MINISTÉRIO DA DEFESA
EXÉRCITO BRASILEIRO
DEPARTAMENTO DE CIÊNCIA E TECNOLOGIA
INSTITUTO MILITAR DE ENGENHARIA
CURSO DE MESTRADO EM SISTEMAS E COMPUTAÇÃO

PROPOSTA DE DISSERTAÇÃO DE MESTRADO

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APPLICATION OF EXPLAINABLE ARTIFICIAL INTELLIGENCE TECHNIQUES INTO AIS ANOMALY DETECTION

Rio de Janeiro
2024

1 TÍTULO DA PROPOSTA DE DISSERTAÇÃO

Título da Proposta de Dissertação:
Application of Explainable Artificial Intelligence Techniques into AIS anomaly detection

Título da Capa:
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Área de Concentração:
Ciência da Computação

Linha de Pesquisa:
Engenharia de Sistemas e Informação

2 INTRODUCTION

The maritime industry is a critical artery of the global economy, responsible for the transportation of approximately 90% of world trade. The importance of this industry is underscored by the United Nations Conference on Trade and Development (UNCTAD), which highlights the fundamental role of the ocean in global commerce (UNCTAD, 2022; RODRIGUE, 2020). With the industry projected to grow in the coming years, the challenge of monitoring large maritime data to detect significant events becomes increasingly complex (VISBECK, 2018; UNCTAD, 2022).

The Automatic Identification System (AIS) has become a pivotal tool in this regard, facilitating the tracking of vessel movements and enhancing maritime safety and surveillance capabilities (VASWANI ET AL., 2017). To further support these capabilities, Vessel Traffic Services (VTS) play an essential role by actively monitoring vessel movements and providing navigational advice for vessel traffic in busy or restricted areas, enhancing the safety and efficiency of vessel operations (WOLSING ET AL., 2022).

Advances in Machine Learning (ML) technologies have significantly expanded the AIS data repository, offering new avenues to detect abnormal vessel behaviors, which are often indicative of illegal activities such as smuggling, piracy, and unauthorized fishing (YAN ET AL., 2021; IKONOMAKIS ET AL., 2022). However, the task of detecting anomalies in maritime data is fraught with challenges, which requires the development of sophisticated methods that can effectively identify irregular patterns in the vast volumes of AIS data (RIBEIRO ET AL., 2023). To support the reliability and adoption of these AI-driven systems, this research will also incorporate the principles of Explainable AI (XAI), which aims to make the decisions made by AI systems transparent and comprehensible to human users. This approach is important, especially in high-stakes environments like maritime surveillance, where understanding the reasoning behind the identification of anomalies is as imperative as detecting the anomaly itself (THAKUR ET AL., 2023).

Current approaches to vessel anomaly detection uses statistical analysis, neural networks, and cluster analysis to model typical vessel behaviors and identify deviations (LI ET AL., 2023). Despite the advances in these methods, the dynamic and complex nature of maritime traffic, coupled with the limitations of existing techniques, requires further innovation in anomaly detection methodologies (YANG ET AL., 2024).

The importance of AIS in maritime safety is further emphasized by international regulations mandating its use on ships, underscoring the system's role in collision avoidance and traffic monitoring. As the volume of AIS data continues to grow, driven by the proliferation of terrestrial and satellite AIS stations, the maritime industry faces a big data scenario, which presents both opportunities and challenges to harness this information for enhanced maritime surveillance (RIBEIRO ET AL., 2023).

In light of these considerations, this dissertation proposal aims to explore the application of XAI techniques for anomaly detection in AIS data, focusing on the context of the Brazilian Navy. By investigating the impact on performance of applying XAI to the model, this study addresses the limitations of current methods by improving transparency and interpretability to enhance the safety, security, and efficiency of maritime operations. The use of XAI will enable a deeper understanding of the decision-making processes involved in identifying abnormal vessel behaviors, allowing maritime authorities to make more informed decisions. Using existing research insights and addressing gaps in traditional anomaly detection strategies, this study seeks to develop a robust and comprehensive framework that not only detects, but also explains abnormal vessel behaviors, thus supporting maritime safety and combating illegal activities at sea.

2.1 CONTEXTUALIZATION OF THE AIS SYSTEM IN MARITIME NAVIGATION

AIS emerged as an innovation under the International Convention for Safety of Life at Sea (SOLAS) regulations, mandating its adoption for vessels of significant tonnage to enhance maritime safety and navigation. Since its implementation on December 31, 2004 (LEE ET AL., 2019), AIS has served as a self-reporting system that uses Very High Frequency (VHF) radio information to exchange a variety of ship data, including static, dynamic and voyage-related information, between vessels and AIS base stations (LEI, 2016). This system contributes significantly to the avoidance of collisions and the management of maritime traffic by providing real-time navigational data, such as position, speed, and course, along with static information such as vessel name, type, and Maritime Mobile Service Identity (MMSI) (SHI ET AL., 2022).

The use of AIS data has deepened profoundly with the advent of advanced technologies, particularly in AI and ML, enabling sophisticated analyses of maritime traffic and ship behavior. These analyses range from predicting ship trajectory, reconstruction, and prediction to collision avoidance and anomaly detection, highlighting the versatility of AIS data and its role in maritime surveillance. Despite its extensive application, the interpretation of AIS data faces challenges, including data quality issues and the potential for intentional manipulation of AIS transponders to evade detection or conduct illegal activities (YANG ET AL., 2024).

Furthermore, the reliance of the AIS system on the input of crews for data provision introduces vulnerabilities to human error, neglect, and fraud, complicating the accuracy and reliability of the data. Environmental conditions, technical limitations, and the system's inherent design flaws further exacerbate these challenges, affecting the accuracy of position and reliability of the navigation status (RIBEIRO ET AL., 2023). Efforts to mitigate these issues have led to the development of methodologies aimed at improving AIS data reliability and improving the effectiveness of anomaly detection algorithms.

Adding to the challenges of data interpretation are the cybersecurity risks associated with the open nature of AIS broadcasts. The absence of encryption and authentication measures exposes AIS data to spoofing and other cyber attacks, highlighting the urgent need for enhanced security protocols to safeguard maritime data integrity and vessel operations (RIBEIRO ET AL., 2023; WOLSING ET AL., 2022).

AIS has revolutionized maritime safety and surveillance, offering an indispensable dataset to monitor vessel movements and behaviors. Despite its significant contributions, the AIS system faces challenges related to data quality, reliability, and security. Addressing these challenges is imperative to maximize the potential of the system in promoting maritime safety and operational efficiency. As the maritime industry evolves, the indispensable role of AIS in ensuring safe and efficient maritime operations is unequivocally affirmed, underscoring the need for continuous research and development efforts in this domain.

2.2 CHALLENGES IN ANOMALY DETECTION IN AIS DATA

Detecting anomalies in AIS data plays a role in ensuring maritime safety and security by allowing the detection of atypical vessel activities that may signal potential dangers or navigation hazards. However, the creation and application of efficient anomaly detection algorithms face various obstacles, including issues related to data accessibility and accuracy, as well as the intricate nature of maritime settings. This section explores these hurdles, incorporating findings from recent scientific research.

2.2.1 DATA AVAILABILITY AND QUALITY

One of the main challenges in anomaly detection within AIS data is the availability and quality of the data itself. AIS data, while abundant, often suffer from issues such as discontinuity, unreliability, and lack of standardization across different datasets (WOLSING ET AL., 2022; POHONTU ET AL., 2023). Discontinued data, resulting from sensor failures or data collection gaps, complicate the anomaly detection process, requiring techniques such as data imputation to address missing information. Furthermore, the unreliability of the data, which can result from human errors in setting static parameters, intentional errors (fraud), irregular time sampling, and spoofing, adds another layer of complexity (RIBEIRO ET AL., 2023).

The lack of established benchmarks and publicly available standardized data sets with labeled anomalies severely hinders the ability to evaluate and compare the effectiveness of different anomaly detection methods (RIBEIRO ET AL., 2023). This situation is exacerbated by the proprietary nature of many AIS datasets, which are often restricted to maritime authorities or defense contractors, reducing transparency and reproducibility in research (WOLSING ET AL., 2022).

2.2.2 ENVIRONMENTAL AND OPERATIONAL CONTEXT

Another significant challenge is to account for the environmental and operational context in which the vessels operate. Vessel behavior is influenced by a variety of factors, including weather conditions, sea state, and nearby vessel traffic (LI ET AL., 2023). The exclusion of weather conditions and sea state from anomaly detection models limits their applicability and accuracy, as these environmental factors can significantly affect vessel behavior (FARAHNAKIAN ET AL., 2023). Furthermore, interaction with other vessels and the specific operational context (e.g., port congestion, navigation in restricted waters) are elements that must be integrated into anomaly detection algorithms (HUAN ET AL., 2022; ZHANG ET AL., 2023).

2.2.3 ALGORITHMIC AND METHODOLOGICAL LIMITATIONS

The development of anomaly detection algorithms for AIS data also encounters algorithmic and methodological limitations. The diversity of vessel behaviors and the complexity of maritime traffic patterns require sophisticated models that can accurately identify anomalies without generating excessive false positives (RIBEIRO ET AL., 2023). However, many existing models are designed for specific types of anomalies (e.g., route deviations) and may not be effective in detecting other forms of anomalous behavior, such as unexpected port arrivals or close approach anomalies (WOLSING ET AL., 2022).

Moreover, reliance on historical data to model “normal” behavior introduces challenges, especially in dynamic maritime environments, where vessel behaviors can change based on numerous factors (ZHANG ET AL., 2023). This issue is compounded by the need for models to be interpretable and transparent, particularly when used to support decision-making by maritime authorities (STACH ET AL., 2023). To address these limitations, the integration of XAI into anomaly detection models can provide insights into the decision-making processes of AI models, highlighting how specific behaviors are classified as anomalies (THAKUR ET AL., 2023). This transparency helps to refine the models to reduce false positives and adapt to new types of anomalous behaviors as they emerge. Furthermore, XAI facilitates the continuous improvement of anomaly detection systems by making it easier for developers to understand and adjust the underlying algorithms in response to evolving maritime conditions, ensuring that the systems remain effective and relevant in changing operational contexts.

2.2.4 PRIVACY AND SECURITY CONCERNS

Privacy and security concerns present another challenge in the use of AIS data for anomaly detection. The open nature of the AIS protocol means that AIS data can be accessed by anyone, potentially compromising the privacy of individuals on board vessels. Although AIS improves maritime safety and security, it also raises questions about the balance between security benefits and privacy risks (WOLSING ET AL., 2022). Addressing these concerns requires careful consideration of data protection and privacy regulations, as well as the development of secure methods for anomaly detection that do not infringe on individual rights.

2.2.5 TECHNOLOGICAL AND INFRASTRUCTURAL CHALLENGES

The implementation of anomaly detection algorithms in real-time maritime surveillance systems faces technological and infrastructural challenges. The vast amount of AIS data, characterized as Big Data, poses significant challenges in terms of data storage, processing, and analysis. Real-time anomaly detection requires substantial computational resources and advanced data processing capabilities, which may not be available in all maritime surveillance systems (STACH ET AL., 2023).

Additionally, the geographic scalability of anomaly detection approaches is limited by the specificity of maritime traffic patterns to different regions. Anomaly detection models trained on data from one geographic area may not be directly applicable to another, requiring retraining or adaptation to local conditions (WOLSING ET AL., 2022).

2.2.6 THE NEED FOR COMPREHENSIVE AND ADAPTIVE MODELS

To overcome these challenges, there is a pressing need for comprehensive and adaptive anomaly detection models that can account for the diverse and dynamic nature of maritime traffic. These models must integrate environmental and operational context, address data quality and availability issues, and be transparent and interpretable to support decision making. Furthermore, they must be designed with privacy and security in mind, ensuring that the use of AIS data for anomaly detection does not compromise individual rights or maritime security (STACH ET AL., 2023).

The challenges in anomaly detection in AIS data are multifaceted, encompassing data-related issues, environmental and operational complexities, algorithmic limitations, privacy concerns, and technological constraints. Addressing these challenges requires a multidisciplinary approach that combines expertise in maritime operations, data science, computer science, and legal and ethical considerations. By tackling these challenges, the maritime community can improve the safety, security, and efficiency of maritime operations, using the full potential of AIS data for anomaly detection.

2.3 JUSTIFICATION OF THE RESEARCH

The exploration of anomaly detection within AIS data has unveiled a significant gap in the current research landscape. Existing methodologies have focused mainly on identifying specific types of anomalies, such as “dark ships” and “spiral vessel movement”, without encompassing the wide array of abnormal behaviors that vessels may exhibit (FARAHNAKIAN ET AL., 2023). This narrow focus reveals an urgent need for a more inclusive approach that can adapt to the complex and dynamic nature of maritime activities. Furthermore, the widespread use of traditional clustering algorithms and the oversight of environmental influences, such as weather conditions and sea state, underscore the need for advanced methodologies capable of integrating and analyzing multifaceted high-dimensional datasets (SHI ET AL., 2022).

The introduction of AI and ML technologies into this domain presents a promising opportunity to bridge these gaps. The use of deep learning algorithms and graph neural networks could revolutionize the classification of ship trajectories, offering unprecedented precision and providing new pathways for the analysis of data on water traffic (XIE ET AL., 2023). This research aims to harness these cutting-edge technologies to develop a robust and versatile anomaly detection system. This system is expected to accommodate the multifaceted aspects of maritime traffic and environmental conditions, significantly improving maritime safety, optimizing traffic management, and supporting the sustainable development of marine industries (FARAHNAKIAN ET AL., 2023; ZHANG ET AL., 2023).

This study is positioned to make substantial contributions to the body of knowledge in computer science, particularly in applying AI to anomaly detection within the maritime sphere. Investigating the integration of Support Vector Machine (SVM) and XAI techniques for AIS data analysis will provide new theoretical insights into AI's capabilities for interpreting complex, dynamic systems. Addressing the current research's lack of diversity in anomaly detection methods will also expand the theoretical frameworks available for maritime studies, pushing the boundaries of our understanding and methodologies.

On a practical level, the results of this research could significantly improve the way maritime authorities and shipping companies monitor and manage maritime traffic. By developing a system that adapts to new data and identifies a range of anomalous behaviors, this work aims to provide maritime stakeholders with an effective tool to address safety risks and improve navigation efficiency. Additionally, incorporating explainability and interpretability into the system's design and ensuring its ability to be used in real scenarios may enhance its usefulness and relevance in various maritime settings.

3 KEY CONCEPTS

This chapter explores the basic concepts for understanding the proposal to integrate AIS with modern anomaly detection techniques, supported by the use of XAI. The adoption of AIS is driven by the need to improve maritime safety and efficiency, establishing it as an essential element in contemporary maritime operations. This discussion will cover both the operational and theoretical aspects of AIS, as well as its potential to synergize with AI technologies to address complex challenges in maritime safety and security. This knowledge sets the stage for an exploration of how these technologies can be effectively combined to enhance navigational practices and safety protocols in the maritime domain.

Initially, the principles and importance of AIS data are delved into, examining the system's inception and evolution. Originally developed in the early 1990s under the International Maritime Organization's auspices, AIS was designed to mitigate collision risks, enhance maritime safety, and improve communication between ships and shore. Today, it serves broader objectives, providing a rich dataset for monitoring vessel behaviors and detecting anomalies that could indicate potential threats or inefficiencies.

The next section presents the role of Vessel Traffic Services (VTS) in conjunction with AIS. VTS systems are essential for managing and safeguarding vessel traffic, especially in congested or hazardous areas. The integration of AI techniques with VTS can significantly amplify the capabilities of traffic monitoring and incident response.

Subsequent sections will address clustering techniques for anomaly detection, specifically through Density-Based Spatial Clustering of Applications with Noise (DBSCAN). This method stands out in its ability to identify dense clusters and anomalies within AIS data, offering a robust framework for interpreting complex maritime traffic patterns. The adaptability of DBSCAN to various operational scenarios underlines its relevance and efficacy for this study.

In addition, the application of SVM for anomaly detection within AIS data will be explored. SVM, a robust and versatile kernel-based method, is known for its effectiveness in classification and regression tasks. This section will detail how SVM can be employed to classify AIS data into distinct categories, enhancing our ability to identify and understand patterns of normal and abnormal vessel behavior. Specifically, SVM can be used to identify outliers or anomalies by learning the normal behavior boundary of the vessel and detecting instances that deviate significantly from this learned boundary.

The discussion then transitions to XAI, an important concept in modern AI applications. XAI aims to demystify the operations of AI systems, providing clarity on how decisions are made. This is especially pertinent in high-stakes environments like maritime navigation, where understanding AI's reasoning and ensuring its alignment with safety and regulatory standards are paramount. By integrating XAI with AIS, our aim is to enhance the transparency and accountability of anomaly detection processes, strengthening trust and dependability in automated systems.

This chapter aims to provide a comprehensive overview of these technologies and methodologies, illustrating their interconnections and individual contributions to maritime safety and efficiency.

3.1 PRINCIPLES AND IMPORTANCE OF AIS DATA

The AIS has emerged as a cornerstone in maritime safety and security, playing a central role in the modern maritime domain. Its inception aimed to enhance maritime safety through enhanced ship-to-ship and ship-to-shore communication, facilitating the real-time exchange of vessel information as presented in FIG. 3.1. This section delves into the principles of AIS operation, its fundamental concepts, applications, and the critical role it plays in anomaly detection within AIS data, underscoring its importance in promoting maritime safety, security, and navigation efficiency.

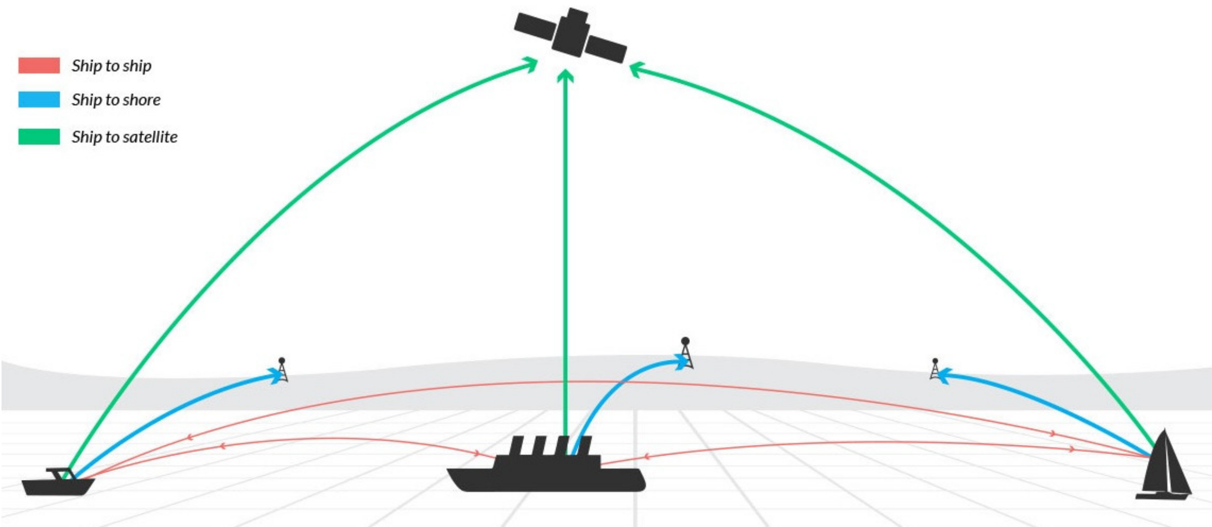

FIG. 3.1: AIS communication architecture. (NATO, 2021).

AIS technology provides a dynamic platform for automatic exchange of vessel information, significantly improving maritime safety and navigational efficiency. With the mandatory implementation of AIS in commercial ships, it has become an invaluable tool for monitoring maritime traffic, offering detailed data on vessel characteristics, movements, and voyages. This wealth of information is important for detecting abnormal behaviors and anomalies in maritime traffic, addressing the increasing challenges in maritime safety and security (ZHOU ET AL., 2023; WIDYANTARA ET AL., 2023).

Developed under the auspices of the International Maritime Organization (IMO) in the early 1990s, AIS was primarily aimed at collision avoidance. It enables ships and maritime authorities to exchange vital information, such as vessel identity, position, speed, and course, among other data, enhancing situational awareness and maritime safety (CUTLIP, 2017). The system broadcasts information through VHF maritime bands, ensuring that vessels within a certain range can communicate effectively, helping to avoid collisions, navigation assistance, and environmental protection (NATO, 2021).

AIS operation is governed by specific regulatory frameworks established by the IMO, mandating its use on vessels greater than 300 gross tons (GT) engaged in international voyages, cargo ships over 500 GT not engaged in international voyages, and all passenger ships regardless of size (YANG ET AL., 2024). This widespread adoption underscores the crucial role of AIS in international maritime operations, emphasizing its importance in ensuring safety and regulatory compliance.

AIS transmits various types of data, classified into static, dynamic, voyage-related and safety-related information, as shown in TAB. 3.1. Among these, the MMSI number stands out as a unique identifier for vessels, facilitating their identification within the AIS system (YANG ET AL., 2024). This comprehensive data exchange enables the monitoring and analysis of vessel movements, contributing to efficient maritime traffic management and improved safety measures.

The significance of AIS extends beyond safety and navigational efficiency, it also plays a key role in maritime security. Detecting anomalies within the AIS data is essential for the identification of illegal activities such as smuggling, illegal fishing, and unauthorized transshipment of illicit products. The techniques developed for anomaly detection use rich AIS data to combat these maritime security threats, demonstrating the utility of the system in supporting national and international maritime security strategies (BERNABÉ ET AL., 2023; HUAN ET AL., 2022; LIU ET AL., 2022).

Furthermore, the evolution of anomaly detection methods has paralleled technological advances, incorporating sophisticated data mining techniques, AI, and machine learning to address the challenges posed by high-dimensional data sets and dynamic maritime environments (SINGH ET AL., 2022b). These advances highlight ongoing efforts to improve maritime monitoring capabilities to ensure the safety and security of maritime domains.

TAB. 3.1: Information Provided by the AIS

Type	**Data**	**Obs**
Static	MMSI number	Unique nine-digit identifier for maritime communication.
	Call sign & name	International identifier and vessel's official name for communication.
	Length & beam	Dimensions critical for navigation and berthing.
	Ship type	Classification based on purpose or cargo type.
	Antenna location	Affects AIS signal transmission and reception.
Dynamic	Position, accuracy, and integrity	Geographic location of the vessel and reliability of the data.
	Time in UTC	Time of AIS data transmission, in Coordinated Universal Time.
	Course over ground (COG)	Direction of vessel movement relative to the ground.
	Speed over ground (SOG)	Speed of vessel movement over the ground.
	Heading	Direction the vessel's bow is pointing.
	Rate of turn (ROT)	Speed at which the vessel is turning.
	Navigational status	Vessel's current operational condition.
Voyage Related	Draught	Vertical Distance Between the Waterline and the hull bottom.
	Hazardous cargo	Indicates if dangerous goods are onboard.
	Destination & ETA	Intended port of arrival and estimated arrival time.
Safety-Related	Text messages	Communication for safety and operational coordination.

(WEI ET AL., 2022; POHONTU ET AL., 2023)

The development of the AIS system was motivated by the need to improve maritime safety by tracking ships, establishing safe corridors, detecting unusual maneuvers, and optimizing shipping channels. Its application has expanded to various areas including safety, accident prevention, smart infrastructure, transport planning, cargo management, economy, and environmental protection. The integration of AIS data with machine learning and data mining techniques has significantly improved the ability to analyze maritime traffic, predict vessel trajectories, assess collision risks and detect anomalies, thus contributing to maritime safety, efficiency, and environmental sustainability (BERBIC ET AL., 2023).

Challenges such as data quality issues, including inaccuracies and signal loss, require rigorous data processing and analysis methods to ensure the reliability of AIS data. Addressing these challenges is crucial to maintain the integrity and effectiveness of AIS applications in maritime safety and security (YANG ET AL., 2024). The application of AIS data in maritime logistics, supported by innovative methods for anomaly detection, underscores its importance in maritime traffic monitoring and strategic logistics planning (OH AND KIM, 2023).

3.2 VESSEL TRAFFIC SERVICES

VTS represent a critical component in the management and safety of maritime navigation, ensuring the efficient and orderly flow of ship traffic in congested or hazardous areas(WOLSING ET AL., 2022) using AIS data. The data received by VTS comes from the vessel AIS system. This section delves into the key concepts surrounding VTS, their historical evolution, regulatory frameworks, and the role of international organizations in standardizing VTS operations globally.

VTS are shore-based systems designed to optimize maritime traffic flow and improve navigational safety. These services range from providing simple information messages to ships, such as the positions of other vessels or weather hazards, to comprehensive management of traffic within ports or waterways. Ships entering a VTS area typically report their presence to the authorities, often by radio, and are tracked by the VTS control center. They are required to monitor specific frequencies for navigational or safety warnings and can receive direct instructions from VTS operators to mitigate incident risks or manage traffic flow effectively(STACH ET AL., 2023).

The genesis of VTS can be traced back to traditional maritime practices, where shipmasters, with the help of pilots, navigated using flag signals. The advent of radio in the late 19th century introduced a new communication method, but it was the development of radar during World War II that revolutionized shipping traffic monitoring. The world's first harbor surveillance radar system was inaugurated in Liverpool, United Kingdom, in 1948, marking the beginning of formal VTS systems. These early systems combined radar tracking with radio communications to manage maritime traffic efficiently (IMO).

IMO has played a crucial role in the recognition and standardization of VTS. Initial recognition followed with Resolution A.158(ES.IV) in 1968, acknowledging the importance of VTS in navigation safety. Subsequent resolutions, particularly A.578(14) in 1985 and A.857(20) in 1997, outlined guidelines for establishing VTS, emphasizing that the ultimate responsibility for vessel navigation and maneuvering rests with the ship's master. These guidelines addressed the operational, organizational, and technological aspects of VTS, including the qualification and training of VTS operators (IMO).

SOLAS explicitly addressed VTS in its revised Chapter V, adopted in 2000. Regulation V/12 clarifies the conditions under which VTS can be implemented, highlighting the role of VTS in enhancing maritime safety, navigation efficiency, and environmental protection. It requires contracting governments to establish VTS where necessary and to follow the IMO guidelines for planning and implementation.

The International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA) works in conjunction with the IMO to create standards, suggestions, and directives for VTS operations. IALA strives to promote worldwide uniformity in VTS, guaranteeing reliable and efficient services on a global scale. By focusing on these objectives, IALA facilitates safe and smooth vessel traffic, thus improving maritime navigation safety.

3.3 DBSCAN

Clustering techniques to detect anomalies in AIS data leverage intrinsic patterns and distributions of maritime traffic to identify irregularities, potentially indicative of navigation issues, illicit activities, or data integrity concerns. Clustering, a key component in data mining, encompasses the organization of data into subsets or clusters, where elements within a cluster exhibit higher similarity to each other than to those in other clusters (SINGH ET AL., 2022a). This section explores the underpinnings of clustering, with a specific emphasis on DBSCAN, the most widely used method for detecting anomalies in AIS data.

Clustering is an active research domain that spans statistics, pattern recognition, machine learning, and data mining, the latter referring to the examination of large datasets to uncover patterns or relationships. The essence of clustering in data mining encompasses several steps, notably pattern representation, data definition through proximity tests, and the clustering operation itself, potentially followed by data abstraction and output evaluation (SINGH AND MESHRAM, 2017). Clustering algorithms are broadly classified into hierarchical, partitional, nearest-neighbor, fuzzy, density-based, grid-based, and K-means clustering, each with its distinct approach to organizing data based on features such as Euclidean distance, density, or grid partitioning (GUPTA ET AL., 2022).

DBSCAN stands out for its effectiveness in parsing large noisy datasets to identify clusters of arbitrary shape, which makes it particularly suitable for AIS data analysis. Unlike partitioning or hierarchical methods that may falter with non-convex shapes or in the presence of outliers, DBSCAN thrives by leveraging two critical parameters: Eps (ϵ), the radius within which to search for neighboring points, and MinPts, the minimum number of points required to form a cluster. This methodology allows DBSCAN to distinguish between core points (indicative of dense areas), border points, and noise (outlier data points), thereby facilitating the identification of significant clusters while excluding anomalies(SINGH ET AL., 2022a; ALAHMARI ET AL., 2021; SINGH AND MESHRAM, 2017).

The application of DBSCAN to AIS data begins with the identification of dense clusters that represent typical maritime traffic patterns. Anomalies or outliers are those points that do not belong to any cluster, potentially signaling irregular vessel behaviors or erroneous AIS signals.

DBSCAN's advantages include its ability to discover clusters of any shape and its robustness against noise, making it a one-scan algorithm that does not predefine the number of clusters. However, it exhibits sensitivity to its parameters and struggles with data of varying densities or high-dimensional spaces(ALAHMARI ET AL., 2021). To address these limitations, various modifications and enhancements have been proposed, such as reverse closest neighbor-DBSCAN, grid DBSCAN, and adaptations using locality sensitive hashing for high-dimensional data, reflecting ongoing efforts to refine the efficacy of DBSCAN in various applications, including anomaly detection of AIS data (SINGH ET AL., 2022a; GUO ET AL., 2021).

DBSCAN's adaptability to arbitrary cluster shapes and its proficiency in handling noise make it an invaluable tool for anomaly detection in AIS data. Continuous advancements and refinements in DBSCAN algorithms aim to enhance their applicability, efficiency, and accuracy to extract meaningful patterns from complex datasets, such as those encountered in maritime surveillance and navigation systems.

3.4 SUPPORT VECTOR MACHINE

The SVM belongs to a category of kernel-based techniques used for pattern classification and regression. This classifier operates by taking an input pattern, known as a feature vector, and identifies the class to which it belongs. Consider x_i, where i ranges from 1 to M, as feature vectors in a training set X, classified into two distinct classes, ω_1 and ω_2. Utilizing this training data, the SVM algorithm seeks to identify an optimal hyperplane (HUSSAIN ET AL., 2011) with the largest margin that divides the unknown input patterns into two classes, as illustrated in FIG. 3.2. While numerous hyperplanes capable of separating the feature vectors exist, SVM identifies the one with the maximum margin, offering superior generalization performance for classification.

Essentially, SVM functions as a binary classifier, but it can also handle multiclass classification by decomposing the larger classification challenge into smaller, more manageable binary classification tasks. In situations where datasets are non-linear, the "kernel trick" technique is utilized. This approach transforms the dataset from the input space to

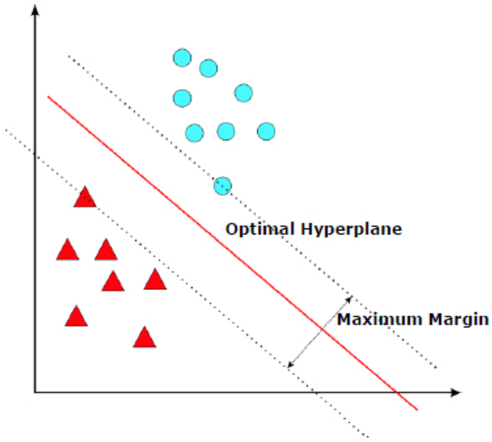

FIG. 3.2: Example of SVM classification. (HUSSAIN ET AL., 2011)

a higher-dimensional feature space, where it then constructs a hyperplane. The kernel is a function that facilitates the mapping of vectors from the input space to the feature space and calculates the inner product between two vectors. Commonly used kernel functions in SVM include polynomial, RBF (Radial Basis Function), sigmoid, and linear kernels (PRAKASH ET AL., 2012).

To adapt SVM to multiclass problems, various methods have been developed, which involve the combination of multiple binary SVM classifiers. Among the well-known techniques are the one-versus-all method, employing a winner-takes-all strategy (WTA), and the one-versus-one method, using a max-wins voting approach (MWV) (HSU AND LIN, 2002; BREDENSTEINER AND BENNETT, 1999).

3.5 EXPLAINABLE ARTIFICIAL INTELLIGENCE

In the world of AI today, the search for systems that not only perform high-efficiency tasks, but also provide an understanding of their operations has led to the appearance of XAI. At its core, XAI tries to make the decisions and processes of AI systems transparent and comprehensible to human beings (THAKUR ET AL., 2023). This section deals with the basic aspects of XAI and focuses on its significance, methodology, and application in various sectors.

XAI refers to a set of methods and techniques that explain how an AI model makes decisions based on input data. Unlike traditional AI systems, which often function as "black boxes", XAI aims to reveal the reasons behind AI decisions, ensuring that they are understandable and legitimate for human users (HAMILTON ET AL., 2020). The importance of XAI stems from the need to ensure the integrity, ethical alignment, and compliance with regulatory standards for the use of AI. By elucidating the workings of AI, XAI enhances trust among users and stakeholders and encourages the broader implementation of AI technologies (THAKUR ET AL., 2023). The methodology base of XAI is diverse and reflects a multidisciplinary nature that includes computer science, psychology, ethics, and more. The explanation technique can be largely categorized into model-specific and model-different approaches, local and global explanations, and pre-model, in-model, and post-model approaches (AHMED ET AL., 2022).

- Model-Specific vs. Model-Agnostic Approaches: Model-specific methods are customized to the inner workings of particular AI models, offering insight based on the intrinsic properties of the model. In contrast, model-agnostic techniques provide explanations regardless of model architecture, making them widely applicable across different AI systems (AHMED ET AL., 2022).

- Local vs. Global Explanations: Local explanations aim to clarify the decision-making process for individual instances or predictions. However, global explanations seek to impart an overarching understanding of the behavior and logic of the model throughout all its operations (AHMED ET AL., 2022).

- Pre-model, In-model, and Post-model Approaches: These categorizations reflect the timing of the explanation relative to the lifecycle of the AI model. The pre-model explanations focus on the data and features before model training. In-model explanations are integrated into the AI system itself, while post-model techniques analyze and interpret the model's behavior after it has been trained (AHMED ET AL., 2022).

Several techniques have been developed to advance the goals of XAI:

- Feature Importance Analysis and Model Decomposition: These methods illuminate the significance of data features and deconstruct complex models into more manageable components for easier analysis (THAKUR ET AL., 2023).

- Decision Trees, LIME, and SHAP: Decision trees offer a straightforward means of understanding model predictions. LIME and SHAP are advanced techniques that provide detailed explanations for individual predictions, highlighting the impact of each feature on the model's output (THAKUR ET AL., 2023).

- Class Activation Maps (CAM) and Gradient-Class Activation Maps (Grad-CAM): Particularly useful in image analysis, these methods identify the regions of an input image that are most influential in the decision-making process of the model (VOLKOV AND AVERKIN, 2023).

XAI has found applications in various areas to improve transparency and accountability in areas such as healthcare, finance, and defense. Among the notable examples are the analysis of autonomous robot behavior, smart home elderly care, and anomaly detection in complex systems (AHMED ET AL., 2022; HAMILTON ET AL., 2020). These applications not only illustrate the practical utility of XAI, but also emphasize its role in ensuring that AI systems are ethical, equitable and compatible with human values. XAI represents an important evolution in AI, which addresses the necessity of transparency, trust, and interpretability in AI systems. The combination of methods and innovative technologies allows XAI to provide a more responsible and understandable way of applying AI. As AI continues to penetrate various aspects of human life, XAI's principles and practices will play an indispensable role in shaping the future of technology in a way that is accessible, responsible, and in line with social norms and values.

4 RELATED WORK

In this chapter, a comprehensive review of the literature relevant to the field of maritime anomaly detection is provided, specifically focusing on advances using AIS data. Before conducting this Systematic Literature Review (SLR), a focused research initiative was undertaken to assess the application of XAI in the context of anomaly detection within AIS data. The initial investigation involved querying key academic databases with specific search strings to identify studies directly connecting XAI with AIS-based anomaly detection, Section 4.1 provides a detailed explanation of the XAI research. Surprisingly, this preliminary search did not yield direct references, indicating a conspicuous gap in the existing research landscape.

This discovery of a research gap led to the adoption of the SLR approach detailed here, aiming to perform a broader and more structured evaluation of the field. The methodological framework proposed by (CARRERA-RIVERA ET AL., 2022) was rigorously followed, ensuring an unbiased, structured evaluation, and synthesis of the literature. This was crucial to help delineate the current research landscape and identify potential avenues for future studies.

The SLR process began with a broad database search, initially capturing literature from the last five years, ultimately narrowing the focus to publications after 2021 to include only the most recent and relevant studies. Inclusion and exclusion criteria were meticulously applied to distill the review into the most pertinent studies. This was followed by a rigorous quality assessment of each article, using the criteria and Likert-type scale suggested by (ZHOU ET AL., 2015), which helped maintain the integrity and validity of the review. Out of an initial pool of 789 articles, our refined selection process led to a final set of 23 significant articles that were thoroughly analyzed and discussed in this chapter.

The findings of our SLR are structured around three pivotal research questions, as delineated in Table 4.1, which guide the discussion in this chapter. The insights gained from the review are instrumental in framing the scope of our dissertation, providing a foundational context for our proposed research, and identifying gaps that our study aims to fill.

This chapter not only synthesizes the current state of knowledge, but also critically examines the strengths and challenges of the methodologies employed in recent studies,

TAB. 4.1: Research Questions

Research Question (RQ)
RQ1. How effective are machine learning techniques in detecting anomalies in maritime navigation?
RQ2. Which machine learning models are most prevalent in the literature for AIS anomaly detection?
RQ3. Which data attributes are critical for the success of machine learning algorithms in AIS anomaly detection, and how do these algorithms incorporate geographical patterns to enhance their detection capabilities across global maritime navigation systems?

as highlighted by the works of (STACH ET AL., 2023), (RIBEIRO ET AL., 2023), and further studies by (FARAHNAKIAN ET AL., 2022), among others. By integrating these diverse perspectives, our review sets the stage for a deeper understanding of how AIS data can be leveraged more effectively in anomaly detection, ultimately contributing to safer maritime navigation practices.

4.1 REVIEW OF XAI IN AIS ANOMALY DETECTION LITERATURE

XAI has become an important point in the development of AI systems in various sectors due to its ability to make complex models transparent and understandable to users. The significance of XAI extends across fields such as healthcare, banking, commerce, Internet of Things (IoT), robotics, and autonomous systems. In these domains, XAI improves the trustworthiness and accountability of AI decisions, which are critical for user acceptance and regulatory compliance (CHAMOLA ET AL., 2023).

To explore the application of XAI in maritime anomaly detection, specifically using the AIS, a brief research was performed using the string: (Explainable AND AI OR XAI OR Explainable AND Artificial AND Intelligence) AND (AIS OR Automatic AND Identification AND System OR Maritime) across key academic databases: IEEE, Scopus and ACM. The objective was to identify the literature that directly connects the principles of XAI with anomaly detection in AIS data.

The search did not yield any direct references to studies that integrate Explainable AI with anomaly detection in the AIS data, indicating a gap in the current research landscape. Despite the absence of direct references, the widespread application of XAI in other technologically intensive and data-driven fields suggests the potential for significant benefits if applied to maritime anomaly detection.

In healthcare, XAI is used to provide clarity on AI-driven diagnostic decisions, helping medical professionals understand AI suggestions and building trust in AI-powered medical devices. In the financial sector, especially in banking and commerce, XAI helps to detect fraudulent transactions and explaining credit decisions to customers, which is crucial for maintaining transparency and fairness. Similarly, in IoT, robotics, and autonomous systems, XAI facilitates the understanding of autonomous decisions, enhancing safety and efficiency in operations (AHMED ET AL., 2022; CHAMOLA ET AL., 2023).

Given the complexity of maritime traffic patterns and the critical safety implications of accurate anomaly detection, the principles of XAI can be beneficial in this domain. By making AI decision-making processes transparent, XAI could help maritime authorities understand and trust AI-driven anomaly detections, thus facilitating more informed decision-making. Furthermore, XAI could help to address the challenges of dynamic environmental conditions and diverse vessel behaviors, which are common in maritime operations.

The lack of specific literature on XAI applications in AIS anomaly detection highlights a significant research opportunity. Building on the use of XAI in other fields, future studies should investigate how these principles can be adapted and integrated into maritime surveillance systems to enhance their effectiveness and reliability. This could potentially lead to breakthroughs in how maritime anomalies are detected and managed, contributing to safer and more secure maritime operations.

4.2 ANOMALY-DETECTION TECHNIQUES

In the field of maritime anomaly detection, a variety of machine learning techniques have been used to address the challenges posed by the complex and dynamic nature of maritime data, as shown in TAB. 4.2. This section focuses on exploring and comparing these techniques as presented in recent studies. Key methods include clustering algorithms like DBSCAN, used for segmenting dense maritime data (FARAHNAKIAN ET AL., 2023), (LI ET AL., 2023), (ZHOU ET AL., 2023)–(WIDYANTARA ET AL., 2023), (SINGH ET AL., 2022b), (WEI ET AL., 2022), (JIAO AND LI, 2023), (ZHANG ET AL., 2023), and neural networks for advanced pattern recognition and trajectory prediction (LI ET AL., 2023), (BERNABÉ ET AL., 2023), (ZHANG ET AL., 2023). The integration of deep learning models, such as autoencoders, enhances the accuracy of anomaly detection by learning complex data representations (XIE ET AL., 2023), (SINGH ET AL., 2022b). Statistical models and probabilistic approaches, like Kernel Density Estimation and Rayda's criterion, are employed for identifying significant deviations from expected patterns (SHI

ET AL., 2022), (RONG ET AL., 2021). Additionally, the use of transfer learning demonstrates the adaptability of these models to different maritime contexts (HU ET AL., 2023).

(FARAHNAKIAN ET AL., 2023) utilized a range of techniques, including K-means, DBSCAN, AP, and GMM. These algorithms were applied to a dataset collected from the Baltic Sea, which included a blend of static and dynamic vessel information. The methodology was further refined by experimenting with different combinations of 2D and 3D data inputs in the clustering process, enhancing the robustness and accuracy of anomaly detection.

In (LI ET AL., 2023), Li et al. combined neural networks and cluster analysis. Neural networks are used for pattern recognition in vessel data, while cluster analysis, including techniques like the isolated forest algorithm and DBSCAN, helps analyze data distribution changes. The CS-DBSCAN algorithm clusters vessel trajectories into normal and abnormal patterns. Additionally, an LSTM network-based model predicts vessel trajectories and identifies deviations. A hybrid approach, merging CS-DBSCAN with LSTM, enhances real-time detection efficiency, particularly in identifying unusual vessel speeds and courses.

The study presented in (XIE ET AL., 2023) introduces a novel anomaly detection model for ship trajectory data, utilizing the GMVAE with an unsupervised classification approach. The model enhances the traditional VAE by integrating a Gaussian mixture model into both the prior distribution and the approximate posterior. It constructs a high-dimensional hidden space to effectively learn the characteristics of multi-class trajectory data. Additionally, the Dynamic Time Warping (DTW) method is employed to calculate the discrepancy between the reconstructed and original trajectories, thereby determining the abnormality of ship movements.

In their research (ZHOU ET AL., 2023), the core methodology begins with the application of an Improved Adaptive Douglas-Peucker Algorithm, which is instrumental in compressing ship trajectories, thereby facilitating a more efficient analysis of navigation patterns. This is complemented by an analysis of lateral displacement, where the distribution of trajectory points is compared against a benchmark curve to identify deviations indicative of abnormal navigation. To assess the potential risks associated with these detected anomalies, the study leverages a Dynamic Bayesian Network. This probabilistic model is adept at evaluating the impact of abnormal behaviors on the likelihood of maritime accidents. Additionally, the research incorporates data-driven techniques, including similarity measures and dimensionality reduction, to refine the process of trajectory clus-

TAB. 4.2: Summarized survey results

Publication	Features	Methods	Region	XAI
Farahnakian et al. (2023)	PO, SOG and COG	DBSCAN, AP, GMM and K-means	Baltic Sea	no
Li et al. (2023)	PO, SOG and COG	CS-DBSCAN, Attention Mechanism, Isolated Forest and LSTM	Gulf of Mexico	no
Xie et al. (2023)	PO	MANUALLY LABELED, GMVAE and DTW	Juan de Fuca Strait (USA)	no
Zhou et al. (2023)	PO, Draft, SOG, COG and heading	DBSCAN, Douglas-Peucker, Dynamic Bayesian Network	Yangtze River (China)	no
Shi et al. (2022)	PO, SOG, COG, Avg. SOG, and Avg. Acc	DBSCAN, GMM, Graph Structure Learning, Rayda's Criterion, Isolation Forest	Bohai Sea, Yellow Sea, East China Sea and South China Sea	no
Ferreira et al. (2023)	PO	TRACLUS, DTW, MD, HDBSCAN, Compression Algorithms	Juan de Fuca Strait and Francisco Bay (USA)	no
Widyantara et al. (2023)	PO, SOG, COG and timestamp	Douglas-Peucker, LCSS, MDS, DBSCAN	Lombok Strait (Indonesia)	no
Bernabé et al. (2023)	PO, timestamp, SOG, time difference, latitude difference, longitude difference, distance to the port and second of the day	Self-Supervised Training, Transformer Models	All over the world	no
Antunes et al. (2022)	PO, Avg. SOG	Dynamic Grid, Binary Search Tree	Southern coast of Portugal	no
Huan et al. (2022)	PO	Cubic Splines Interpolation, Isolated Forest, Geographical Model-Based	Ban Sagar lake (India)	no
Hu et al. (2023)	Displacement, Displacement sin and cos, Avg. SOG, COG sin and cos and Time Interval	VAE, GMVAE, TD3, Transfer Learning	Yangtze River (China)	no
Singh et al. (2022b)	PO, SOG, COG, time and edge of the graph G(V, E)	GTRA, DBSCAN, RDP, RNN-EDL, EDL	Arabian Sea	no
Wei et al. (2022)	Mean Latitude (X), Latitude Std. Dev. (X), Mean Longitude (X), Longitude Std. Dev. (X), Mean Speed (S), Speed Std. Dev. (S), Mean Trajectory (C) and Trajectory Std. Dev. (C)	SVM, DBSCAN, Weighted Hybrid Kernel Function, Differential Operator	Chengshan Jiao (China)	no
Rong et al. (2021)	SOG and COG	OPTICS, KDE, Graph Theory	Continental coast of Portugal	no
Pohontu et al. (2023)	Duration of four status: sailing, docked, waiting and signal lost	Multivariate Outlier Detection, Ensemble Methods	Black Sea (Romania)	no
Liu et al. (2022)	PO, SOG and COG	Immune Genetic Spectral Clustering Algorithm	Lianyungang to Qingdao port (China)	no
Jiao and Li (2023)	PO, SOG, geographical location, sea environment	KD-Tree, Enhanced DBSCAN	Bayuquan to Yingkou Port (China)	no
Zhang et al. (2023)	PO, COG and SOG	DBSCAN, BiGRU, Gaussian Distribution, DTW and Douglas-Peucker	Tianjin Port (China)	no
This proposal (2024)	Mean Latitude (X), Latitude Std. Dev. (X), Mean Longitude (X), Longitude Std. Dev. (X), Mean Speed (S), Speed Std. Dev. (S), Mean Trajectory (C) and Trajectory Std. Dev. (C)	SVM, DBSCAN, Weighted Hybrid Kernel Function, Differential Operator	Brazil	yes

Note: AP (Affinity Propagation); BiGRU (Bi-directional Gated Recurrent Unit); COG (Course Over Ground); DBSCAN (Density-Based Spatial Clustering of Applications with Noise); DTW (Dynamic Time Warping); GMM (Gaussian Mixtures Model); GTRA (Graph-Based Trajectory Representation and Association); GMVAE (Gaussian Mixture Variational Autoencoder) KDE (Kernel Density Estimation); LCSS (Longest Common Subsequence); LSTM (Long Short-Term Memory); MDS (Multi-Dimensional Scaling); PO (Position); RNN-EDL (Recurrent Neural Network-based Evidential Deep Learning); SOG (Speed Over Ground); SVM (Support Vector Machine); and VAE (Variational Autoencoder).

tering.

Exploring advanced techniques in anomaly detection(SHI ET AL., 2022), the authors adopt a novel approach by analyzing both spatial and thematic information from moving ship trajectory data. Their methodology begins with the development of a model to conceptualize abnormal ship behaviors. To delve into the spatial aspects of ship movements, they utilize a graph structure learning method for mining maritime routes. For the detection of spatial anomalies, the study employs Rayda's criterion, which is based on the assumption that a dataset predominantly contains random errors. This criterion calculates the standard deviation of these errors to determine a threshold, beyond which deviations are considered significant and are thus eliminated. In addition to spatial analysis, the authors also focus on thematic information-based anomalies.Here, they apply the isolation forest algorithm to detect and describe abnormal behaviors related to thematic attributes of ships.

In the article (FERREIRA ET AL., 2023), the authors focus on improving anomaly detection in AIS data through a combination of clustering algorithms and compression techniques. Key methods include the TRACLUS algorithm for segmenting and clustering trajectory data, and the DBSCAN algorithm for identifying outliers by analyzing data density. They also use DTW and MD to measure trajectory distances, accommodating variations in speed and sampling. The HDBSCAN algorithm further refines clustering by creating a hierarchy based on density. Additionally, the study evaluates the effectiveness of compression algorithms like DP, TR, and SB in reducing data size for faster processing, while maintaining the accuracy of clustering results.

The framework proposed in (WIDYANTARA ET AL., 2023), integrates the Douglas-Peucker algorithm for efficient trajectory compression, the Longest Common Subsequence for accurate similarity measurement of vessel movements, and Multi-Dimensional Scaling combined with the DBSCAN algorithm for effective density-based clustering. Their approach successfully accelerates the similarity measurement process, accurately distinguishes between different vessel trajectories, identifies noise, and creates high-quality clusters, all within a relatively short processing time.

In a recent study (BERNABÉ ET AL., 2023), researchers employed transformer models, renowned for their effectiveness in Natural Language Processing and computer vision, to detect abnormal missing AIS receptions. These models are particularly adept at handling sequential data, making them suitable for analyzing AIS message history as time series. The approach involves using the transformer's encoder to create a fixed-size representation vector from the AIS data, which is then concatenated with the vessel's latest position. This combined vector is processed through a specialized subnetwork comprising dense layers with ReLu activation and dropout, culminating in a classification layer.

The study (ANTUNES ET AL., 2022), explores machine learning techniques for predicting maritime routes using historical AIS data, focusing on overcoming the limitations of traditional grid-based methods. By introducing a dynamic grid size and a binary search tree algorithm, the researchers enhance the scalability of these methods for large-scale abnormal trajectory detection. The system's ability to learn from new data and generate realtime alerts for unusual maritime activities is a key feature. However, challenges arise in handling new vessels without historical data and in defining deviations from normal routes, especially for vessels with unpredictable paths like leisure boats.

Introducing an approach to ship trajectory analysis (HUAN ET AL., 2022), the researchers developed a novel approach to detect anomalies in maritime vessel trajectories. Their method combines similarity-based techniques and the IAVT detection method, which uses cubic splines interpolation for reconstructing trajectories and the isolated forest algorithm adapted for maritime contexts. This approach effectively identifies anomalies by analyzing trajectory data through sub-sampling, partitioning, and applying geographical model-based approaches. These techniques collectively enhance the accuracy of anomaly detection in vessel movements, addressing the challenges of regional data dependency and subjective rule-based methods.

Hu et al. (HU ET AL., 2023) presents a Transfer Learning based Trajec- tory Anomaly Detection (TLTAD) strategy for IoT-enabled Maritime Transportation Systems. It employs a variational autoencoder for analyzing normal ship trajectories and a graph variational autoencoder for assessing spatial similarities. The anomaly detection model is trained using the Twin Delayed Deep Deterministic policy gradient (TD3) algorithm, and transfer learning is applied to adapt the model across different or similar maritime areas, enhancing efficiency.

Advancing the field of maritime anomaly detection (SINGH ET AL., 2022b), the authors developed a method for detecting anomalies in maritime trajectories using a combination of graph-based clustering and deep learning. They first clustered AIS data into maritime routes using the GTRA method, which employs DBSCAN and RDP algorithms. Then, they applied an RNN- EDL regressor to analyze these trajectories. This model detects anomalies by identifying significant shifts in uncertainties within the data. Additionally, Evidential Deep Learning (EDL) classifiers are used to distinguish between normal and abnormal trajectory patterns, effectively identifying unusual vessel movements and AIS on-off switching anomalies.

In their research (WEI ET AL., 2022) by Zhaokun Wei, a method is developed using an improved SVM combined with data mining and statistical techniques. This approach analyzes vessel trajectories in high-dimensional space, capturing spatiotemporal and motion characteristics. The method integrates the DBSCAN algorithm to identify standard traffic patterns. The SVM model is enhanced with a weighted hybrid kernel function and a differential operator, enabling adaptive kernel function selection for improved anomaly detection accuracy. The method's effectiveness is validated using AIS data, demonstrating its capability in accurately detecting abnormal maritime activities.

Rong et al. (RONG ET AL., 2021) developed an anomaly detection method for maritime traffic using AIS data. This method involves creating new ship motion patterns, including departure and arrival points, and sub-trajectories. It uses KDE to estimate ship movement probability densities, identifying anomalies by comparing with expected distributions. The method clusters similar ship trajectories and applies graph theory for analysis and visualization. Anomalies are detected by deviations from conditional probabilities of routes, considering ships' speed and course. The method is dynamic, continuously updated with KDE, and was effectively demonstrated in a case study off the coast of Portugal

In the study (POHONTU ET AL., 2023), a comprehensive approach for detecting anomalies in maritime data is presented. It combines classical outlier detection methods, spatial outlier detection, and various supervision modes (unsupervised, supervised, and semi-supervised) to identify deviations in maritime data. The methodology includes multivariate outlier detection using clustering, Multivariate Local Outlier Factor, Principal Component Analysis, and distance calculations. Ensemble methods are also used to combine multiple estimators for improved accuracy.

In their research (LIU ET AL., 2022), Hongdan Liu and colleagues developed a method for detecting abnormal vessel behavior using an immune genetic spectral clustering algorithm. This approach focuses on analyzing vessel trajectory data, optimizing clustering centers, and setting specific parameters for trajectory characteristics. The method was tested using AIS data from Lianyungang to Qingdao port, demonstrating improved detection accuracy and reduced false alarm rates compared to traditional methods.

In this particular study (JIAO AND LI, 2023), the authors developed a method to detect abnormal ship behavior by combining the KD-Tree algorithm and an enhanced DBSCAN clustering algorithm. The KD-Tree algorithm is used to analyze ship trajectory data, identifying unusual positions and movements. The DBSCAN algorithm then clusters these data points based on density, differentiating between normal and abnormal behaviors.

Bohan Zhang et al. (ZHANG ET AL., 2023), designed a method for detecting ship anomalies in three steps: First, it ensures the quality of AIS data. Second, it uses the DBSCAN algorithm and an improved DTW algorithm to extract and measure the similarity of normal ship trajectory clusters. Finally, these clusters train a BiGRU neural network, which predicts ship trajectories and detects anomalies in real-time.

4.3 COMPARATIVE ANALYSIS

The DBSCAN algorithm, noted in (FARAHNAKIAN ET AL., 2023), (LI ET AL., 2023), (ZHOU ET AL., 2023)–(WIDYANTARA ET AL., 2023), (SINGH ET AL., 2022b), (WEI ET AL., 2022), (JIAO AND LI, 2023), (ZHANG ET AL., 2023), is a cornerstone in clustering-based anomaly detection. Its ability to identify outliers and cluster data based on density is crucial in maritime contexts where trajectory data is often noisy and irregular. The versatility of DBSCAN is evident in its application across different studies, from trajectory segmentation (FERREIRA ET AL., 2023) to standard traffic pattern identification (WEI ET AL., 2022). The TRACLUS algorithm in (FERREIRA ET AL., 2023) and the GTRA method in (SINGH ET AL., 2022b) emphasize trajectory segmentation and clustering, akin to the Douglas-Peucker algorithm's role in (WIDYANTARA ET AL., 2023) and (JIAO AND LI, 2023) for trajectory compression. These methods underscore the importance of reducing data complexity for more efficient analysis.

Studies like (LI ET AL., 2023), (XIE ET AL., 2023), (BERNABÉ ET AL., 2023), and (ZHANG ET AL., 2023) demonstrate the adaptability of neural networks in maritime anomaly detection. LSTM networks in (LI ET AL., 2023) are pivotal for trajectory prediction, while (XIE ET AL., 2023) and (HU ET AL., 2023) explore the potential of autoencoders (GMVAE and graph variational autoencoder, respectively) in learning complex data representations. The use of transformer models in (BERNABÉ ET AL., 2023) for sequential data analysis is particularly innovative, reflecting the cross-disciplinary application of these models. The combination of clustering algorithms with neural networks, as seen in (LI ET AL., 2023) and (ZHANG ET AL., 2023), highlights a trend towards hybrid models. These approaches leverage the strengths of both clustering for data segmentation and neural networks for pattern recognition, enhancing the overall efficiency and accuracy of anomaly detection.

The application of statistical techniques, such as Rayda's criterion in (SHI ET AL.,

2022) and KDE in (RONG ET AL., 2021), provides a foundational approach to anomaly detection. These methods focus on identifying significant deviations from expected patterns or distributions, offering a more traditional yet robust means of analysis. The emphasis on outlier detection in (POHONTU ET AL., 2023) and (LIU ET AL., 2022) is notable. (POHONTU ET AL., 2023) employs multivariate outlier detection techniques, while (LIU ET AL., 2022) introduces an immune genetic spectral clustering algorithm. These approaches are tailored to the specific challenges of maritime data, which often includes sparse and irregular patterns.

In the study (HU ET AL., 2023), the authors uniquely integrate transfer learning into their model, allowing it to adapt to various maritime regions. This methodology reflects a growing trend towards the development of models capable of generalizing across varied contexts, an essential attribute in the ever-changing maritime environment. The common thread in these studies is the use of clustering algorithms and machine learning models. However, a notable trend is the integration of multiple methodologies, reflecting a shift towards more nuanced and comprehensive approaches to maritime anomaly detection. Each study contributes uniquely to the field. For example, the use of transformer models in (BERNABÉ ET AL., 2023) for sequential data analysis and the integration of graph-based clustering with deep learning in (SINGH ET AL., 2022b) are indicative of innovative approaches being explored in this domain. In summary, comparative analysis of these studies reveals a dynamic and evolving field, where traditional statistical methods intersect with advanced machine learning techniques to address the multifaceted challenges of maritime anomaly detection. The diversity of approaches underscores the complexity of the domain and the need for continued innovation and interdisciplinary collaboration.

5 PROPOSAL

This work aims to develop a dissertation in order to meet the objectives and questions described in this chapter.

5.1 RESEARCH PROBLEM

How integrating XAI techniques into AIS anomaly detection models can improve their interpretability without reducing their performance, and how this integration affects the trust and satisfaction of maritime stakeholders.

5.2 HYPOTHESIS

Hypothesis 1. Integration of XAI techniques into AIS anomaly detection models will improve their interpretability without significantly compromising performance;

Hypothesis 2. Maritime stakeholders will demonstrate a higher degree of trust and satisfaction with anomaly detection models that incorporate XAI features.

5.2.1 JUSTIFICATION OF THE HYPOTHESIS

- XAI techniques are designed to make AI decision processes transparent without altering the core predictive capabilities of the models. This hypothesis is supported by research suggesting that interpretability layers like feature importance explanations can be incorporated without degrading the accuracy or efficiency of the model, which is critical in safety-focused applications like maritime navigation.
- Transparency in AI models creates trust. By making AI decision-making processes understandable, XAI helps stakeholders verify and rationalize outputs, potentially increasing their trust and satisfaction. This is crucial for acceptance and operational reliance, especially in sectors where decision accuracy has significant safety implications.

5.3 OBJECTIVES

The objectives of this dissertation are to integrate XAI techniques into AIS anomaly detection models and evaluate their impact on interpretability and performance. It aims to assess how XAI influences model transparency and enhances stakeholder trust and satisfaction without compromising the models' effectiveness. The research will involve quantitative comparisons between traditional and XAI-enhanced models, alongside stakeholder feedback to measure trust and operational reliance. Ultimately, the study seeks to provide insights into the benefits and practical implementations of XAI in high-stakes maritime safety applications.

5.4 METHODOLOGY

The methodology for developing the experiment will be based on the steps described in FIG 5.1.

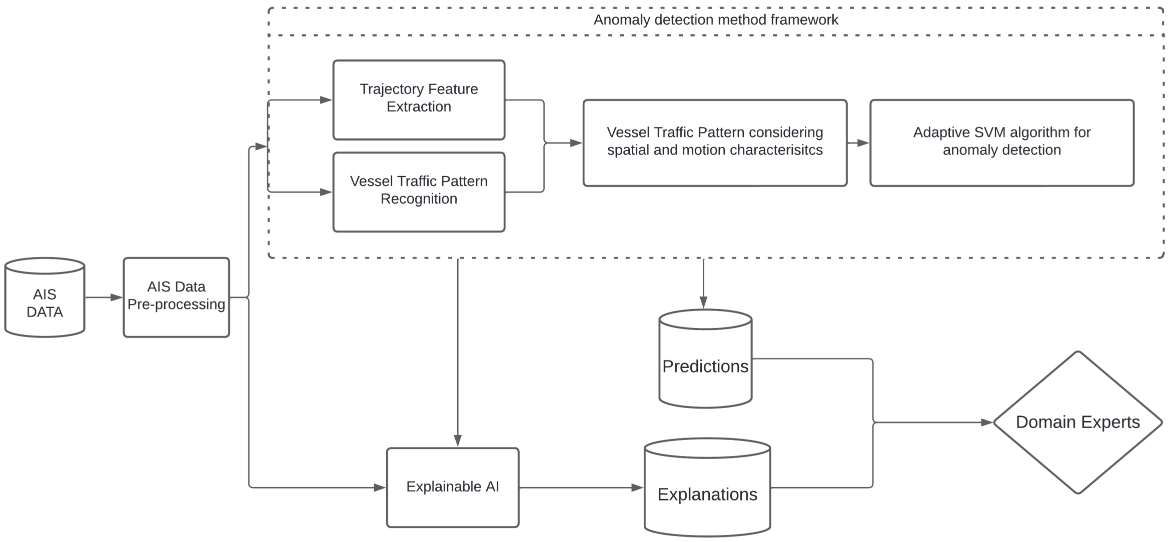

FIG. 5.1: Proposed method.

The methodology presents a two-part framework designed to detect anomalies in maritime traffic using data from the AIS. The first part of the framework, called "Anomaly detection method framework", focuses on the preparation of AIS data for analysis and will be reproduced based on the study detailed in (WEI ET AL., 2022). This step involves cleaning and refining the data to ensure its reliability.

The subsequent phase is dedicated to the anomaly detection method, which is the centerpiece of this research. This method is intricately partitioned into three processes.

The process begins with trajectory feature extraction, which aims to meticulously capture the spatial and motion characteristics from the ships' navigational paths. It sifts through the raw AIS data to pick out defining features such as coordinates, speed, and direction changes that are crucial for understanding vessel movements.

Following this, the vessel traffic pattern recognition algorithm comes into action, leveraging the extracted features to decipher recognizable patterns in maritime traffic. This algorithm meticulously considers both the spatial positioning and the kinetic behavior of the vessels to map the standard traffic patterns, thus setting a benchmark for normal vessel behavior.

The cornerstone of the anomaly detection phase is the deployment of an adaptive SVM algorithm. This sophisticated algorithm is engineered to be responsive to the dynamic nature of maritime traffic, fine-tuning itself to better identify inconsistencies against the established patterns. The adaptive SVM algorithm is tasked with the critical role of identifying those movements that contrast starkly with usual vessel activity, marking them as anomalies.

The second part of the framework incorporates Explainable AI, which is about making the results from the SVM understandable to humans. In this context, Explainable AI takes the SVM's findings and breaks them down into insights that domain experts can easily digest and trust. This means that instead of just being told that a particular movement is an anomaly, experts can understand why it's been flagged as such, enabling them to make better-informed decisions.

In essence, the proposed framework is not just about finding unusual patterns in maritime traffic it's also about providing clear explanations for these findings. By combining these advanced AI techniques, the methodology aims to provide a thorough and trustworthy system for maritime surveillance.

5.5 EXPECTED CONTRIBUTIONS

The expected contributions of this study are:

(i) Application of XAI in a new field of research not found in the literature of the area;

(ii) This study aims to make the outcomes of AIS anomaly detection more understandable to users, providing clear insights into AI decisions;

(iii) By making AI processes transparent, this research will build greater confidence among stakeholders in AI's reliability and effectiveness;

(iv) The insights gained from XAI will inform ongoing refinements, enhancing the model's accuracy and operational efficiency;

(v) Enhancing maritime surveillance through advanced AIS data analysis for Brazilian Navy operations.

6 ACTION PLAN

The plan for the development of this research includes the activities in TAB. 6.1 which are described next.

TAB. 6.1: List of Activities

	Activity
1	Literature Review
2	Design of the Proposed Model
3	Prototype Implementation
4	Initial Testing and Refinement
5	Experimental Setup
6	Run Experiments
7	Analyze Initial Results
8	Extended Experiments
9	Document Findings
10	Paper Writing
11	Iterative Drafting and Feedback
12	Finalize Dissertation
13	Prepare Defense Presentation
14	Dissertation Defense

- Literature Review: This stage is designed not only to identify research gaps and understand current methodologies, but also to continuously update and expand the theoretical base of the proposed study. The literature will be regularly reviewed and augmented throughout the dissertation process to incorporate the latest research findings and ensure the relevance and accuracy of the research context.

- Design of the Proposed Model: The design of the proposed model will be conceptualized and outlined, detailing the use of SVM for anomaly detection and the integration of XAI to ensure transparency and understandability of decisions. This model design sets the foundation for the implementation phase.

- Prototype implementation: The prototype implementation will translate the model design into a functional prototype, incorporating the SVM algorithm and XAI features. This prototype serves as the initial iteration of the solution, ready for preliminary testing.

- Initial testing and refinement: Initial testing of the prototype is conducted under controlled conditions to identify any technical issues and verify functionality. Based on the outcomes, refinements will be made to enhance the model's accuracy and operational efficiency.

- Experimental setup: The experimental setup involves preparing the necessary tools, data sets, and evaluation metrics to perform rigorous model tests. This setup is designed to emulate real-world conditions as closely as possible, providing a robust test environment.

- Run experiments: Experiments will be conducted using the established setup to evaluate the performance of the model in detecting anomalies in AIS data. These experiments are important for gathering data on the effectiveness and reliability of the model.

- Analyze initial results: Following the experiments, the initial results will be analyzed to assess the performance of the anomaly detection model. This analysis focuses on understanding the strengths and limitations of the model, emphasizing both its detection capabilities and the clarity of its explanations.

- Extended experiments: Based on insights gained from the initial analysis, extended experiments will be conducted to further test and refine the model. These may involve varying conditions or parameters to optimize performance and adaptability.

- Document findings: The findings of the experiments will be systematically documented, providing a detailed, clear, and structured presentation of the research process and the results.

- Paper writing: A scholarly paper will be drafted to articulate the research questions, methodology, results, and conclusions. This paper aims to formally present the research to the academic community, highlighting its contributions and implications.

- Iterative drafting and feedback: The paper and dissertation draft will undergo iterative revisions based on feedback from advisors and peers.

- Finalize dissertation: Final adjustments will be made to the dissertation, incorporating all feedback to prepare the definitive version for submission and defense.

- Prepare defense presentation: A presentation will be prepared, summarizing the research methodologies, findings, and significance. This presentation is intended to communicate the research contributions to the dissertation committee.

- Dissertation defense: The final stage involves presenting and defending the dissertation before the committee, addressing their questions and demonstrating the research contributions to the field.

The schedule for developing activities related to this proposal can be seen in FIG. 6.1.

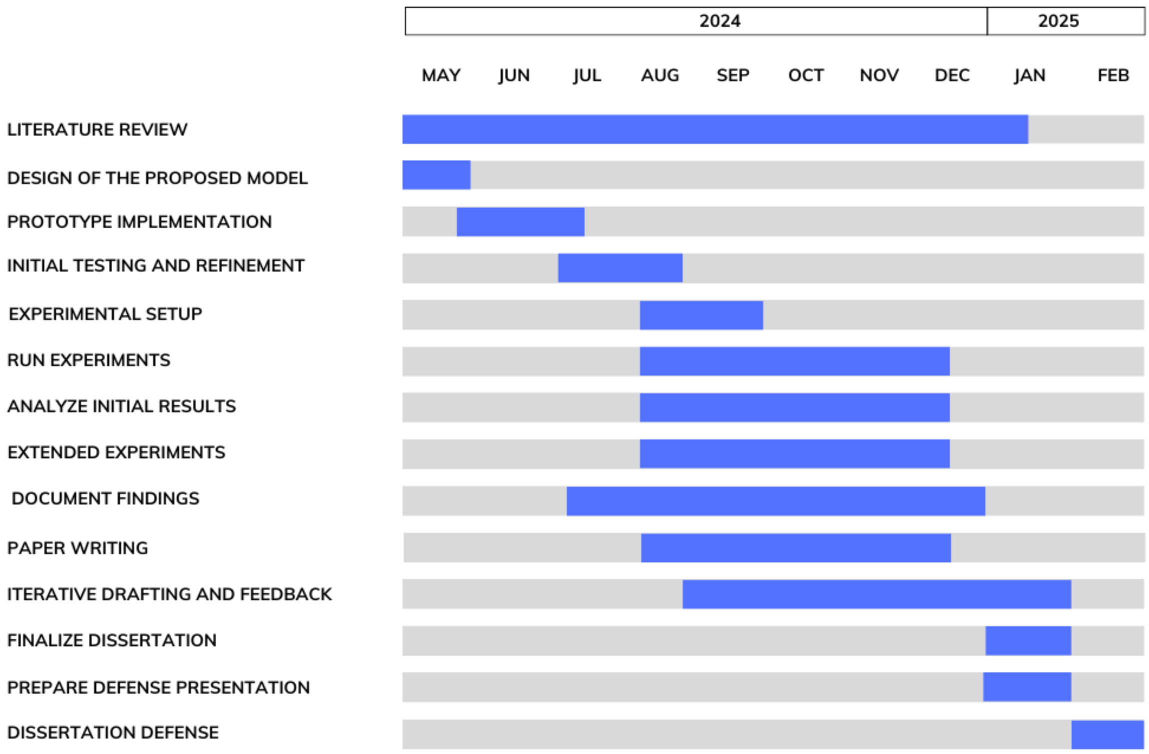

FIG. 6.1: Schedule of activities.

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Concordo com a presente Proposta de Dissertação e declaro que as necessidades para sua execução serão garantidas pela Seção.

IME, em 24 de Maio de 2024.

Cel Julio Cesar Duarte

CHEFE da SE/9