHAP in determining the influence of AIS features on cluster formation. Results from two distinct AIS datasets demonstrate the efficacy of this method. This approach effectively unravels the 'black box' nature of clustering, providing maritime stakeholders with a clearer understanding of vessel behaviour patterns. For instance, in one dataset, the course of the vessel was identified as the most significant feature impacting clustering outcomes. Furthermore, the study explores SHAP's potential for anomaly detection by identifying data points with inconsistent feature influences. This study demonstrates that integrating Hi-DBSCAN clustering with SHAP analysis offers a transparent and interpretable method for understanding vessel behaviour patterns from maritime movement information and extraction of meaningful insights. This framework provides maritime stakeholders with insights beyond traditional pattern recognition, with transparency and explainability, allowing for a deeper understanding and more informed and data-driven decisions in maritime operations.

Keywords: Data Analytics, DBSCAN, Explainable AI, AIS, SHAP.

1. Introduction

Maritime traffic analysis plays a crucial role in various domains. Automatic Identification Systems (AIS) data, initially envisaged to enhance the safety of vessels at sea by avoiding collisions, now plays a pivotal role in maritime operations by providing real-time information about vessel movements. This data is essential for various applications, including collision avoidance, vessel traffic management, search and rescue, and environmental monitoring.

Assessing AIS data and extracting actionable insights poses significant challenges due to its volume, velocity, and variety. Traditional methods are often unable to process the deeper intricacies of maritime data effectively, and understanding such vessel behaviours requires advanced techniques. Machine learning (ML) techniques have often been used to assess AIS data and determine traffic patterns. However, even in such cases, the interpretation of the ML models is often limited, which makes it difficult to understand why certain predictions have been made. This is particularly in the case of unsupervised machine learning techniques, amongst which Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is a more commonly used technique in the maritime domain (C. Huang etc., 2023).

The intention of Explainable AI (XAI) techniques is to find a solution to this problem by providing an understanding of the internal functioning of models. XAI models are required in marine policy towards bringing in trust, transferability, fairness, improvements in the models and extracting inputs for decision making in the future (Yan etc., 2022).

This paper proposes an XAI approach to understanding vessel behaviour patterns within AIS data by leveraging the high dimensional DBSCAN algorithm and SHAP (SHapley Additive exPlanations) values to enhance the interpretability of clustering results in maritime movement data, facilitating more informed decision-making in the maritime domain. The effectiveness of this approach in extracting meaningful insights from maritime movement information is demonstrated experimentally, which also provides transparency and interpretability. It empowers maritime stakeholders to gain a deeper understanding of vessel traffic patterns and make data-driven decisions.

The motivation of the paper is to examine enhancements in the exploration of maritime movement information. While clustering algorithms, such as DBSCAN, are extensively utilised for pattern determinations of maritime movement data, these are predominantly black-box implementations to the user, which does not have much interpretability of the results. An insight into the rationale of how the features of the data influenced the outputs will go a long way in better understanding the exploration and derivation of more significant applications. Another motivation was also the limited study that has been undertaken on Explainable AI (XAI) in the maritime movement data context, specifically related to AIS data clustering using DBSCAN. Also, XAI is a fairly new research area, and methods like SHAP offer a solution by providing interpretable explanations for model outputs. Significantly, in the assessment of the authors, such a study combining high-dimension DBSCAN clustering and SHAP for exploring maritime movement information has not been attempted before.

It is useful to understand the significance of features in AIS in the maritime traffic domain which are affecting the clustering results for several reasons, including enhancing clustering results and insights by understanding features that influence the results of the clustering significantly, anomaly detection by determining features known to indicate abnormal behaviour, optimisation of resources by including only significant features during further processing, improved decision making by knowing the important features to focus on, amongst others.

The contribution of the paper is that it provides a significant advancement in exploring maritime movement information by moving away from a black-box method to a more transparent and interpretable approach using explainable AI concepts along with higher dimension unsupervised clustering. By explaining the underlying reasons for cluster formation, the study empowers maritime stakeholders to make more informed, data-driven decisions based on an enhanced and deeper understanding of vessel behaviour patterns.

The paper sections are: Section 2 introduces DBSCAN and XAI in brief, Section 3 reviews existing relevant literature, Section 4 brings out the proposed methodology, and Section 5 explains the details of the experiments. Section 6 examines the results and analysis of the experiments undertaken. The conclusion and future activities that could be progressed are brought out in Section 7.

2.Brief introduction to DBSCAN and SHAP

2.1 DBSCAN

DBSCAN Data Clustering attempts to segregate data into groups wherein some element of commonality exists between each data point of an individual group. There is no requirement to train a model on the data to determine clusters using Clustering methods. DBSCAN requires two parameters as inputs, viz. Eps (a point's neighbourhood indicated by an appropriate distance measure) and MinPts (minimum number of points required within the neighbourhood). DBSCAN has the ability to detect clusters which may be of arbitrary shape and, therefore, is well suited for clustering AIS data.

The popularity of DBSCAN in the maritime domain has resulted in considerable research and adaptations to be evolved on it. There have been various attempts to enhance the clustering results by including parameters other than spatial while clustering. One such attempt to optimise DBSCAN is by using additional parameters from AIS data, viz. speed indicated as Speed Over Ground (SOG), course indicated as Course over Ground (COG) and Heading, apart from the spatial parameters, i.e. Latitude (LAT) and Longitude (LON) (Han etc., 2021). This higher dimensional DBSCAN (Hi-DBSCAN) enables more refined clusters to be determined and enhances the clustering outputs.

2.2 Explainable AI and SHAP

The black-box nature of machine learning models often limits the understanding and interpretation of how the outputs have been reached at, which can lower the trust and affect debugging or analysis. In the domain of AI, explainability can be considered as undertaking additional actions to understand an ML model which cannot be interpreted by humans (Yan etc., 2022). Explainable AI (XAI) can be defined as the production of details or rationales of the functioning of a model to enhance the understandability of a target audience (Barredo Arrieta etc., 2020).

SHapley Additive exPlanations (SHAP) is one method which enables explaining how the output of a model has been determined. It provides the contribution made by each feature to a particular output. This is done by determining the marginal contribution of a particular feature by the variation in the results of combinations of features by including and neglecting the particular feature. A positive value of SHAP shows that a particular feature increases the predicted value, and on the other hand, a negative value leads to a decrease. A representation is shown in Fig 1. This thus helps in assessing how the various features interact to determine the output of the model, which can be plotted in various ways to enable explainability.

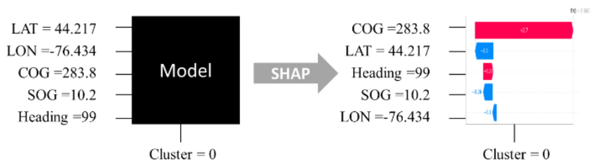

Fig 1. Explaining a model using SHAP.

The SHAP values can be analysed from a Global perspective by averaging the absolute values of each variable to assess the importance of the feature or Locally by the influence of each feature on selected samples of data. Detailed explanations of SHAP have been brought out in (Lundberg etc., 2017, 2020; L. Wang etc., 2022). A simplified version of the calculation of SHAP is given in Eq. (1), in which F is the features set, S is the features subset, the function v generates the prediction value of the model from the features, i is the feature of interest index, $|F|$, represents feature permutation numbers in set S and $SHAPi$ is the feature i SHAP value (Su etc., 2024).

$$SHAPi = \sum_{S \subseteq F-i} \left[\frac{|S|!(|F|-|S|-1)!}{|F|!} - v(S)\right] \qquad (1)$$

There are several advantages of using SHAP. It assists in debugging a model in case the predictions are not correct, thus enabling informed modifications. It also enables the generation of explanations which can be understood for each prediction and the model as a whole. This is particularly important when certain applications require that there be some sort of explanation for the results. It is also a valuable method of data exploration, which can assist in determining various insights that may not be readily evident, as well as interactions between features. This can lead to much better development of models.

3.Review of existing literature

There are various models that have been developed for XAI. While comparing the performance of three XAI models in assessing the automatic docking of vessels, viz. SHAP, Local interpretable model-agnostic explanations (LIME) and Linear Model Trees (LMT), it has been brought out that SHAP provides smooth explanations that are intuitive within a reasonably fast time (Lover etc., 2021).In a study undertaken to evaluate XAI methods for assessing results of the classification of ships, it has been brought out that these methods are also applicable for time series information with multiple variables (Veerappa etc., 2022). Furthermore, SHAP-based methods have been found to be more robust than (LIME) and Path integrated gradients (PIG).

SHAP was proposed to help understand why certain predictions have been made by a model since this can be a difficult task for complex models, which generally are more accurate (Lundberg etc., 2017). SHAP achieves this by assigning an importance value to each feature for a specific prediction. It has also been brought out that both local and global explanation have their advantages in providing a richer understanding of the models (Lundberg etc., 2018, 2020).

While proposing a new model for deciding the detention of a ship towards reducing traffic risks, SHAP has been utilised to interpret the model and provide the contribution of the features of the model (He etc., 2021).

SHAP has also been used to determine the contribution that sensors have in an anomaly in the main engine of a vessel (Kim etc., 2021). It has been indicated that the SHAP algorithm is robust and can perform with various types of ML algorithms.

A study has been undertaken to determine the factors responsible for accidents in the maritime domain (C. Zhang etc., 2022). It classified the accidents into six different categories depending on the circumstances of the collisions. These results were then analysed and interpreted using the SHAP model. This interpretation added further value to the study by analysing factors and elements and correlating characteristics.

A hybrid technique has been proposed to develop a model in order to predict the risk of maritime accidents with enhanced accuracy (Lan etc., 2024). This model is then assessed through SHAP to determine the acts that a seafarer may commit, which could be deemed as unsafe and lead to accidents. This has the potential to predict an accident in advance, enabling preventive measures to be initiated.

Towards safe navigation by vessels, a high degree of vigilance needs to be maintained by the Vessel Traffic Controllers (VTC). Using 45 eye-tracking features, a prediction model has been evolved (Z. Li etc., 2024). A hierarchical analysis has been undertaken, in which SHAP plays an important role by identifying the significant features.

One method of safeguarding maritime transportation activities is by the port control, which undertakes inspection of ships that visit the port. A model has been developed to enable the selection of ships for inspection (Yan etc., 2022), which is then assessed using SHAP. This can help determine information on fairness, validation, and prediction. Reasons for the importance of explainability in the maritime domain are also elucidated, which are brought out later in the paper.

A number of studies have been undertaken with regard to fuel cost estimations and energy efficiencies, which have exploited XAI methods. These include providing the correct shaft power magnitude to the propeller of a ship (Kim etc., 2023), prediction of the consumption of fuel through various models using data from sensors (Ma etc., 2023), determining average draught and relative wind speed as the dominating operational and environmental factors, respectively (Handayani etc., 2023), prediction of consumption of fuel in ships (H. Wang etc., 2023), determining feature importance while addressing energy efficiency concerns in short-sea shipping (Abuella etc., 2023), prediction of fuel cost using wherein static and dynamic parameters related to the vessel (Su etc., 2024) and prediction of the fuel consumption and emissions of a vessel (Lee etc., 2024).

In an effort to assess the temporal features' effect on the prediction of ship routes, two models have been developed using a K-nearest neighbour classifier, with one of them incorporating the date and time features (Lo Duca & Marchetti, 2022). SHAP assessed the contributing features, bringing out that the temporal features result in lowering the predicted class value, which is why it tends to perform inferior to the other model.

Using features from AIS data, an attempt has been made to determine the status of congestion in ports and also predict the time in ports using XGBoost and SHAP (T. Zhang etc., 2023). SHAP helps in assessing the impact of each feature, enabling modification of the model to optimise the scheduling of ships.

In an effort to understand bike-sharing utilisation for leisure or as part of the public transport system in various roles, DBSCAN was used to separate leisure or transit trips. Thereafter, using gradient boosting and SHAP, the effect of variables in each trip is assessed. (X. Li etc., 2024).

One of the studies on road traffic attempted to explain the prediction in real traffic using Random Forest and Recurrent Neural Networks by SHAP (Barredo-Arrieta etc., 2019). The study brings out that forecasting models should be assessed beyond prediction, accuracy and other scores by assessing deeper information that the contributing variable can provide.

XAI has primarily been applied to supervised learning techniques in machine learning, which include prediction, as seen in the literature above. XAI, however, cannot be applied directly to unsupervised methods. In order to apply XAI to unsupervised techniques, the problem needs to first be converted into a supervised task, enabling the clustering results to be represented in a manner suitable to XAI techniques (Bobek etc., 2022). Summarising the activity into three basic steps, the first step involves undertaking a cluster of the data under consideration. Thereafter, the clusters are used as target variables to build a classifier. Finally, using XAI techniques, this classifier is explained (Horel etc., 2020; Lötsch & Malkusch, 2021; Morichetta etc., 2019). Various improvements are also being proposed, such as those which take into consideration data quality (Alvarez-Garcia etc., 2024).

A summary of the literature addressing maritime related aspects is brought out in Table 1.

Table 1. Summary of Maritime related literature.

Reference (First Author, Year)	Application Area	Key Findings & Role of XAI
Lover, 2021	Automatic Docking of Vessels	Compared SHAP with LIME and LMT for explaining automatic docking, finding that SHAP provides smooth, intuitive explanations quickly.
Veerappa, 2022	Ship Classification	Showed the applicability of XAI methods, particularly SHAP, for time series data with multiple variables, finding SHAP to be more robust than LIME and PIG
Lundberg, 2017, 2018, 2020	General Model Interpretability	Emphasised the use of SHAP for understanding predictions made by complex models by assigning importance values to features. Highlighted the value of both local and global explanations.
He, 2021	Ship Detention Decisions	Used SHAP to interpret a model for deciding ship detention to reduce traffic risks, providing insights into feature contributions.
Kim, 2021	Anomaly Detection in Ship Engines	Utilized SHAP to identify sensor contributions to anomalies in ship engines, indicating SHAP's robustness across different machine learning algorithms.
Zhang, 2022	Maritime Accident Risk Prediction	Developed a hybrid model to predict accident risk and used SHAP to identify unsafe seafarer actions potentially leading to accidents.
Lan, 2024	Maritime Accident Analysis	Classified maritime accidents into categories and employed SHAP to analyze and interpret the factors contributing to each accident type.
Li, 2024	Vessel Traffic Controller Vigilance	Used SHAP in a hierarchical analysis to identify significant eye-tracking features for predicting the vigilance of Vessel Traffic Controllers.
Yan, 2022	Port Control Ship Inspection	Developed a model for selecting ships for inspection and used SHAP to determine fairness, validation, and prediction information. Emphasised the importance of explainability in the maritime domain.
Kim, 2023	Ship Propeller Shaft Power Optimisation	Applied XAI methods to provide correct shaft power magnitude, aiming for fuel cost estimation and improved energy efficiency.
Ma, 2023	Ship Fuel Consumption Prediction	Used sensor data and XAI for fuel consumption prediction, highlighting XAI's role in understanding and improving model accuracy.
Handayani, 2023	Fuel Consumption and Vessel Factors	Identified average draught and relative wind speed as dominant operational and environmental factors affecting fuel consumption using XAI for analysis.
Wang, 2023	Ship Fuel Consumption Prediction	Applied XAI techniques to predict ship fuel consumption, focusing on understanding the factors influencing consumption patterns.
Abuella, 2023	Energy Efficiency in Short-Sea Shipping	Used XAI, specifically SHAP, to determine feature importance in addressing energy efficiency concerns, aiding in targeted optimization efforts.
Su, 2024	Ship Fuel Cost Prediction	Predicted fuel costs using static and dynamic vessel parameters and employed XAI to understand feature influences and improve cost estimation accuracy.
Lee, 2024	Vessel Fuel Consumption and Emissions	Predicted fuel consumption and emissions, utilizing XAI to analyze the factors driving both and potentially guide emission reduction strategies.
Lo Duca, 2022	Ship Route Prediction	Analyzed two K-nearest neighbour models for ship route prediction, with SHAP revealing that incorporating temporal features negatively impacted prediction accuracy.
Zhang, 2023	Port Congestion Status and Prediction	Used XGBoost and SHAP to predict port congestion and ship time in ports, with SHAP helping assess feature impact and optimize ship scheduling.

While this method has been applied to explain clustering results in various fields, the survey of the literature reveals that this has not been used in the maritime domain to assess results of clustering of maritime movement data, particularly those utilising DBSCAN and its variants.

4.Proposed Methodology

The proposed methodology uses an Explainable AI (XAI) approach for determining insights into the vessel behaviour patterns from AIS data. This uses a combination of a high-dimensional Density-Based Spatial Clustering of Applications with Noise (Hi-DBSCAN) algorithm and SHapley Additive exPlanations (SHAP) values. The proposed model is comprised of three phases. Phase 1 involves undertaking data preprocessing and clustering using Hi-DBSCAN. Phase 2 undertakes conversion to a supervised model. Finally, Phase 3 brings in the explainability of the clustering using SHAP.

In the proposed model, Hi-DBSCAN is used to cluster real AIS data, and thereafter, XAI using SHAP is used to add explainability to the cluster determination. Hi-DBSCAN includes additional non-spatial features while clustering, as brought out in (Han etc., 2020, 2021). The Hi-DBSCAN algorithm clusters AIS data, incorporating non-spatial features (speed, course, heading) along with spatial parameters (latitude and longitude) for refined cluster identification. While this improves the cluster determinations, it renders it more difficult to understand since multiple features have now been combined to produce the clusters. However, SHAP is to be applied to a supervised model, while clustering is to be applied to an unsupervised model. Therefore, as brought out in the literature review section, the model needs to be converted from a clustering to a supervised model. There are various machine learning algorithms in supervised learning techniques. In a study for the classification of ships using AIS data, it emerged that Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) performed better than six other algorithms (I. L. Huang etc., 2023). For this study, Random Forest has been used to convert the clustering results into a classification model. The resulting clusters are used as target variables to train a Random Forest classifier. The classification model is, thereafter, analysed using the SHAP algorithm, and the SHAP values are assessed through various methods to reveal explanations and insights.

A representation of the workflow for the exploration of the maritime movement information using Hi-DBSCAN and SHAP is shown in Fig 2.

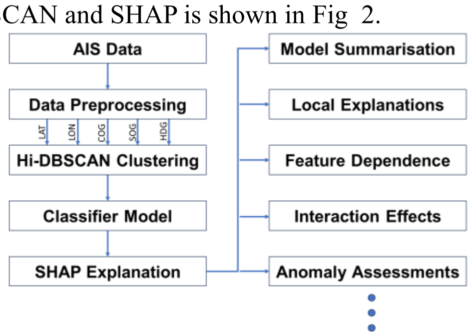

Fig 2. Model for AIS data exploration using HiDBSCAN and SHAP.

Briefly, the AIS data is pre-processed to ensure that the data is without errors and is limited to what is required for the experiments. Thereafter, the selected spatial and non-spatial parameters are passed on to the Hi-DBSCAN clustering algorithm.

Hi-DBSCAN introduces non-spatial AIS features along with the latitude and longitude values while calculating the distance using the Mahalanobis distance measure between data points for clustering. These additional features selected are the movement-related parameters from the AIS data, such as SOG, COG and Heading. The multidimensional data point ‘A’ consists of the attributes as seen in Eq. (2).

$$A = [LAT, LON, SOG, COG, Heading] \quad (2)$$

A suitable Classifier model is then trained on the Clustering results. This trained model is then processed through the SHAP explainable AI model to determine the SHAP values. Using these values, various explanations of the data and exploration of the results are undertaken to determine insights.

5.Experiments

In order to test the proposed methodology of exploration of data using XAI, real AIS has been sourced to enable a realistic assessment of the experiments. AIS system onboard a ship transmits messages at regular intervals. AIS data provides details on maritime movement and other information about vessels, represented by 27 different messages (UNSD_MM, 2020). These messages contain various features, which can be categorised into dynamic, viz. location, speed, course, heading, etc.; static, viz. name, flag, destination, length, etc.; and voyage related, viz. next port of call, expected time of arrival, etc. Two diverse datasets were selected for the exploration. The first dataset comprises segments of a ferry between Wolfe and Kingston region. The second data set comprises selected AIS data from the US east coast. This data was pre-processed to remove inconsistencies and relevant features as well as spatial and temporal extent as required for experiments. This involved data cleaning to remove errors or inconsistencies in the raw AIS data, such as missing values, invalid data points, or duplicate entries. Feature selection was undertaken to select only those features directly related to vessel movement information and exclude others like vessel type or size ince these parameters remain static during the passage of a vessel. For the experiments, while the AIS data from Marine-Cadastre comprises 18 features, only spatial and non-spatial features were selected for clustering, viz. Speed Over Ground (SOG), Course Over Ground (COG),

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Heading, Latitude (LAT), and Longitude (LON). Data closer to the harbours has been excluded due to the inconsistent, complex and dense traffic patterns in these areas which do not reflect general vessel behaviour. The parameters for Hi-DBSCAN, i.e. minimum points and reachability distance, have been selected iteratively. Selecting appropriate values for MinPts and Eps is critical for effective clustering since different values can significantly influence the clusters that are ascertained. The optimal values depend on the specific dataset and the characteristics of the clustering being sought. Iterative assessment undertaken involved starting with an initial parameter selection, which in these experiments were MinPts equal to 5 and Eps equal to 1. The Hi-DBSCAN algorithm was run with the selected parameters and the quality of the resulting clusters evaluated visually. Based on the evaluation, the MinPts and Eps values were adjusted. This has been repeated, experimenting with different combinations of MinPts and Eps, until a satisfactory clustering result has been achieved for each data set. Python has been the development environment, while QGIS (Quantum Geographic Information System) has also been used towards the visualisation of the data.

The data used for the study was from 01 January 2021 between 1000hrs and 2300hrs and sourced from MarineCadastre (AccessAIS - MarineCadastre.Gov, 2023). After the data has been prepared, Hi-DBSCAN clustering is undertaken on it. An iterative assessment for the determination of parameters for clustering results in minimum points as three and maximum distance as 1.75. The result of the clustering is shown in Fig 3. The clustering has resulted in two primary clusters, which represent directional traffic movement. In Fig 3, each dot represents a single data point, which corresponds to a vessel's position at a specific time. The clustering algorithm analyses these positions, along with other features like speed and course, to group together vessels exhibiting similar movement patterns. The clustering results in the determination of two primary clusters, indicating Directional Traffic Flow. One cluster represents a ferry travelling from one location (Wolfe) to another (Kingston). The other cluster represents the same ferry travelling in the opposite direction (Kingston to Wolfe).

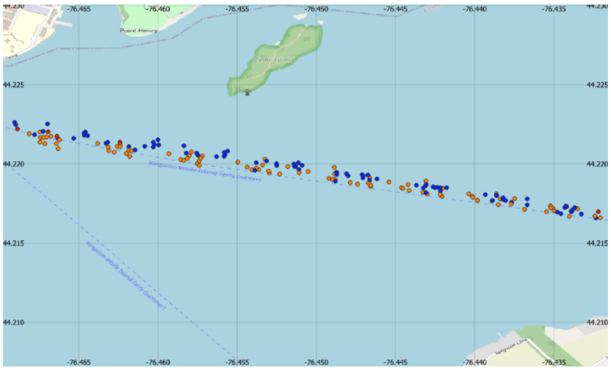

Fig 3. Hi-DBSCAN clustering.

The models trained by the Classifier are then processed through the SHAP algorithm. This results in the determination of SHAP values for the dataset, which can then be assessed by various methods to lend explainability to the results. The results and analysis of the data using SHAP are presented in the next section.

6.Results and Analysis

6.1.SHAP based assessment of Hi-DBSCAN Clustering on Dataset 1

i. SHAP Global Explanation - Bar Plot

The SHAP Bar plot in Fig 4 shows the absolute average SHAP values of every feature of the dataset using Random Forest. It enables determining the contribution of each feature in the clustering to the others since a large value can influence the change in output more. It can be seen from the plot that in the given dataset, COG has the maximum SHAP value of 2.45 and is the most significant feature, having the most impact on the clustering. The other features do not have a significant impact on the clustering results, with the next significant feature being Heading. This plot helps identify the most influential features of AIS data which are crucial for separating groups of vessels, detecting anomalies, understanding traffic patterns and risk zones, etc.

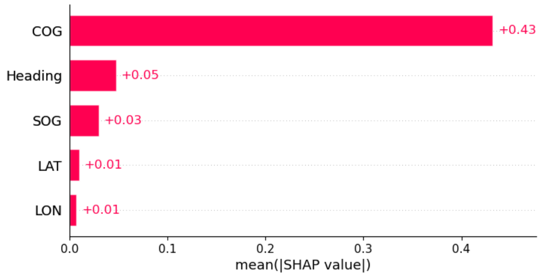

Fig 4. Bar plot – Random Forest.

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ii. SHAP Global Explanation - Beeswarm Plot

The Beeswarm plot is shown in Fig 5. Beeswarm plots enable a comprehensive understanding of the way in which the SHAP values are distributed using both positive and negative values. The SHAP values are represented along the x-axis, and the distribution along this axis indicates the influence and impact that a feature has on the output. Since it plots both positive and negative values, it enables the determination of whether the feature increases or decreases the value of the prediction. Each dot indicates the SHAP value of one of the samples for a feature from the AIS data. The colour of the dot is a gradient from blue, representing a low feature value, to red, indicating a high feature value. Multiple dots at the same position are stacked up to indicate the density. Here again, it is seen that COG has a major influence on the output of the model, and both high and low values play an important role in the Clusters that are formed. Since both extremes are associated with SHAP values that are positive, it implies a non-linear relationship between the model's output and COG. The other features are generally centred around zero, which implies a minimal impact on the clustering. However, some low values of Heading are seen on the positive side, implying instances of having an increased influence in certain local cases. For an analyst, it enables the determination of whether the feature increases or decreases the value of the prediction. Identification of outliers, visualisation of feature interactions, potentially risky manoeuvres and undertaking comparisons across predictions are some of the other ways in which a maritime traffic analyst can exploit the Beeswam plots.

The global Bar and Beeswarm plots enable a useful high-level summary of influences as assessed by the model. The information obtained from the Bar plot and Beeswarm plot also enables an assessment of the features to be selected in case further analysis is required. As in this case, for DBSCAN clustering, only COG, along with the mandatory spatial components, need to be considered if further clustering assessments are required. This will speed up the processing with a lesser amount of data.

A tabular representation of the minimum, maximum and average SHAP values and the relative feature ranking in each case is shown in Table 2.

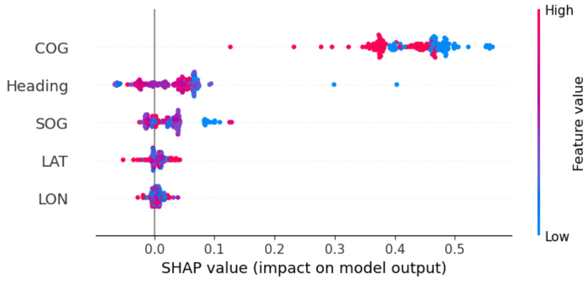


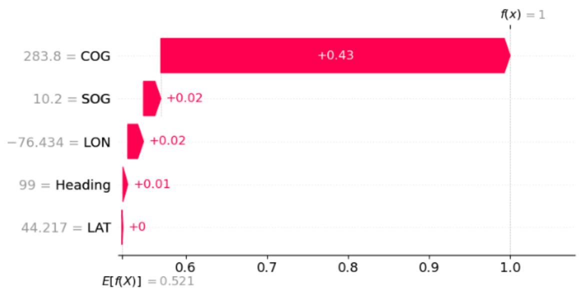
Fig 5. Beeswarm plot – Random Forest.

Table 2. SHAP Values

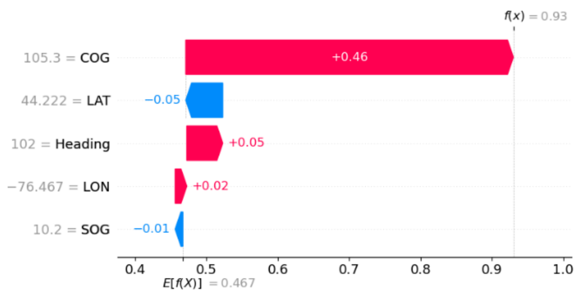
Feature	Min SHAP Value	Max SHAP Value	Absolute Mean SHAP Rank	Min SHAP Rank	Max SHAP Rank	Absolute Mean SHAP Rank
COG	0.126498	0.562583	0.432059	5	1	1
Heading	-0.065910	0.403263	0.047758	1	2	2
LAT	-0.051871	0.042487	0.009826	2	4	4
LON	-0.027482	0.039224	0.007080	3	5	5
SOG	-0.024708	0.128751	0.030036	4	3	3

iii. SHAP Local Explanation – Waterfall Plot

While the above two plots visualised the SHAP values for the entire data, it is important to explore how the various features influence the clustering of a single data point. This is also possible in SHAP with the use of Waterfall Plots. This can be seen in Fig 6 for Random Forest, which shows the plots for a single instance of two different clusters. Fig 6(a) is of an instance in one cluster in which the predominant feature is a high value of COG, but SOG and LON also contribute some influence. Fig 6(b) shows another instance in another cluster in which the dominating feature is again a high value of COG. In this case, LAT and Heading contribute in opposite ways. Therefore, an explanation of why a particular point has been put in a particular cluster is evident. These plots provide a clear, intuitive way to indicate the aspects determining a vessel's cluster assignment to stakeholders, such as port authorities or shipping companies and help the maritime analyst to identify patterns, misclassifications, relationships between features, etc. which can improve the understanding of the maritime traffic.



(a)



(b)

Fig 6. Random Forest Waterfall Plots (a) Cluster 0 and (b) Cluster 1

iv. Anomaly Assessment

The Waterfall plot can also be used to assess the reasons for anomaly or outlier detection. From the data, one of the outlier points was analysed and is shown in Fig 7. It has been observed that the Heading feature has an influence not consistent with other data points and, hence, has been identified as an outlier. This can be thereafter further analysed to detect further rationale for its occurrence.

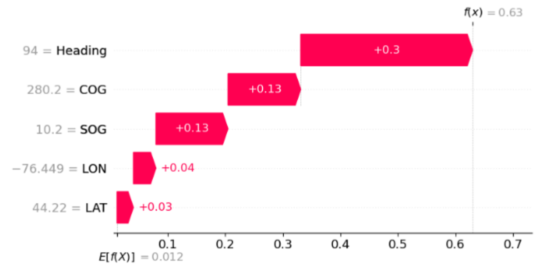
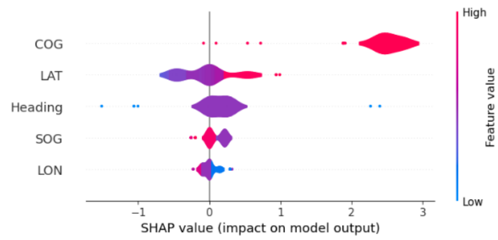


Fig 7. Anomaly assessment

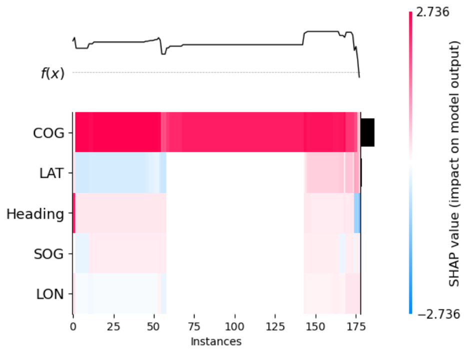
v. Additional Plots

There are a number of additional plots that can be generated using SHAP values, providing insights and exploration capabilities, and can be exploited for further analysis of SHAP values and the model depending on the use case. Some of these plots are shown in Fig 8. The Force plot is particularly useful to a maritime traffic analyst for comparing the relative impact of different features on a vessel's cluster assignment and for real-time traffic monitoring, where it is important to understand sudden changes in patterns. Examination of the Heatmap plot can help to identify features that have strong interactions, and enable understanding the underlying relationships in the data. The violin plot enables the determination of consistent trends or variations, e.g. if the speed is showing a narrow impact on clustering. It will help the analyst assess that there are expectable speed patterns among vessels. A dependence plot demonstrates the impact of a feature changes with variation of its value and thus helps reveal the relationship to the analyst.

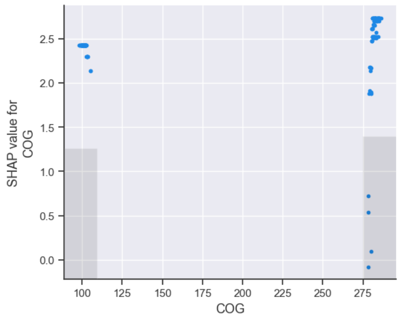
A comparative assessment of global mean SHAP values with region-specific SHAP values can also be undertaken, in which areas of divergence could indicate influential features which may be location-dependent and help in explaining outliers. Thus, targeted SHAP assessments can help discover contextual influences along with globally stable features.



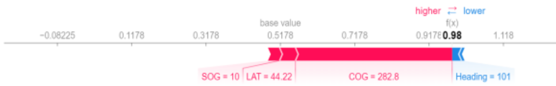
(a)



(b)



(c)



(d)

Fig 8. Additional SHAP Plots (a) Violin (b) Heatmap (c) Dependence and (d) Force

6.2. SHAP based assessment of Hi-DBSCAN Clustering on Dataset 2

Explanation by SHAP using XGBoost has also been assessed on another data set, in which the selected AIS data has been sourced from the east coast of the USA on 31 December 2020. Hi-DBSCAN clustering result is shown in Fig 9. It comprises of paths of eight vessels. Each of these vessels has a distinct path, with variation in its movement parameters as well as spatial parameters, leading to the formation of eight separate clusters. The Bar plots indicate a higher contribution of SOG and Heading than the others, which also have a certain amount of contribution, unlike Data Set 1. SHAP plots are shown in Fig 10. An analysis of the Beeswarm plot indicates that both high and low values influence the clustering for most variables, with SOG having a higher influence and variation around 0. Two examples of waterfall plots of clusters are shown, which show how SOG and COG can have differing influences in the two clusters.

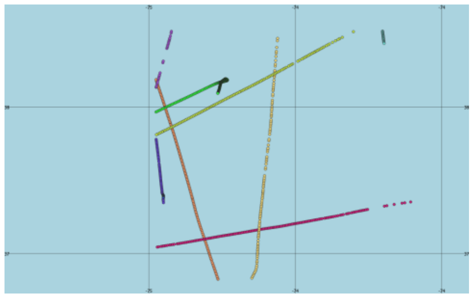
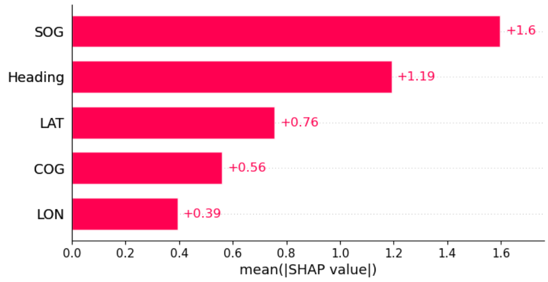
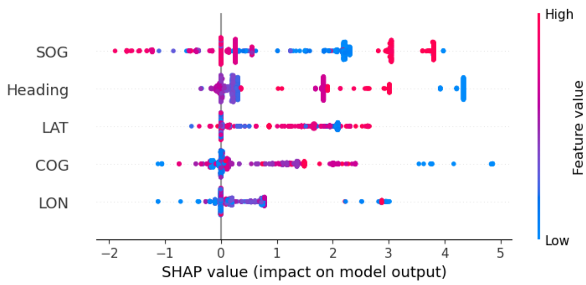


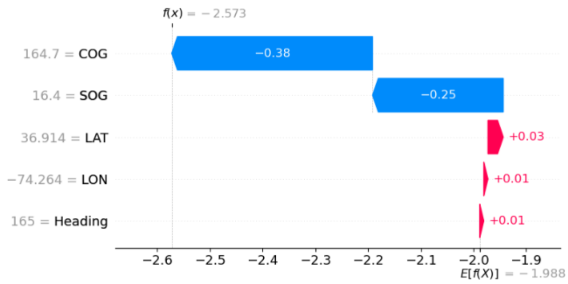
Fig 9. Dataset 2 Hi-DBSCAN Clustering.



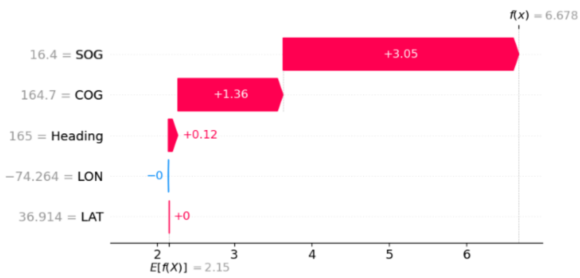
(a)



(b)



(c)



(d)

Fig 10. Dataset 2 SHAP plots (a) Bar (b) Beeswarm (c) Waterfall Cluster 0 and (d) Waterfall Cluster 1.

7. Discussions

The experiments and results demonstrate that SHAP has significant application in assessing the influence of individual features in the output of a higher dimension DBSCAN clustering of AIS data. Using the global assessments through Beeswarm and Bar plots, the average influence exerted by all the variables on the model can be determined to understand the overall impact of clustering. The local assessments using Waterfall plots, on the other hand, enable determining the contribution each variable has to the final cluster that has been determined. These two assessments enable the explainability of the clustering and provide an insight into the internal functioning of the clustering model. Thus, using SHAP analysis as a second stage after implementing the clustering machine learning model in the first stage enables explanations of the clustering results. This study has explored the clustering results of AIS data and enables an explanation of the factors influencing the overall clustering as well as individual instances. This has wide-ranging applications in the maritime domain while exploring maritime movement information such as AIS and providing valuable insights from explanations using SHAP, including, assessment of anomalies and outliers. The transparency and interpretability obtained through XAI techniques like SHAP enables maritime stakeholders to understand the factors affecting the clustering results and thereafter make more learned decisions. Therefore, there is a significant impact that this framework will have towards enhancing the understanding and management of maritime activities, and facilitate contributing to a safer, more efficient, and sustainable maritime domain, including the following:

(a) Enhancing Maritime Situational Awareness: It has been seen that the factors driving vessel behaviour patterns can be understood through SHAP analyses of Hi-DBSCAN clustering results. The traffic flows can be anticipated and managed better, thereby enhancing safety and reducing congestion.

(b) Improved Anomaly Detection: It emerges that the proposed approach can help identify outliers or unusual vessel behaviours. These may indicate illegal activities, safety violations, or potential hazards, which would assist the maritime analysts in their processes.

(c) Formulating Policy Decisions: Since the framework enables understanding of the influencing factors behind vessel movements, these can enable the formulation of more effective and targeted policies related to areas like maritime safety, environmental protection, and port management.

(d) Optimised Logistics and Efficiency: The insights that are determined using this approach into vessel traffic patterns can help in optimising shipping routes, improving logistics planning, and reducing fuel consumption and emissions.

While XAI has been used to interpret supervised learning techniques in maritime applications, its application to unsupervised methods like clustering remains under-explored, particularly in the context of AIS data and DBSCAN. The model proposed in this paper addresses a gap in existing research by applying SHAP to explain Hi-DBSCAN clustering outcomes. As a future scope of work, comparative studies with other classification algorithms and the XAI model are recommended, which then facilitate additional assessment studies.

The results of the study directly contribute to enhancing the exploration of maritime movement information by providing a framework for ascertaining not just what clusters are formed, but also why those clusters formed. This in-depth understanding because of the interpretability brought in by SHAP, enables maritime stakeholders to progress ahead from just pattern recognition towards actionable insights and informed decision-making.

8. Conclusion and Future Scope

SHAP, an XAI method, has been exploited to bring in explainability to higher dimension DBSCAN clustering of maritime movement information, viz. AIS data. It has been shown how the various features of AIS data influence the formation of clusters, thereby making it more understandable to both model developers and policymakers. For a given scenario, the combination of AIS data, Clustering and SHAP is effectively utilised to glean valuable information for further understanding and assessments.

Significantly, the study moves beyond just unsupervised clustering results of AIS data, diving instead into the rationale for the formulation of the clusters. One of the crucial highlights of the research includes examining the interplay of both global and local SHAP assessments and their ability to uncover insights. This research introduces an innovative framework for maritime movement data combining higher dimension unsupervised clustering with explainability through SHAP, enabling an insightful understanding of the dynamics at play within the maritime movement information.

Machine Learning and AI have considerable potential in the maritime field, and this study has demonstrated the way in which XAI models such as SHAP can be effectively utilised for the explainability of clustering models.

Future opportunities in the utility of SHAP plots in the analysis and application of clustering through DBSCAN are considerable. It has been shown how it can be used for anomaly/ outlier detections, which can be dwelled into in more detail, including a deeper analysis of regions towards the determination of anomaly detection systems. SHAP assessments can also be utilised to determine the weighting of certain features depending on the outcomes required. It can also be used in studies to determine significant parameters and thereafter optimise further processing. Also, additional features of AIS data can be considered in the higher dimensional DBSCAN, and clustering can be assessed using SHAP. Some other XAI models and classification techniques can also be studied, and a comparative assessment can be undertaken.

In conclusion, this study demonstrates a powerful framework for explaining the clustering results in the complex maritime movement information landscape, enabling more transparency to all concerned towards informed decisions by examination of global, regional and outlier behaviours. This can help in more informed exploration and understanding of maritime movement data and facilitate advances in secure and efficient maritime traffic movements.

Acknowledgement

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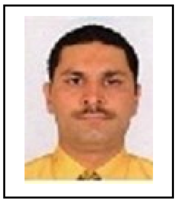

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