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Machine Learning Techniques for Intrusion Detection of Fishermen and Trespassing into Foreign Seas

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Abstract

Issues regarding trespassing and intrusion of fishermen in the maritime boundary line is of great importance to be discussed nowadays. One of the main reasons still existing is transgression for better catch of fishes in foreign waters. Thus is a concern, and in order to prevent this issue from becoming a national security threat, it should be taken care of, by identifying the intruders as the first step to get a better view on the situation. Finally, in the hope to slim the chances of transgressions by marine fisher folk, a SVM model based on Automated Identification System that makes use of real-world data is implemented that will analyse the possibility of successful detection of intrusions of fisherman by categorising the vessel as normal or anomalous one. Convolution Neural Network model is used to find whether it is ship or not a ship, and if it is ship then it will categorize whether it belongs to anomalous or non-anomalous. The model's validation accuracy of 96% shows that it can correctly identify whether a ship is present in each image.

Keywords: Intrusion, Trespassing, Machine Learning, SVM, Anomalies, Convolution Neural Network

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1. Introduction

Recently there has been controversies that has arisen due to illegal trespassing by fishermen and illegal fishing activities. Due to adverse aftereffects of such activities, it is now of great concern to find a solution to prevent such activities from occurring in the near future. With developing technology and human knowledge, this could be possible. Thus, this work mainly focuses on building a model that will help in identifying vessels and their status on the waters. Thereby reducing the chances of such illegal activities from happening.

With the growth of navigation globalization and artificial intelligence, there is a conflict between the growing need for ship behavior monitoring and the resources that are available for traffic service, and it is a problem when accidents at sea happen often. Combining marine information on board and ashore is a potential improvement to safeguard matters at sea and avoid unwanted conflicts. In this way, when precautions are taken beforehand, there is a possibility that this initiative can solve many problems.

The world's fish populations are now threatened by both aggressive legal fishing practices, and Illegal, Unreported, and Unregulated (IUU) fishing. The entire catch from pirate fishing is impossible to calculate with accuracy. Apart from this, there are poor fishermen who are not able to benefit themselves from their work. Illegal fishing is the term used to describe fishing operations carried out by foreign vessels without authorization in waters under the jurisdiction of another state or that otherwise violate that state's fisheries laws and regulations, such as by disobeying fishing seasons or the existence of the state's protected areas. In some countries, the resources to set up efficient fisheries with proper management is nearly impossible, this is where the IUU vessels are frequently allowed to operate freely.

In many regions of the world, IUU fishing directly jeopardizes both socioeconomic stability and access to food. The most vulnerable nations to the effects of IUU fishing are developing nations that rely on fisheries for export revenue and food security. For instance, overall catches in West Africa are thought to be 40% more than what has been recorded. Many of the crew members are from underdeveloped and underprivileged regions of the world, and they frequently operate in hazardous conditions.

Recently there has been lots of controversy that has arisen due to illegal trespassing by fishermen and illegal fishing activities. Due to adverse aftereffects of such activities, it is now of great concern to find a solution soon, to prevent such activities from occurring. With developing technology and human knowledge this could be possible. Thus, this work mainly focuses on building a model that will help in identifying vessels and their status on the waters, thereby reducing the chances of such illegal activities from happening.

The Automated Identification System (AIS) base station was created to ensure navigational safety. The AIS is an automated reporting system that allows information about ships both onboard and on shore to be known for navigational and safety purposes. This work mainly focuses on using real world AIS data to identify anomalies and keep track of all information of the ships with the help of their unique MMSI number. The MMSI number is unique nine-digit number that is used by AIS to uniquely identify a ship. This work helps in identifying an algorithm that will detect anomalous ships from normal ships.

2. Literature Survey

In paper [1], the author states that, for marine traffic situation awareness, the AIS reports information on vessels. However, AIS transponders may be turned off to cover up shady activities like piracy or illegal fishing. In order to examine the likelihood of successfully detecting various abnormalities in the maritime environment, the author uses real-world AIS data. For the purpose of classifying deliberate and unintentional AIS on-off switching anomalies, the multi-class anomaly framework designed using a multi class ANN detects purposeful or unintentional AIS message dropouts for carrying out illicit actions, among other causes, such as channel impacts. The models have an accuracy of almost 99.9% and can categorize a test sample in a matter of microseconds.

In paper [2], the author suggested that the problem of recognising ship trajectories with regard to seas is addressed by developing an algorithm for categorizing ship trajectories based on machine learning techniques. Three machine learning classification techniques such as Support Vector Machine (SVM), Broad Learning System, and the Back Propagation Neural Network were used in the study.

In paper [3], the author proposed that, in the maritime sector, automation is crucial and works toward reducing operational manpower. However, efficient control at multiple stages, from shipbuilding to navigation, is necessary for effective automation. Although there are several conventional ways for automation and control, the marine industry is increasingly drawn to artificial intelligence schemes due to their advantages. Results from the AIS and fuzzy logic systems are encouraging. For new researchers, the expanding use of AIS in various nautical applications might serve as a reference point. The objective of this research is to perform a reliable AIS study and to investigate the various machine learning techniques applied in various marine applications.

In research [4], small marine targets must be detected by radar with particular care given to suppressing sea clutter returns, which can occasionally be challenging to distinguish from target returns. The author investigates a fresh application of machine learning techniques to this well-known issue. The results of two machine learning algorithms for the reduction of marine clutter were compared, and the findings were reported. An experimental radar named NetRAD was used to collect the data for this investigation. Using the k-Nearest-Neighbor (kNN) and SVM algorithms, this radar system was watching a coastline area and classifying the data as either target or clutter. The findings are displayed as the mean probabilities of detection and false alarm.

In paper [5], the author stated that, for border protection, harbour protection, and the security of different commercial sites, surveillance is a major issue. Protecting the expansive near coast sea surface and bustling harbour regions against intrusions by unauthorized marine vessels, such as trespassing boats and ships, is particularly difficult. The study described a cutting-edge method for detecting ship intrusions utilizing support vector machines and image processing. The primary goal is to find ships that enter or leave guarded industrial areas and borders. With the help of the processes that these two procedures interact with one another, the author can identify the intrusive ship in the continually shifting marine environment. By exposing the system to various seaside situations, SVM may be utilized as a machine learning technique to train the system.

In paper [6], the author found that, the majority of marine surveillance systems in use today depend on this AIS which is a requirement for certain categories of vessels. Finding patterns in data that deviate from expected behaviour is referred to as anomaly detection. When traveling in areas where piracy assaults are common or there is a chance of unlawful activity, many vessels turn off their AIS transponders in an effort to conceal their whereabouts and fool either the authorities or other piracy vessels. Additionally, fishing boats turn off their AIS transponders to prevent other fishing boats from fishing in the same region. In order to prevent other fishing boats from fishing in the same region, vessels turn off their AIS transponders. To the best of knowledge, little research has been done specifically on real-time AIS switch-off. The authors offer a system that can handle high volume, high velocity streams of AIS data received from terrestrial base stations and detect such instances in real time. The authors assess the proposed method using data obtained from actual AIS receivers and demonstrate the attained detection accuracy.

In paper [7], the author found that, the health of the marine ecology and the human food supply are seriously threatened by illegal, unreported, and unregulated fishing. It not only results in large economic losses but also has negative long-term repercussions on the ecosystem,. Beginning in the early 2000s, there has been a battle against this issue. Since then, numerous strategies and techniques have been created and documented. Coastal Surveillance Systems (machine learning and IoT), play a key role in this topic. This paper's major goal is to inform the reader on the scope of this phenomenon, possible solutions, and the state of the field's study at this time.

In paper [8], the author suggested that, monitoring of fishing activity patterns over vast geographic areas has been made possible by analysis of ex situ vessel tracking technology like AIS. The study shows how openly the available data on the web may be utilized to learn more about remote places, where conducting in-person research would be logistically and financially impossible.

In paper [9], the author stated that, mariners frequently employ the AIS at sea as a required on-board collision prevention technology. Ever since collaborative platforms were first developed large global AIS datasets that compile AIS messages received by a network of stations can be assembled, allowing a number of analyses, and were subjected to abuses also; this made the data unreliable. This has led to the identification of maritime risks in support of maritime monitoring activities, and a system for evaluating the integrity and authenticity of AIS messages that has been created in this regard. In the study, a proposed exemplification was predicated on potential AIS integrity problems with kinematic data.

In paper [10], the author found that, global trade and business rely heavily on maritime transports. Massive ships traveling the globe in constant motion produce vessel trajectory data that contains rich spatial-temporal patterns of vessel navigations. For the administration and surveillance of maritime traffic, it is useful to analyse and comprehend these patterns. Visualization and visual analysis are commonly employed in vessel trajectory data analysis as key methods for comprehending and analysing complex data. The authors evaluated the literature on vascular trajectory data visualization and visual analysis. First, the authors discussed the frequently used vessel trajectory data types and listed the primary preparation steps for vessel trajectory data. Then, based on current methodologies, the authors provided a taxonomy of visualization and visual analysis of vessel trajectory data and thoroughly described a few typical works. Finally, the authors discussed the outlook for the remaining problems and the lines of inquiry for future study.

In paper [11], the author stated that, a crucial element for marine security is the AIS. The efficiency of several AI algorithms in addressing anomalies in the marine environment utilizing AIS data was compared in this research. Since AIS technology is prone to manipulation and may be turned on and off to conceal criminal activity, the AIS On-Off Switching (OOS) anomaly is crucial for maritime security. So, by creating a framework for AI-assisted anomaly identification, the authors attempted to identify and separate AIS OOS abnormalities that are deliberate from those that are not. The authors investigated the performance of seven AI approaches, including ANN, SVM, LR, KNN, DT, RF, and NB, in identifying the AIS OOS anomalies using AIS data, namely location and navigational status of vessels.

In paper [12], the Convolutional Neural Networks (CNNs), a type of Deep Learning technology, were utilized to resolve the issue in anomaly detection in maritime as well as coastal traffic and also the automation of the vessels. In order to determine the optimal structure for classifying anomalies, 1458 convolutional neural networks with various architectures were trained. How different network architectural factors affected overall categorization accuracy was investigated. Class prediction rates for the top networks were studied. In order to explain how the network functions in a clear and approachable manner, activations of a few chosen convolutional layers were researched and shown.

In paper [13], the author's objective is to locate a target vessel quickly. The triggering report simply includes details on the type and displacement of a vessel engaging in an illegal conduct, simulating operating circumstances. In order to decrease the number of waypoints in the flight plan, a neural network trained to categorize vessels is paired with clustering of vessels. The neural network receives information from the UAVs onboard sensors on each vessel in the search area, prioritizing which vessels should be visited. The authors have studied three techniques to choose which planning process to apply in different operational circumstances because the classification-accuracy and the clustering potential rely on a number of operational aspects and on the UAVs sensor ruin. The findings demonstrated that a UAV can quickly locate the unidentified target vessel using this flexible and reliable technique.

In paper [14], a data preparation method for controlling and identifying fishing vessels was proposed. The approach involves categorizing ship trajectories into non-fishing ships or fishing ships using a binary classifier. The utilized data was characterized by the common issues, such as noise and inconsistency, encountered in traditional data mining applications employing real-world data. The data for the two classes was also obviously out of balance, and algorithms that resample the instances were used to fix this issue. From sequences of AIS reports, which contain spatiotemporal data representing the paths of the ships, a number of characteristics were retrieved for categorization. These qualities were suggested for the modelling of ship behaviour; however, the categorization may be used in other situations because they do not contain context-related information. The proposed data preparation method was effective for solving the given classification issue, according to the experimentation. Positive outcomes were additionally attained with little data.

In paper [15], the author stated that with conventional prediction techniques, it is challenging to simulate ship trajectories accurately. There are just a few samples of real-time, at-sea, AIS information on target ships, for instance, and neural networks are prone to entering local optima. A trajectory prediction model based on Support Vector Regression was suggested to address these issues and enhance the precision of ship trajectory predictions.

In paper [16], the author proposed that the overfishing that results from illegal, unreported, and uncontrolled fishing poses a grave danger to marine ecosystems and economies across the world. Effective strategies to make use of the data and information obtained widely through marine intelligence are required for stricter enforcement of conformity with rules by closely monitoring fisheries and their operations. Fishnet is able to determine if a vessel was engaged in fishing at a specific moment and contrast that activity with what the vessel really did. The definition of the suggested solution for the problem of fishing activity identification is given in terms of a binary classification model for deciphering trajectories taken from maritime traffic data.

In paper [17], the author stated that, due to the fast increase in the number of ships, the environment for maritime traffic is growing more complicated, there are occasionally maritime traffic incidents, and the demand for maritime traffic monitoring is rising. The ships were categorized using geometric and behavioural traits, and further abnormalities were found. SVM and RF were used for classification, with RF providing the highest accuracy.

In paper [18], illegal fishing is a problem in many nations. The author states that improving the capacity to determine if a vessel is fishing unlawfully and where illicit fishing is likely to occur in the ocean is a fundamental problem in eradicating illegal, unreported, and unregulated fishing. The data was divided into several subgroups across various trees using random forest. These subset trees decrease data-to-data correlation, which lowers variance and improves predictions. The suggested model was validated using the black cross-validation approach. Random forest was able to identify instances of illegal fishing with an overall accuracy of 70%.

In paper [19], the author stated that, due to IUU fishing, which puts the future of the fishing sector in jeopardy and may worsen living conditions in nearby fishing towns and communities, monitoring fishing vessels is essential in the marine environment. The term "IUU fishing" refers to careless fishing practices including fishing in prohibited regions, reflagging boats to get around restrictions, and failing to report catches.

In paper [20], the authors employed visual analytics to close the gap by using users' reasoning and perception skills in a domain where recognising anomalous trips is a difficult challenge using only automatic approaches. A visual analytics tool that scores journeys by breaking them down into smaller sub trajectories using spatial segmentation was represented. Users can rank journeys by segment to detect local abnormalities using these ratings, which are shown in a tabular presentation. Scores are shown alongside information on sub trajectories' interpolation levels so that users can assess the score's reliability based on both their knowledge and the route shown on the map.

In paper [21], the authors proposed that the AIS vessel tracking system, which continuously communicates vital information about a specific vessel to all other vessels, has been a significant advancement in navigational safety. The drawbacks commodity details are not provided in AIS, or the number of necessities that each vessel is transporting to particular coastal areas. The authors deploy an estimation tool based on ANN to get over the limitations of the current tracking method using AIS. As a result of the assessment and analysis of AIS data and the integration of vessel capacity information, the study created a prediction model that allows a relief manager to predict.

In paper [22], for the purpose of observing IUU fishing in Ghanaian seas, the author established the "Integrated System for Surveillance of Illegal, Unlicensed and Unreported

Fishing”. The Ghanaian coastal management officials can then use a web interface to view the matched and unmatched data along with sensors and image processing techniques.

Paper [23] claimed that the marine border must be recognised in order to warn fishermen while they are fishing. The authors suggested an Automatic Identification System that, by alerting the nation's border, might safeguard fishermen. They will receive a VHF notice if they are getting close to the International Maritime Border Line. AIS can locate a place using the built-in GPS and send that location to embedded systems, which collect the most recent position by comparing autonomous and longitudinal parameters with the current evaluation.

3. Dataset Description

Shipsnet: By detecting vessels displaying suspicious or illegal activity, the shipsnet.json collection, which contains satellite footage of ships on the ocean, can be used to detect illegal fishing activity. The following parameters are part of the dataset (as shown in Figure1).

Data: The pixel values for each image in the dataset are contained in this parameter. Each image has a dimension of 80x80 pixels and is represented as a flattened array of 6400 grayscale values (0–255).

Labels: The binary labels for each image in the dataset are contained in this parameter, where 1 denotes the presence of a ship and 0 denotes its absence.

Locations: To enable geographic analysis and visualisation, this parameter holds the latitude and longitude of each image in the dataset. The locations parameter could be used to identify areas where fishing is prohibited.

Scene_ids: The scene IDs for each image in the collection are contained in the parameter scene ids, which can be used to access more image details.

```
                                                data  labels  \
0  [41, 40, 41, 44, 43, 40, 38, 40, 44, 42, 31, 3...       1
1  [22, 19, 26, 26, 21, 20, 26, 24, 24, 28, 20, 1...       1
2  [112, 112, 106, 104, 107, 109, 113, 115, 108, ...       1
3  [72, 76, 73, 72, 73, 74, 75, 73, 74, 73, 73, 7...       1
4  [63, 58, 58, 63, 65, 66, 70, 66, 59, 67, 71, 6...       1

                                  locations            scene_ids
0  [-122.34270462076896, 37.75058641760489]  20170501_180618_1005
1  [-122.34975593269652, 37.76979644106731]  20170501_181320_0e1f
2  [-122.34908354683306, 37.74935096766827]  20170609_180756_103a
3  [-122.32613080820607, 37.73816285249999]  20170721_180825_100b
4   [-122.3332290637038, 37.721168346437786]  20170702_180943_103c
(2800, 4)
```

Figure 1. Parameters of the Dataset

AIS_2017_01_Zone10: AIS_2017_01_Zone10 dataset from https://marinecadastre.gov/ais/ (as shown in Fig.2) contains AIS data. Automatic Identification System data, also called as Vessel traffic data, are gathered in an onboard navigation safety device by the U.S. Coast Guard to send and track huge vessels' location and the features in international-water in real time.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
MMSI	BaseDateTime	LAT	LON	SOG	COG	Heading	VesselName	IMO	CallSign	VesselType	Status	Length	Width	Draft	Cargo
3.67E+08	2017-01-04T11:	52.4873	-174.023	10	-140.7	267	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T11:	52.48718	-174.028	10	-141.6	266	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T11:	52.48705	-174.036	10	-142.3	267	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T13:	52.41575	-174.6	9.1	-154	251	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T13:	52.41311	-174.617	9.1	-157.3	251	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T14:	52.40527	-174.662	9	-154	252	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T14:	52.39625	-174.715	9.1	-159	249	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T14:	52.39278	-174.733	9.1	-157	250	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T14:	52.38917	-174.752	9.3	-157.9	252	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T14:	52.36916	-174.851	9.2	-157.1	251	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.36112	-174.892	9.3	-152.8	255	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.35662	-174.916	9.2	-155.3	251	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.35323	-174.935	9.3	-154.7	251	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.33886	-175.014	9.4	-153.8	255	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.33776	-175.019	9.5	-159.3	250	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.33328	-175.042	9.4	-158.6	252	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.33142	-175.052	9.4	-156.5	253	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.32379	-175.09	9.4	-157.4	252	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31
3.67E+08	2017-01-04T15:	52.31912	-175.113	9.5	-159.2	252	EARLY DAWN	IMO7821130	WDB7319	1001	undefined	32.95	8.82	4	31

Figure 2. Dataset AIS_2017_01_Zone10 Screenshot

In the U.S., the Coast Guard and commercial vendors gather AIS data, which can be utilized for a variety of coastal planning purposes. It contains information such as location, time, ship type, speed, length, and draft. It has entries of 10224 with 16 data columns as shown in Table 1.

Table 1. Description of Attributes

ATTRIBUTE NAME	DESCRIPTION
MMSI: Maritime mobile service identity	9-digit number that identifies a vessel
Base Date Time	Represents the date and time of each vessel at their particular zone
LAT and LON	Latitude and Longitude of vessel
SOG: Speed over Ground	Speed of vessel in an hour with respect to land
COG: Course Over Ground	Direction of vessel

Vesse lName	Name as shown on the station radio license
IMO: International Maritime Organization	Vessel number as indicated by IMO
Call Sign	Unique identifier for a vessel
Vessel Type	Categorization of vessel based on form and function
Status	Indicates navigation status
Length and width	Length and width of vessel
Draft	Draft depth of vessel

4. Existing System

Currently, the commonly used solution is to constantly monitor for anomalies in the coastal areas that require human labour and tools like radars. It should also be noted that, not all areas in the coast are guarded and monitored constantly due to vast coasts in many countries. This allows for fishermen to invade foreign waters and people of other countries to trespass and pirate contraband. Prevention of such activities involve making use of machine learning models that can detect the anomaly in the vessel. In paper [19], the author has used the learning mechanism of Random Forest to identify the most important features and predict the anomalies with accuracy of 70%. The major challenge in the proposed technique is that the results are accurate only when a very limited set of predictors are being used.

5. Proposed System

A SVM model based on AIS that makes use of real-world data that will analyses the possibility of successful detection of intrusions of fisherman by categorising the vessel as normal or anomalous one, is implemented. Along with that, satellite images are used to find the same. AIS dropouts are effectively visualised by plotting the trajectories of the vessels currently in the sea. A Support Vector Regression (SVR) model based on AIS that makes use of real-world data that analyses the possibility of successful detection of intrusions of fisherman by categorizing the vessel as normal or anomalous, is implemented. A Random Forest Regressor (RFR) is implemented for the same AIS data to check how well the model performs against SVR. Along with that, the shipsnet dataset is used to train CNN and the model finds whether it is ship or not; and if it is ship, then it will categorize whether it belongs to anomalous or non-anomalous. AIS dropouts are effectively visualized by plotting the trajectories of the vessels currently in the sea. The proposed system is shown in figure 3.

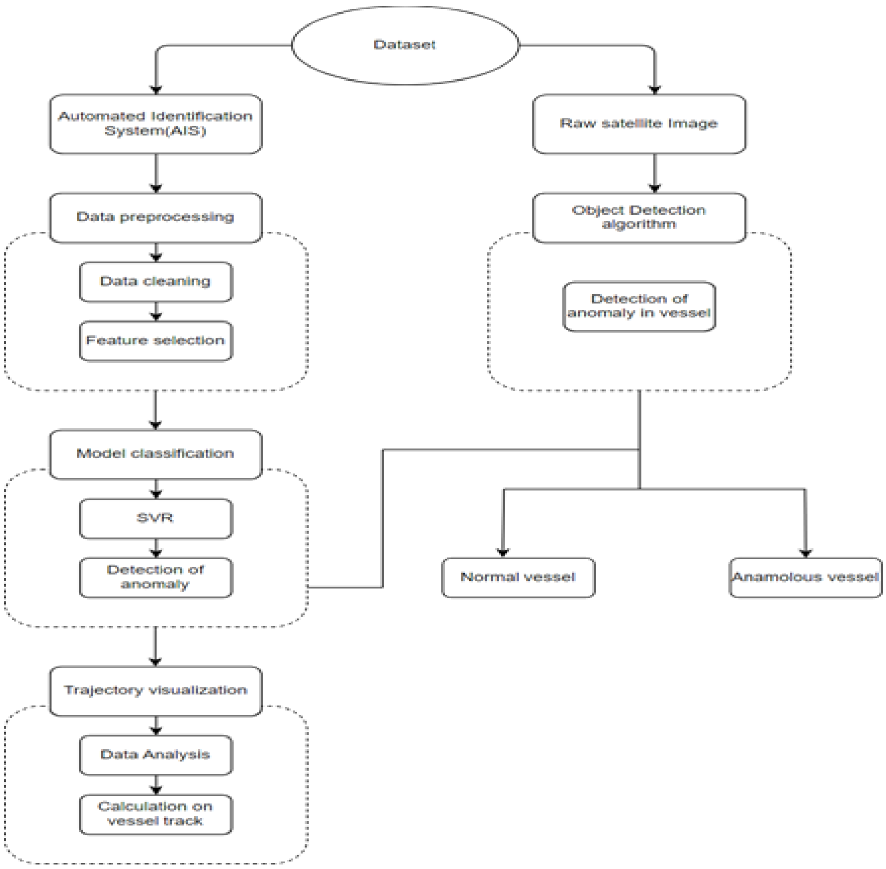


Figure 3. Proposed System

6. Experimental Results

Data pre-processing is essential to format the raw data suitable for a machine learning model. The research work uses publicly available AIS data which can't be utilized directly as it contains few missing data in important attributes. Therefore, linear interpolation is utilized to process and clean the data. It is a method to determine any unknown values when any two neighbouring values are known. Next step is to extract only the important features to train a model. Correlation-based feature selection method is utilized to find the association between features. It is a filter approach solely based on intrinsic properties of data. It is observed from figure 4, that among Speed over Ground (SOG), COG, latitude, longitude, hour, min, day, and Cargo, Cargo is highly correlated.

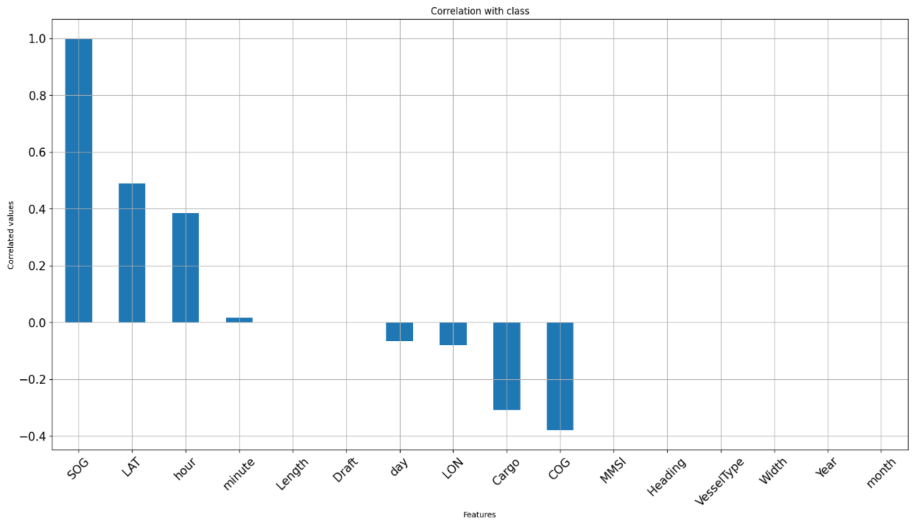


Figure 4. Correlation among all features

Random Forest Algorithm

Step 1: Choose random samples from a given data collection or training set.

Step 2: For each training set of data, this algorithm will build a decision tree.

Step 3: Voting will be conducted using the average of the decision tree.

Step 4: Finally, choose the prediction result that received the most votes as the final prediction result.

SVR Algorithm

Step 1: Load the important libraries.

Step 2: Import dataset and extract the X variables and Y separately.

Step 3: Divide the dataset into train and test.

Step 4: Initializing the SVR model.

Step 5: Fitting the SVR model.

Step 6: Coming up with predictions.

Step 7: Evaluating model’s performance using r2 score.

Step 8: Finding difference between actual and predicted value.

Step 9: Finding the sample which has largest difference.

Prediction Model using Random Forest

Using the correlated features, the whole dataset is split for an unbiased evaluation of prediction performance. For training and testing, 85% and 15% of the dataset is used, respectively. Then the model is built using RFR. The RFR algorithm as stated in the base paper produces an accuracy of 70%. The model built here produces an accuracy of 86%. The model is built with the point of knowing how well the algorithm stated in the base paper performs when the model is built with the chosen dataset. Further, some error metrics are implemented to understand the performance. Consolidated error values are shown in figure 5. The low error values imply that the model performance is well and good.

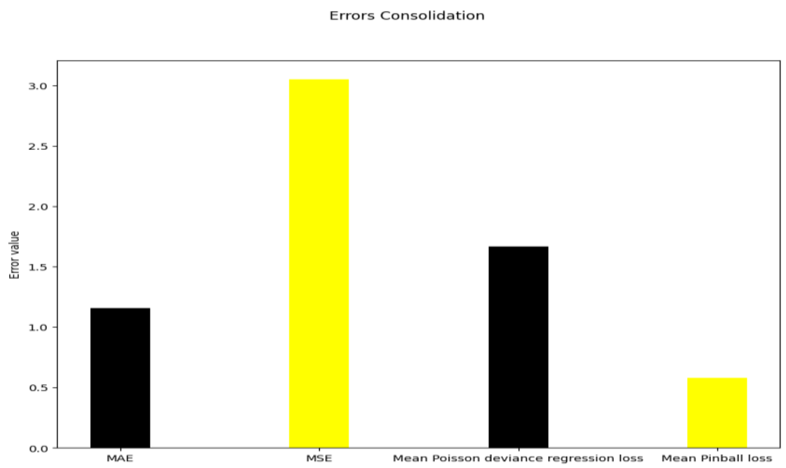


Figure 5. Consolidated error values

Prediction Model using SVR

By using correlated features, the whole dataset is split for an unbiased evaluation of prediction performance. For training and testing, 85% and 15% of the dataset is used, respectively. Then the model building is performed using SVR. Accuracy is measured using r2 score. R2 score estimates how well the data fits the regression line. SVR gives an accuracy around 86% which is competitively equivalent to RF model as described in Table 2 and Figure 6.

Table 2. Comparison of RF and SVR

Model name	R2 score
Random forest regressor	0.86
Support vector regressor	0.86

```
# find accuracy(R2 Score)
from sklearn.metrics import r2_score
print(round(r2_score(y_test, yhat),2))

0.86
```

Figure 6. Accuracy obtained in AIS data using SVR

After model building, the original and predicted data is plotted in the form of a graph (shown in Figure 7).

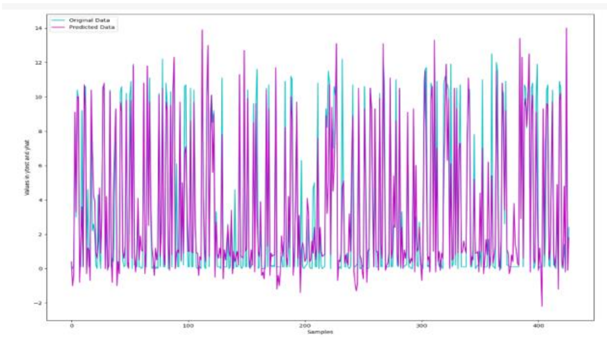


Figure 7. Original and predicted data using SVR model in AIS dataset

Then the difference between the actual and predicted value is determined (shown in Figure 8).

	Actual	Predicted	difference
0	0.1	0.4	-0.3
1	0.0	-1.0	1.0
2	0.2	-0.3	0.5
3	8.3	9.1	-0.8
4	3.0	3.3	-0.3
...	...	...	...
422	1.4	4.8	-3.4
423	0.0	-0.2	0.2
424	12.8	14.0	-1.2
425	0.3	-0.1	0.4
426	2.4	1.8	0.6

427 rows × 3 columns

Figure 8. Difference between actual and predicted data

The one with the largest difference is considered an anomaly (shown in Figure 9 and Figure 10).

	Actual	Predicted	difference	Rounded Difference
9	9.2	3.6	5.6	6.0
90	6.1	0.9	5.2	5.0
159	11.6	2.9	8.7	9.0
197	6.3	1.1	5.2	5.0
219	8.2	3.2	5.0	5.0
220	11.5	5.1	6.4	6.0
225	10.6	5.8	4.8	5.0
232	12.2	4.7	7.5	7.0
304	11.7	6.1	5.6	6.0
319	10.7	5.8	4.9	5.0
325	11.9	6.1	5.8	6.0
360	12.5	5.4	7.1	7.0
365	11.4	6.1	5.3	5.0
399	11.9	3.8	8.1	8.0
406	1.9	7.4	-5.5	-6.0

Figure 9. Rounded Difference of actual and predicted data

```
anamolies_indices = anamolies.index.tolist()
anamolies_indices
```

```
[9, 90, 159, 197, 219, 220, 225, 232, 304, 319, 325, 360, 365, 399, 406]
```

Figure 10. Anomaly indices in AIS dataset

The below figure shows the anomalous and normal ships where red and blue indicate anomalous and normal ships respectively.

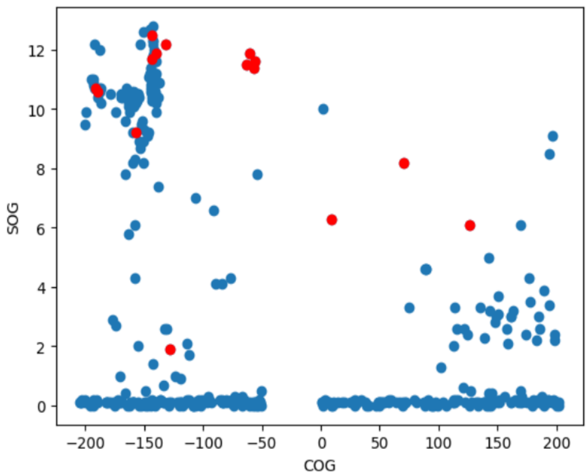


Figure 11. Indication of anomalous (red) and normal (blue) ships

Anomalous detection using image

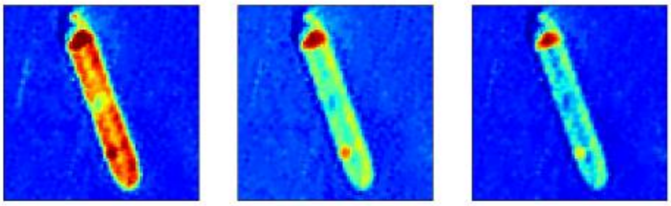
Image processing is the enhancement, analysis, or transformation of digital images using a variety of algorithms and approaches. In order to extract information, a picture's appearance is altered, or prepare for analysis where a variety of operations are applied to the image. Image filtering, edge detection, picture segmentation, color analysis, image restoration, and image compression are a few of the frequent tasks carried out in image processing. Satellite image processing can provide valuable insights and evidence to support enforcement efforts against illegal fishing, which can help to protect marine ecosystems and sustainably manage fish stocks. The navy has utilized image processing in the past for a variety of uses. Ship identification and categorization was one significant use of image processing in the military. The navy has employed image processing methods in the past, to identify and categorize ships in radar, aerial, and satellite photos. To identify the sort of ship present, these procedures entailed analyzing ship characteristics such as size, shape, and orientation and comparing them to known ship profiles.

The ShipsNet dataset contains satellite images of ships at sea, which makes it a suitable dataset for training a CNN model to detect ships, which can then be used for illegal fishing detection. The dataset includes over 2,000 images of ships and non-ships, making it a sufficiently large dataset to train a deep learning model. By training a CNN model on the ShipsNet dataset, the model can learn the visual features of ships, such as their size, shape, and texture, and use this knowledge to detect ships in other satellite images. This can be useful for identifying illegal fishing activity, as ships engaged in illegal fishing may try to hide or disguise their activities. The use of a CNN model can help detect these activities with high accuracy, reducing the likelihood of illegal fishing going undetected.

Convolutional Neural Network

A deep learning system known as a convolutional neural network is particularly effective at processing and recognizing images. Convolutional layers, pooling layers, and completely connected layers are among the layers that make up this structure. The key part of a CNN is its convolutional layers, where filters are used to extract characteristics like edges, textures, and forms from the input image. The output of the convolutional layers is then sent through pooling layers, which are employed to down-sample the feature maps and retain the most crucial data while lowering the spatial dimensions. One or more fully connected layers are then applied to the output of the pooling layers to forecast or categorize the image.

(a) Picture of the ship that we have Visualized using Shipsnet dataset.



(b) Red Spectrum, Green Spectrum, Blue Spectrum.

Figure 12. (a) Ship image in Shipnet dataset (b) RGB Spectrum

The shipsnet data set as shown in Figure 12 is used to train CNN model and the model will find whether it is ship or not. Each of the 4000 photos in the dataset is represented by a vector of length 19200 (80x80x3). To be used as input to the CNN, the input data is reshaped into a 4D tensor with the shape (4000, 80, 80, 3). The result is a vector of binary values with a length of 4000, where 1 denotes the existence of a ship and 0 denotes its absence. In order to be used as the target variable in the training phase, the output data is one-hot encoded. There are four convolutional layers in the CNN model, each followed by dropout and max-pooling layers. Filter sizes range from 3x3 for the first three convolutional layers to 10x10 for the final convolutional layer. After flattening the output, the model adds two fully connected layers, the last of which uses softmax activation to provide the classification probabilities. Using Stochastic Gradient Descent with Built to Create Momentum and a learning rate of 0.01, the model is trained. With a batch size of 32 and 18 epochs of training, 20% of the data is used for validation. The model's validation accuracy of 96% shows that it can correctly identify whether a ship is present in each image. If it is a ship, then it categorises whether it belongs to the anomalous category or non-anomalous category. Here, the anomalous ship pictures are displayed as output.

```
if result[0][1] > 0.90 and not_near(x*step,y*step, 80, coordinates):
    coordinates.append([[x*step, y*step], result])
    print(f'Co-ordinates: {coordinates}')
    print(result)
    plt.imshow(area[0])
    plt.show()
```

Figure 13. Detecting Anomalous Ships

If the point (x, y) is within the square area of any element e in coordinates, the function sets the result variable to False. Otherwise, the result variable remains True. The function then returns the value of the result variable, indicating whether the given point (x, y) is near any of the points in the coordinates list within the given distances. If the prediction has a high confidence score (greater than 0.90) as shown in Figure 13, and the current point is not near any of the previously recorded points in coordinates, a new point is added to the coordinates list. The not_near() function is used to determine if the current point is far enough from any previously recorded points in coordinates.

Comparison of RF and SVR in AIS dataset

SVR gives an accuracy around 86% which is competitively equivalent to that of the RF model (which gives accuracy of 0.86) as shown in graph below.

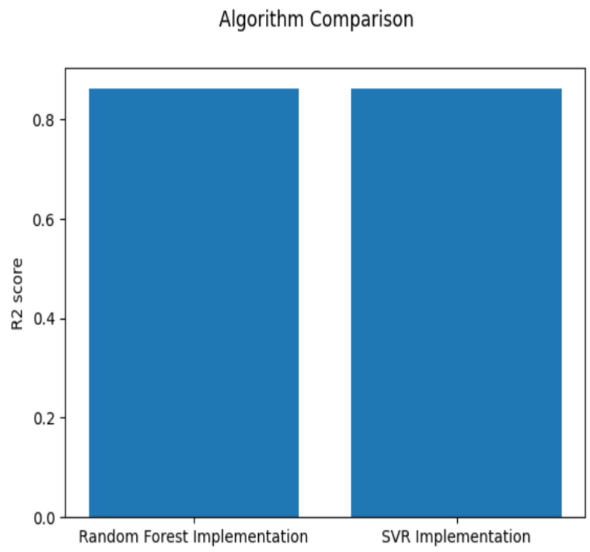


Figure 14. Comparison of RF and SVR in AIS dataset

Trajectory Visualization in AIS dataset

The AIS can recognize ships all around the world, offer detailed information (such as vessel name, vessel type, International Maritime Organization (IMO) number and Maritime Mobile Service Identities (MMSIs)). The AIS has already established itself as a standard for vessel navigation and maritime traffic monitoring. Some well-known systems have also evolved in maritime traffic management and monitoring, including Marine Traffic (Marine T.) (MarineTraffic, 2021), IHS Global (IHS G.) (IHSGlobal, 2021), and FleetMon (2021). To increase the level of intelligence of marine traffic monitoring and management, a lot of researchers have turned their attention to vessel big data analysis, thanks to the considerable data that all these systems give.

Users may benefit from using visualization and visual analysis approaches to detect and explore vessel behavior patterns visually and interactively, as well as to evaluate and comprehend vessel trajectory data. There are several ways to visualize trajectories of vessels. The first could be the average track length. This factor could help in analyzing the track length of vessels and find a central value. With this, data can be easily interpreted, and track lengths that differ way too much from the calculated value can be distinguished. For further analysis, the length of the ship and how it affects the SOG of vessels are used.

The pattern of waves produced by a boat travelling through the water includes a wave that runs down the side of the boat and forms a crest of water at the bow and a trough of water at the stern. The vessel will ultimately face an unbreakable wall of water resistance when the wavelength is comparable to that of the boat because the wave forms a huge crest that forces the boat back into its own trough. A vessel can only overcome the resistance that the bow wave causes by providing it enough speed to lift its bow out of the water and skim, or plane, over the bow wave. Although many power boats skim the surface, it takes a lot of force to overcome the resistance curve's hump. Thus, in this way length is correlated to the speed of the ship. The average speed of the ships is also useful and the primary purpose of this is to ensure that the vessel can be maneuvered safely. Also, in some regions close to land, it is necessary to slow down the ship to limit emissions from the main engine. Thus, the ship performance can be monitored. Finally, one can learn a lot about the vessel using the track of each vessel. If it overlaps abnormally deviating from the usual track, it could be classified under anomalous ships.

367390380	2017-01-29T15:27:45	52.39017	-174.85	8.1	-140.7	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:32:26	52.38755	-174.868	9.4	-156.6	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:39:54	52.38332	-174.895	8.9	-153	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:50:05	52.37765	-174.933	8.8	-149.6	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:08:55	52.3677	-174.998	8.2	-150	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:32:35	52.35827	-175.063	1.5	-133.9	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:20:15	52.39426	-174.822	8.1	-138.1	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:28:55	52.38948	-174.854	8.4	-152.5	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:35:55	52.38568	-174.88	8.2	-150.5	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:41:04	52.38262	-174.899	9	-162.1	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:48:54	52.37834	-174.929	7.7	-153.7	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:07:46	52.36838	-174.994	7.7	-155.3	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:24:25	52.35951	-175.053	6.8	-161.3	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T17:06:55	52.35675	-175.117	1.3	-158.9	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T17:16:57	52.35378	-175.135	8.3	-154.1	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T17:35:05	52.34387	-175.204	8.3	-161.8	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:18:05	52.39542	-174.814	8.3	-151.3	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T15:33:35	52.38692	-174.872	7.3	-147.4	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:16:15	52.36386	-175.023	8	-157.2	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:17:25	52.36319	-175.028	8.4	-143.7	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:19:45	52.36189	-175.036	8.5	-158	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:25:35	52.35908	-175.056	6.2	-152.5	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:30:15	52.35839	-175.062	1.2	-179.4	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T16:34:56	52.35883	-175.064	1.8	-127	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T17:32:15	52.34538	-175.193	9.3	-149.6	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way
367390380	2017-01-29T17:57:46	52.33152	-175.296	9.3	-151.3	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001	under way

Figure 15. AIS data of vessel (367390380)

The above figure shows some of the records of AIS data for the vessel (367390380). Visualizing this data, it can be seen that it has Heading (degrees) of the vessel's hull with a value of 511 which indicates, there is no heading data. There were a lot of readings of 511 degrees in the heading. The relative bearing between ships must be confirmed to find acceptable values to know the Heading of the vessel’s hull. It could be considered an anomalous ship and extracted for proper analysis. SOG is the vessel's speed in one hour concerning the land or any other fixed object such as buoys. When vessels navigate, they move with a value of 0-14 knots generally while they send AIS messages for short intervals and 14-23 for short intervals. Smaller vessels have larger speed. With the help of latitude and longitude of each vessel on the map, it is easier to track the vessels. The following implementation displays the same.

```
latitude = data['LAT'].mean()
latitude
```

```
52.864806201095455
```

```
longitude = data['LON'].mean()
longitude
```

```
-176.49940768681535
```

Figure 16. Calculating mean for latitude and longitude

By using mean, the center points of latitude and longitude are calculated as shown in Figure 16. This could be helpful in finding out an intersection point for all ships.

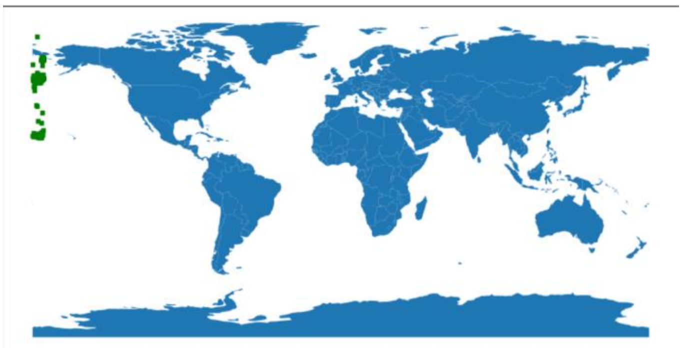


Figure 17. Location of ships on map on geopandas naturalearth_lowres

The above figure shows the ships that are present in the dataset and their location. Here the map is plotted from geopandas naturalearth_lowres. This will display all the contours of countries. A vessel can be tracked from the given dataset provided the information is received correctly. It is important since the data received should be as accurate as the data is displayed.

Figure 18. Location of the ships with markers

Figure 18 shows all the vessels with respect to the average of all latitude and longitude. Tracking a single vessel is possible with the help of matplotlib. A nine-digit MMSI value assigned to all vessels will be considered as a maritime object and is used for communication as shown in Figure 19. IMO seeks to improve reliability and decrease identity theft as shown in Figure 20.

```
data['MMSI'].value_counts()
```

367390380	2846
366940480	2524
352844000	1314
273898000	823
366988820	778
373889000	740
355972000	223
353003000	176
255805913	130
477027500	89
477348200	89
311056400	62
477982600	61
356159000	60
477444700	55
273318720	49
355113000	28
477099600	21
636090965	21
370633000	17
355139000	16
477027300	16
354001000	14
477135600	12
211517000	11
636092722	7
412436952	6
538006238	4
374553000	2
477108100	2

```
trackvessel1 = data[data['MMSI'] == 367390380]
trackvessel1.head()
```

	MMSI	BaseDateTime	LAT	LON	SOG	COG	Heading	VesselName	IMO	CallSign	VesselType	Status	Length	Width	Draft	Carg
3189	367390380	2017-01-29T14:32:05	52.42239	-174.63415	8.9	-154.5	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001.0	under way using engine	89.92	13.52	5.8	52.66666
3190	367390380	2017-01-29T15:30:06	52.38885	-174.85848	9.2	-148.7	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001.0	under way using engine	89.92	13.52	5.8	48.33333
3191	367390380	2017-01-29T15:34:44	52.38635	-174.87590	7.9	-155.3	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001.0	under way using engine	89.92	13.52	5.8	44.00000
3192	367390380	2017-01-29T15:45:34	52.38011	-174.91615	8.2	-159.9	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001.0	under way using engine	89.92	13.52	5.8	39.66666
3193	367390380	2017-01-29T15:46:36	52.37952	-174.91988	9.0	-147.5	511	SEAFREEZE ALASKA	IMO6931043	WDE7203	1001.0	under way using engine	89.92	13.52	5.8	35.33333

Figure 19. MMSI value of all vessels with extraction of data of vessels (367390380)

```
import matplotlib.pyplot as plt
trackvessel1.plot(kind = 'scatter', x = 'LON', y = 'LAT', figsize=(15,7),color='red')
plt.title("Track of Vessel 367390380")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.show()
```

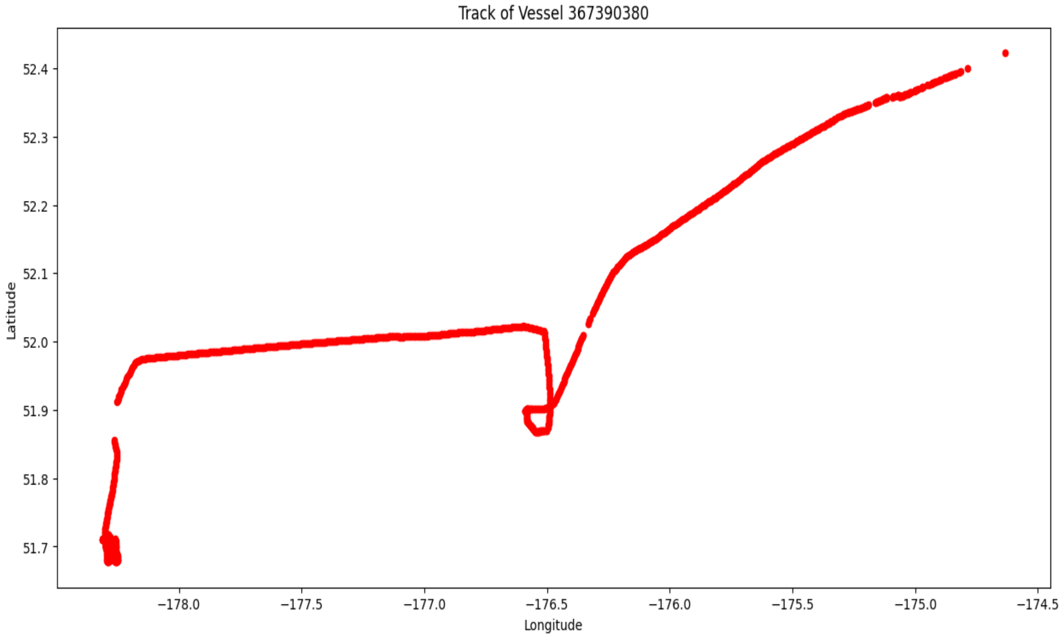


Figure 20. Track of vessel (367390380)

Thus, from an AIS dataset, there is a possibility that almost all the information about ships can be extracted. This information that is gathered through an on-board safety device must be accurate so that the correct information is sent to the AIS GPS antenna. However, there are many smaller boats that lack tracking radios and communication channel that larger boats are expected to have, as they are too little or may have shortage in the power source to run the radios.

7. Conclusion

This proposed work has discussed the use of AIS datasets with advanced machine learning technologies. How AIS data received from devices reach the shore is analysed. Using Random Forest and Support Vector Regression algorithms, which are best for regression analysis, an accuracy of 86% has been achieved. With development in technology and the characteristics of AIS datasets, further analysis is conducted and an accuracy of 97% has been attained using CNN algorithm. Thus, it clearly states that AIS data is very useful in the marine world. With the help of AIS, information can be sent not only from ship to ship but also on shore. AIS helps in identifying the location of each vessel in the waters and other navigational statistics which are important for identification of illegal activities and also which vessel is involved in it. Soon hopefully with further development in technology, this method would decrease the chances of illegal activities and safeguard navigation.

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