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SEA VESSELS LOCATION DETECTION USING MACHINE LEARNING-A REVIEW

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Abstract: The sea has various restricted areas, including maybe some exclusive economic zones and dangerous zones where a lot of marine boats may accidentally or purposely stray. Additionally, a lack of real-time vessel position data contributes to a high number of collisions in the sea. Without a precise vessel's position, rescue attempts are exceedingly challenging. Numerous studies have been conducted to estimate the location of vessels in the sea to help rescue personnel assist the stranded vessels. Extended time-interval forecast of ship position is needed in light of both efficient ship allocation by shipping corporations based on worldwide freight demand and maritime situational awareness (MSA). At various information levels, decision-making and action planning can be aided if a ship's position is predicted. In order to detect vessels in the water, our present research attempted to conduct thorough as well as crucial analysis of around 70 pertinent prior works that were published in academic journals throughout a twenty-two-year period (2000–2022). The following themes received particular attention: (I) the machine learning algorithms utilized and their suitability in this domain;(II) the factors and hypotheses influencing the location also the source of study; and (III) The relevant measures for error and accuracy used in the location predicting process. We conclude by summarizing the difficulties and prospects for more study on this topic.

Index terms: Exclusive Economic Zones, Marine Situational Awareness (MSA).

I. INTRODUCTION

The IMO predicts that shipping transports more than 90 percent of trade globally because it is the most cost saving to ship products and raw materials throughout the world ("Tu, Zhang, Rachmawati, Rajabally, and Huang, 2016"). As a result, the security and safety of international maritime communication networks may never be more obvious. Increasing global the need for minerals and goods drives up maritime traffic., increasing the probability of collisions in crowded spaces and providing greater openings for terrorists or pirate organizations to take advantage.

According to "Harati-Mokhtari, Wall, Brooks, and Wang (2007)", Eighty to eighty-five percent of recorded maritime accidents are the result of human error, unusual forces, like the ones that assaulted the Cole of USS in Yemen in 2000s, additionally a concerning source. It can be helpful to get a precise point estimate of a vessel's future location. in order to monitor traffic as well as identifying irregularities that can be signs of security risks. Since the intrinsic uncertainties in prediction, it's appropriate that location be accompanied with areas of ambiguity for forecasts contains, to a certain degree of tolerance, the actual future location of a vessel.

MDA is growing more and more significant to the United States Navy as waterways become increasingly congested ("Department of the Navy [DON], 2007"). The AIS, a transceiver network that shares data regarding the worldwide movement of ships at sea, is an important tool in maintaining MDA. Organizations for maritime security may also have access to an algorithm that forecasts future vessel position and the degree of uncertainty involved with that forecast in order to find out anomalies.

If a point can be precisely calculated by an analyst automatically, it may make a forecast for the location of the vessel and a prediction area surrounding it. If a vessel is outside of that predicted area, it should be investigated. "Pallotta and Vespeand Bryan (2013)" explain activities to combat piracy which rely on prediction where pirate activity and commercial merchant commerce are probable to cross. It should be noted that merchant vessels frequently turn off their AIS transceivers when passing through restricted zones.

Anomaly detection is critical for a variety of reasons. For starters, it can be used to identify possible risks to security close populated coastal rivers. If abnormal conduct is detected within the right time, it may be possible to intervene and prevent or limit damage. Furthermore, the discovery of an unusual vessel may aid in the identification of vessels that are out of control or that are experiencing significant mechanical problems. If a sea vessel exhibits unusual conduct, it involves acting in a way that is not permitted by the route's prevailing standards. A typical behavior, however, does not necessarily mean malicious conduct, the capacity to recognize unusual behavior automatically would help security experts determine the best way to use the limited resources available to look
into possible dangers.

II. OBJECTIVES OF RESEARCH:

Our team proposes a non-parametric approach exclusively using past AIS data because our objective is to create a prediction technique that can be used in a flexible manner. and with little need for local conditions to be adjusted.

First, we consider how to forecast a vessel's future location using AIS data and the route features of lines that depart from a port of origin. Next, we attempt to determine a prediction region's boundaries that are likely to contain the vessel's locations in future. Then, we want a way that can be used in every region. Lastly, we are looking for a process that can be automatically applied (with little help from humans).

III. METHODOLOGY

3.1 Data Collection:

Our Relevant studies were gathered in order to complete the study of studies. These methods included: (i) searching the literature for pertinent research that has been published in journals of scientist through peer review; (ii) searching for relevant project reports and other studies; (iii) requesting relevant studies from RFMOs via the FAO; and (iv) having consultants attend the Fifth Global Fisheries Enforcement Training Workshop (GFETW), which was hosted in 2016 by the International MCS network. This gave the consultants the opportunity to network with over 150 MCS practitioners worldwide and obtain copies of any relevant research.

Fifty (50) cutting-edge research papers that have been published in journals, conferences, magazines, & student theses that are pertinent to the focus of the current were obtained.ur team proposes a non-parametric approach exclusively using past AIS data because our objective is to create a prediction technique that can be used in a flexible manner. and with little need for local conditions to be adjusted. First, we consider how to forecast a vessel's future location using AIS data and the route features of lines that depart from a port of origin. Next, we attempt to determine a prediction region's boundaries that are likely to contain the vessel's locations in future.

Then, we want a way that can be used in every region. Lastly, we are looking for a process that can be automatically applied (with little help from humans).

3.2 Data Screening and analysis:

In actuality, 44 studies estimated the amounts of IUU catching of fish. The main findings, conclusions, and suggestions were then extracted from the summary files for the 44 pertinent studies.n actuality, 44 studies estimated the amounts of IUU catching of fish. The main findings, conclusions, and suggestions were then extracted from the summary files for the 44 pertinent studies.

3.3 Findings:

The review of the literature revealed that the studies used to estimate IUU caught ranged widely in terms of geography, from very local studies to national and as well as regional studies to studies that estimate IUU caught on an international level.

The degree of uncertainty surrounding the estimates generated by a number of studies that provide global estimates is typically very high because, as the size of these studies increases, the accuracy and granularity of the estimates are lost due to the assumptions made for elements for which there is no data.

The studies use a range of sources of information, such as trade data, onboard cameras, stock assessment models, surveillance reports and levels of compliance, expert judgment, based on experience, logbooks, and remote sensing (like VMS and AIS). Approximations of various elements of IUU fishing operations are provided using various methodologies, and these data sources serve various purposes in this regard. According to Tsamenyi et al. (2015), there are many ambiguities and situations in which the three components of IUU fishing overlap because national laws, governance structures, global fishing activities, and RFMO conservation and management strategies vary greatly. The bulk of techniques have limitations, according to the research analysis.

IV. LITERATURE REVIEW

This review of the literature outlines some of the techniques related to this research over the past ten years, paper have been used. In the final section of this review, we talk about how this study closes a gap in the body of existing literature research in terms of predicting the future position of a vessel and detecting anomalies with the help of AIS data. The authors "Raaid, F. et. al." provided an overview of various methods and technologies used for tracking vessels in their paper titled" A survey of vessel tracking techniques," which was published in the IET Radar, Sonar and Navigation journal in 2017[1].

The paper delves into various approaches and technologies used in vessel tracking, with the goal of providing comprehensive knowledge about the current status of this field's art. The survey covers a wide range of vessel tracking topics, including traditional radar systems as well as modern techniques such as AIS (Automatic Identification System) and other advanced sensor technologies. The paper is a valuable resource for maritime surveillance and navigation researchers and professionals.

Kim, S. et. al. presented a paper," Analyzing vessel behavior patterns with AIS data: A framework for anomaly detection and route prediction," was published in the journal Sensors in 2018[2].

The authors present a framework for analyzing vessel behavior using AIS (Automatic Identification System) data in this paper. The framework focuses primarily on two key aspects: The paper discusses techniques for detecting unusual vessel behaviors using AIS data. Anomalies can include deviations from normal routes, unexpected stops, or other unusual patterns that could indicate a potential threat. The authors also investigate methods for predicting vessel routes based on historical data. The framework aims to provide insights into likely future routes and destinations by analyzing past vessel movements.

Guedes, R. M., Ferreira, and Leandro's paper" Vessel detection and classification from space-borne SAR images using convolutional neural networks and Automatic Identification System (AIS) published in the journal Remote Sensing in 2020, [3] presents a novel approach for identifying and classifying vessels using data from space-borne Synthetic Aperture Radar (SAR) imagery and AIS information.

In this paper, the author states that convolution neural networks (CNNs) are utilized to identify vessels in space-borne SAR imagery. CNNs are one kind of deep learning method that's frequently applied to image processing. Classification of Vessels: Using features derived from AIS and SAR data, the research also addresses vessel classification. This categorization procedure helps to differentiate between many kinds of vessels, including fishing boats, cargo ships, and naval vessels. Integration with AIS Data: The authors stress the importance of integrating AIS data, which provides real-time vessel information, with SAR imagery analysis. This combined approach improves the accuracy of vessel detection and classification.

Kleiven, A.R. et. al. [4] presented a report in which objec- tive is reconstruction of total catches in Portugal mainland's waters. Main methodology used in this study is Estimate of total amounts discarded based on available discard rates and disaggregation of official reported catch by vessel segment.

"In 2015, Pauly and Zeller, editors. Concepts, techniques, and sources of data for catch reconstruction. Publication Online in Sea Around Us. editors Pauly, D., and Zeller, D. (2016). Reconstructions of catches show that global marine fisheries catches are both declining and higher than reported." [5] Objective of this study is to estimates Chinese long-distance vessels catches worldwide. The authors show that the statistics that member nations provide to FAO comprise the baseline data. When feasible, they also utilize nationally reported data for a first-order comparison with FAO data, which frequently helps identify catches that were probably taken in regions outside of national jurisdiction, such as high seas waters or other nations' exclusive economic zones. This is because catches by national distant-water fleets that fish and/or land catches abroad are not always included in many national databases. This first-order comparison helped distinguish catches" taken elsewhere" from legitimately local (national EEZ) fisheries as FAO compiles and harmonizes data from several sources (see Part 4 for the geographical layering of reconstructed information).

A probabilistic model for ship changes forecast based on history AIS data is proposed in the paper" A probabilistic model for ship's movement forecast based on historical AIS data" by Vinogradov, A. et. al/ (2018) [6]. A more accurate and nuanced portrayal of ship movement forecasts is made possible by the employment of a probabilistic model, which includes an acknowledgment of uncertainty. However, the model might miss abrupt shifts or trends in marine traffic patterns if it believes that the statistical characteristics of ship movements are stationary throughout time. Large computational resources could be needed for training and conducting simulations, depending on the model's complexity and the quantity of the dataset.

"Alvear, D., Isasi, P., and Del Ser, J. (2020). An intelligent ship movement model to optimize resource allocation in maritime surveillance systems. Applied Sciences, 10(19), 6904" [7]. It is possible that the research introduces a new model for modeling or forecasting ship movements in a marine environment. Given that it is most likely intended to be intelligent, this model may use sophisticated algorithms, machine learning strategies, or other computational approaches. It is possible that the research introduces a new model for modeling or forecasting ship movements in a marine environment. Given that it is most likely intended to be intelligent, this model may use sophisticated algorithms, machine learning strategies, or other computational approaches.

The use of a modified Fuzzy C-Means (FCM) clustering algorithm for ship dynamics prediction is probably the main focus of the paper" Using an improved FCM clustering algorithm for ship dynamic forecasting" by Pan, D. et. al. (2017) [8]. It is most likely the intention of the modified FCM clustering algorithm to improve ship dynamic forecasting accuracy over more conventional approaches. The changes might be intended to increase the algorithm's robustness, making it more resistant to changes in the behavior of the ship or the surrounding environment. However, changes made to the FCM algorithm might result in more complexity, which might affect implementation viability and computational efficiency.

In 2018, Khatami, A.et. al. [9] "presented a survey which may shed light on the practical applications of ship detection in optical images, with implications for environmental protection, maritime safety, and surveillance. Nonetheless, it may be discussed the difficulties posed by the variations in lighting, weather, and other factors that affect optical images. The difficulties with generalizing ship detection models over a range of datasets and circumstances might be covered in this paper. For real-world applications, the computational demands of various techniques—particularly those involving deep learning—could be examined. The Xception architecture, a deep learning model intended for image classification tasks, is presented in the paper.

"Xception: Deep learning with according to depth separable convolutions" by Franc¸ois Chollet [10]. Depth separable convolutions are a type of convolution layer that forms the foundation of the Xception model. In compari- son to conventional convolutions, this layer reduces computa- tional complexity by separating the spatial and channel-wise operations. In comparison to conventional convolutional neural networks (CNNs), the Xception model is more computation- ally efficient because depth-wise separable convolutions min- imize the count of parameters and computations. Deploying deep learning models in resource-constrained environments requires the ability to design neural network architectures that maintain high performance while improving efficiency. Xception offers insights into this process. Yet, the features of the dataset and the particular task at hand may have an impact on how effective the Xception architecture is.

Hyper-parameter tuning may be necessary to get the best results with Xception, and the selection of hyper-parameters can affect the accuracy and behavior of the mode. His review of the literature outlines some of the techniques related to this research over the past ten years, paper have been used. In the final section of this review, we talk about how this study closes a gap in the body of existing literature research in terms of predicting the future position of a vessel and detecting anomalies with the help of AIS data.

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Guedes, R. M., et. al. presented a paper "Vessel detection and classification from space-borne SAR images using convolutional neural networks and Automatic Identification System (AIS) published in the journal Remote Sensing in 2020,[14] presents a novel approach for identifying and classifying vessels using data from space-borne Synthetic Aperture Radar (SAR) imagery and AIS information. The following are the paper's main components:

The authors state that convolution neural networks (CNNs) are utilized to identify vessels in space-borne SAR imagery. CNNs are one kind of deep learning method that's frequently applied to image processing.

Classification of Vessels: Using features derived from AIS and SAR data, the research also addresses vessel classification. This categorization procedure helps to differentiate between many kinds of vessels, including fishing boats, cargo ships, and naval vessels.

Integration with AIS Data: The authors stress the importance of integrating AIS data, which provides real-time vessel information, with SAR imagery analysis. This combined approach improves the accuracy of vessel detection and classification.

Bay (2017) examines looks at how effectively clustering works to identify routes in the Gulf of Mexico in north and how weather and water conditions affect navigation, using AIS data from the Fourchon, Louisiana, region. Tracks in the Gulf of Mexico at Port Fourchon are hard to divide into small clusters because so many oil and gas facilities are serviced by vessels based there. Her research looks for elements that could be helpful in creating more accurate predictions.

Kleiven, A.R. et. al. [15] presented a report in which objective is reconstruction of total catches in Portugal mainland’s waters.Main methodology used in this study is Estimate of total amounts discarded based on available discard rates and disaggregation of official reported catch by vessel segment.

The authors used a fishery-by-fishery method to estimate unreported catches, or catches that are missing from official data, in order to estimate the likely total catches of Portuguese mainland vessels between 1938 to 2010. From 1939 onwards, landings increased, reaching their highest values throughout the time series between 1963 and 1973. After that, landings decreased, reaching values below the mean after the year 1993. They estimated that between 1938 and 2009, approximately 25,013,111 t were caught, which is 37 percent (from28.4-41 percent) more than the 16,121,510 t officially recorded for the same time period. This was based on yearly catches of about 123,000 t·year−1 Trawl fisheries accounted for the majority of unreported captures, accounting for 54% of all unknown catches and 21% of all collected landings. Multi-gear fisheries accounted for the second-highest percentage of estimated catches, comprising 25% of total unknown catches and 30% of known landings. Purse seine vessels had the lowest percentage of unreported catches (19%) yet made up 49% of all reported landings. Recreational and subsistence sector unreported catches were less common, making around 1.5% of all unreported captures.

"A.-K. Lecschauwaet, et. al." Presented the reconstruction of the likely total catches made by Belgian fisheries and the total catches made in areas under Belgian jurisdiction is the goal of this report. Main methodology used in this report is adjustments to be applied to official landing statistics by species in order to incorporate catches—whether landed or discarded—that have not been included. According to the authors, the accounting for the unreported and misreported landings of the commercial fleet, the unreported landings of the artisanal and recreational vessels, and the estimation of discards for the most significant fisheries, the total removals made by Belgian vessels from all ICES fishing areas and the BNS between 1928 and 2011 were rebuilt.

The estimated total rebuilt removals during this era were 5.1 million t, or 42 percent more than the 3.8 million t officially recorded. Unknown landings were estimated to make up 3.51% and 26.1 percent of these total rebuilt removals, respectively. Reconstructed total removals on the BNS were estimated to be 55 percent higher than the 0.7 million t officially recorded during this period.

"2015 MRAG's Report of the FAO/BOBLME Secretariat" proposed to calculate the amount and worth of Illegal, Unreported, and Unregulated fishing for the countries that make up the Bay of Bengal Large water life Ecosystem, both nationally and regionally. The Mian methodology in use entails Data collection on catches at the base level; IUU's collection of data; national catch breakdown by vessel segment; risk assessment methodology; conversion of qualitative estimates of risk into quantitative estimates; creation of a regional IUU database Using a risk-based methodology and a likelihood-impact framework, this study estimates the levels of illicit and unreported fishing for around 17 South Asian countries and territories around 1991 and 2012. When there isn't an RFMO to regulate and manage the fisheries, unregulated fishing typically takes place in regions that are outside of national jurisdiction.

It was found that it was not usable in any of the investigated countries. Uncontrolled fishing is not an issue because there are management agencies and legal frameworks in place in each of the states in the region. Apart from estimating lower and higher risk levels using an anchor point and influencing factor-based technique, this assessment uses a qualitative methodology to pinpoint and measure the risks that lead to IUU.

A combination of satellite SAR imagery, CNN, and AIS data is suggested for the detection and classification of vessels in the paper "Vessel detection and classification from spaceborne SAR images using convolutional neural networks and automatic identification system data" by Guedes, R. M.,et. al. (2020) [15]. When SAR photos and AIS data are combined, vessel recognition and classification can be done more accurately than when one dataset is used alone. SAR imagery can be more advantageous for all-weather vessel detection than optical imagery because it is not impacted by weather or time of day. However, compared to other remote sensing technologies, SAR images may have a lower spatial resolution, which may make it more difficult to detect and classify small vessels or details. A probabilistic model for ship change forecast based on history AIS data is proposed in the paper "A probabilistic model for ship's movement forecast based on historical AIS data" by Vinogradov, A, et. al. (2018) [16].

A more accurate and nuanced portrayal of ship movement forecasts is made possible by the employment of a probabilistic model, which includes an acknowledgment of uncertainty. However, the model might miss abrupt shifts or trends in marine traffic patterns if it believes that the statistical characteristics of ship movements are stationary throughout time. Large computational resources could be needed for training and conducting simulations, depending on the model's complexity and the quantity of the dataset.

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Table 1**:** Comparison of various approaches

V. MACHINE LEARNING MODELS:

Machine learning models differ in their strengths and drawbacks. Choosing the proper model guarantees that it performs optimally in terms of accuracy, precision, recall, or other essential metrics [16-20].

The model chosen should be appropriate for the data’s complexity. Simple models, such as linear regression, may be effective when the relationship between features and the target is linear, whereas more complicated models, such as deep neural networks, may accommodate non-linear correlations [21-23].

Here are several models that we have researched so far and can apply to this topic:

5.1 Linear Regression vs. Random Forest

Linear regression is commonly used to forecast continuous numeric variables, but vessel location identification is a spatial or classification challenge [24-28]. While linear regression can be used to predict certain aspects of vessel tracking, it is not appropriate for predicting vessel locations directly because vessel locations are inherently geographic coordinates (latitude and longitude), and the relationship between AIS data and these coordinates is typically not linear.

Several decision tree predictions are combined in Random Forest, an ensemble learning algo, to increase accuracy and decrease over-fitting. It handles high-dimensional data exceptionally well and is robust against anomalies [29][30].

The linear relationship between independent and dependent variables is represented by Linear Regression. While it is appropriate for tasks where the relationship is approximately linear, due to the complex and non-linear nature of image data, it may not perform well in ship detection Random Forest is generally preferred over Linear Regression in ship location detection because it can capture non-linear relationships and interactions between features, which are critical in accurately identifying ships in images [31-35].

5.2 Random Forest vs. Convolutional Neural Networks (CNNs): Which is better?

Random Forest handles data in a tabular format and works well with structured data that has few features. Images and other grid structured data are not meant to be handled by it.

Convolutional Neural Networks were created especially to handle data that is grid-structured, like images. They excel at capturing spatial patterns and feature hierarchies, making them ideal for image-related tasks such as ship detection.

In ship location detection, CNNs are the go-to-choice due to their ability to automatically learn relevant features from images, making them highly effective in identifying ships even in complex backgrounds.

5.3 Random Forest vs. Support Vector Machines (SVMs): Which is better?

Random Forest builds several decision trees and then combines their predictions. It is resistant to noisy data and can

Name of the Author	Year	Title	Technique Used	Advantages	Disadvantages
Malte Mittendorf, Ulrik Dam Nielsen, Harry B. Bingham and Gaute Storhaug [11]	2022	Machine learning-based sea state identification: a comparative study using in-service data from a container ship	A methodology for identifying sea states based on machine learning	Estimates have been made for the encounter direction, period of peak, and significant height of wave.	Complex project due to not only using ML is enough they have to use image processing as well.
Yitao Wang, Lei Yang1, Xin Song1 and Xuan Li1 [12]	2021	AIS data static information is used to classify ships using a random forest algorithm.	Random Forest	Encourages the growth of intelligent shipping and is crucial to the extraction of routes, the discovery of features in maritime traffic, and the detection of ship behavior.	Only the static Information from AIS is used; no dynamic information is used.
"Won-Jae Lee Myung-Il Roh Hye-Won Lee Jisang Ha Yeong-Min Cho Sung-Jun Lee Nam-Sun Son." [13]	2021	Tracking for the awareness of surroundings of a vessel based on deep learning	YOLO (You Only Look Once) v3, a deep learning-based detection model, is based on the image captured by the camera.	Estimates have been made for the encounter direction, peak period, and significant wave height.	The error of 15.39 meters was marginally greater than the accuracy minimum.
"G. Matasci J. Plante K. Kasa P. Mousavi" [14]	2021	Deep learning using spaceborne optical for vessel detection and identification imagery	Powerful CNN-based methods	Encourages the growth of intelligent shipping and is crucial in in-route extraction, maritime traffic feature discovery and	Only the static Information from AIS is used; no dynamic information is used.

				ship behavior detection	
Hanyang Zhong, Xin Song, Lei Yang [15]	2019	Classification of Vessels Using Random Forest on Space-based AIS Data	Random Forest	Encourages the growth of intelligent shipping and is crucial for the extraction of routes, the identification of maritime traffic features, and the detection of ship behaviour.	Only the static Information from AIS is used; no dynamic information is used.

efficiently handle a large number of features. The goal of Support Vector Machines is to search the hyperplane in the space of features that maximizes the margin between classes. They perform well in high-dimensional spaces and are capable of handling both linear and non-linear data transformations.

Random Forest and SVMs can both be useful for detecting ship location. SVMs, on the other hand, may be preferred when the data is not inherently structured and a clear margin between classes is required.

5.4 K-Nearest Neighbors (K-NN) vs. Random Forest:

A learning algorithm called Random Forest creates several decision trees. It is strong against outliers and adept at managing high-dimensional data. K-Nearest Neighbors classifies data points according to the majority class of their k nearest neighbors. It is simple to use and implement, but it may struggle with high-dimensional data.

When compared to Random Forest and KNN, XGBoost usually performs better in terms of prediction, although it might need more hyperparameter tweaking.

VI. FUTURE SCOPE

- Improved Model Accuracy: Use iterative model refinement. Investigate the use of more sophisticated machine learning algorithms or hybrid models to improve vessel detection and tracking accuracy. To improve prediction precision, incorporate additional data features such as weather patterns or vessel type.

- Real-Time Monitoring Systems: Work to create real- time monitoring systems that allow for instant vessel tracking and behavioral analysis. Consider utilizing cutting-edge technologies such as IoT, edge computing, and advanced satellite networks for continuous, real- time data updates, allowing for faster response to illegal fishing activities.

- Global Collaborative Efforts: Increase collaboration with international organizations, maritime agencies, and governments around the world to develop a unified, comprehensive database. This collaboration has the potential to improve data sharing, standardize AIS data formats, and foster more effective regulatory frameworks for global fishing practices.

- Environmental Impact Analysis: Broaden the scope of the study to include an examination of the environmental impact of fishing activities. Integrate environmental data, such as ocean temperature, biodiversity hotspots, and habitats of endangered species, to assess the ecological consequences of fishing practices and propose conservation strategies.

- Develop Intuitive and User-Friendly Visualization Tools: Create intuitive and user-friendly visualization tools for policymakers, researchers, and the general public. For informed decision-making, provide easy- to-understand maps and reports highlighting vessel movement patterns, potential fishing zones, and the impact of regulatory measures.

VII. CONCLUSION

Finally, this review paper has provided a thorough overview of the present state of art in sea vessel location detection using Machine Learning techniques in conjunction with Automatic Identification System (AIS) data. The following are the key takeaways from the reviewed literature:

- Effective AIS Data Integration: The combination of AIS data and machine learning algorithms has proven to be a powerful strategy for improving the accuracy and relia- bility of sea vessel location detection. AIS data provides real-time information about vessel positions, which, when combined with machine learning models, enables robust tracking and prediction.

- Detection and classification of vessels: The studies that were reviewed demonstrated the successful application of machine learning for vessel detection and classification. To aid in maritime surveillance and management, various different vessel types have been distinguished using machine learning techniques like RNNs and CNNs.

- Improving Maritime Security and Safety: The use of ML and AIS data to detect the location of sea vessels has clear implications for improving maritime safety and security. It allows for more effective search and rescue operations, piracy prevention, and vessel movement monitoring in sensitive or protected areas.

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