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Anomaly Detection in Maritime Ship Trajectory using Deep Learning Approach: A Comprehensive Survey, State of The Art, and Future Perspective

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***Abstract*—Prediction of ship trajectories using data from the Automatic Identification System (AIS) has garnered increased attention due to its potential in averting collision incidents and resolving navigational conflicts. Hence, there exists a pressing need to systematically review the literature on deep learning prediction techniques to elucidate their benefits in ensuring maritime safety across various scenarios. This task holds particular importance and relevance in the realm of unmanned vessels coexisting with manned ships, shaping a novel hybrid maritime traffic paradigm in the upcoming era. The present study aims to undertake a thorough review of deep learning methodologies, encompassing Recurrent Neural Networks, Long Short-Term Memory, auto-encoder, and Hybrid methods. The outcomes elucidate the distinctive features of diverse prediction approaches, offering valuable insights for stakeholders to navigate the selection of the most suitable method tailored to specific circumstances. Furthermore, it contributes to identifying the research challenges in ship trajectory prediction and proposing corresponding remedies to steer the course of future investigations. Future perspectives in maritime anomaly detection involve leveraging advanced technologies like Automatic identification Systems (AIS), radars, and Decision Support Tools (DST) to enhance surveillance capabilities and ensure maritime traffic safety. These approaches contribute to improving detection performance, reducing false alarms, and anticipating proper actions in response to anomalous behaviors, ultimately enhancing maritime situational awareness and operational efficiency in complex maritime environments. Anomaly detection in maritime performs a crucial part in enhancing safety of marine traffic and security leveraging advanced technologies and innovative approaches.**

***Keywords*—Anomaly detection; trajectory prediction; AIS data; deep learning; maritime safety.**

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I. Introduction

Maritime transportation data pertain to the total weight of commodities, movements of passengers, and various vessel activities on the aquatic domain. The activities at sea continue to be vigorous, with a consistent rise in volumes. This method of transportation stands as a fundamental mechanism for conveying goods across the globe, particularly for different categories of cargo vessels. The escalating level of activity has been noted has published by the International Union of Marine Insurance (IUMI) in their annual information globally (Jurkus et al., 2023). Anomalies, in simplistic terms, refer to occurrences that deviate from the expected or usual outcome. Utilizing AIS data for real-time monitoring can identify various categories of anomalies, including intrinsic, contextual, and behavioral anomalies. Each instance of anomaly detection necessitates a unique methodology. Typically, the most intriguing anomalies pertain to behavioral aspects. Are the vessels adhering to the projected route? Are they being identified accurately? Are they approaching restricted areas? Subsequent to anomaly identification, the next steps involve making choices such as a) recording and proceeding to the subsequent stage of the procedure; b) recording, categorizing, and proceeding; c) issuing alerts and submitting reports. If measures are taken and reports are generated, further actions must be executed in the subsequent phase (Apriyanto et al., 2023). The atypical conduct of a ship may be detected through the identification of singular or multiple occurrences that compel the vessel to stray from its usual trajectory, leading to unanticipated adjustments in both course and velocity, as well as unauthorized passage through restricted zones, among other factors (Riveiro, 2018), classifying deviations and irregular vessel movements involves categorizing them as positional anomalies (variations from a predicted position), contextual anomalies (atypical navigation instances or vessel types in a particular location), kinematic anomalies (unusual speeds, courses, maneuvers, and halts), complex anomalies (which necessitate multiple anomaly detection methods to identify particular behaviors), and data-related anomalies (trajectories that are incomplete).

A. Definition and Characteristics of Anomalies in Maritime Ship Trajectories.

Anomalies in maritime ship trajectories refer to unusual or unexpected behaviors in the movement of ships, which can be problematic and require further investigation. These anomalies can be detected using various techniques and methods, such as, retrieval of trajectory patterns and the identification of anomalies: This approach emphasis lies in the extraction of diverse trajectory patterns for marine vessels and identifying anomalies based on their deviation from normal behavior (Boztepe et al., 2021).

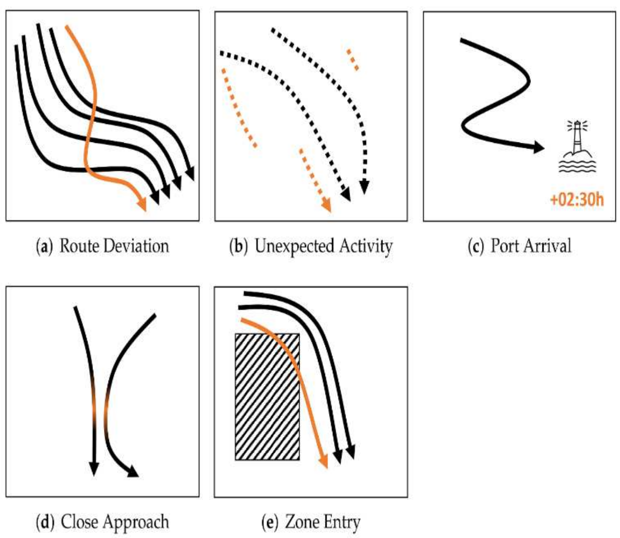

Fig. 1 General Five AIS Anomaly Types (Abghari, 2012).

B. Characteristics of Anomalies in Maritime Ship Trajectories.

Anomalies in maritime ship trajectories can take various forms, indicating potentially forbidden or unexpected behaviors. These anomalies can include deviations from predicted courses, random stops in open water, unusual speeds, or conspicuous rendezvous maneuvers. Anomalies in ship trajectories are often detected using methods such as trajectory pattern extraction, anomaly detection tests incorporating physical constraints, clustering models, deep recurrent neural networks, as well as machine learning techniques. These techniques aim to recognize unusual vessel behaviors, which could be indicative of illicit activities such as illegal fishing, environmental pollution, piracy, espionage, and smuggling. By analyzing ship trajectory characteristics and utilizing various anomaly detection models, maritime authorities and enforcement agencies can work to improve maritime security and safety.

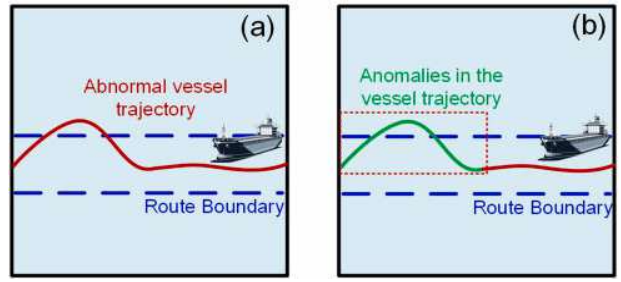

Fig. 2 Illustration of (a) abnormal vessel trajectory and (b) anomalies in vessel trajectory (Liang et al., 2024).

C. Major Contribution

The primary contribution lies in addressing the challenges associated with satellite signal acquisition in close proximity to hydraulic structures, heightened inaccuracies in vessel coordinate measurements, and an increased risk of collisions and incidents in such regions. Further exploration is required to identify key specification for enhancing the brain network training to enhance the accuracy of predicting ship trajectories during maneuvers. However, certain approaches have proven inadequate in addressing the discrepancies between projected and actual values, along with the complexities linked to overseeing substantial quantities of dynamic vessel information and guaranteeing data reliability.

II. Material and Method

Traditional approaches to anomaly detection include various methods such as statistical techniques, machine learning algorithms, and data clustering. These approaches can be categorized into unsupervised, supervised, and semi-supervised techniques:

A. Rule-Based Methods

Rules- based techniques in anomaly detection depend on setting clear guidelines or cutoff points in order to spot abnormalities. These guidelines frequently draw from domain expertise and expert judgment, or specific business requirements. Anomaly detection in maritime ship trajectory can be done using rule-based methods or deep learning approaches. Rule-based methods involve clustering and trajectory pattern extraction, while deep learning methodologies use recurrent brain networks, convolutional neural networks, auto-encoders. Some studies have proposed ensemble deep learning approaches and physics-guided gap-aware anomaly detection tests. Anomaly detection can be searching for erratic, unlawful, along with others unusual appearances in vessel trajectory analysis-based trajectory data, and abnormal vessel movement. The methods can be used for data from utilizing the Automatic Identification System (AIS) enable actual ship anomaly detection (B. Zhang et al., 2023)(Boztepe et al., 2021)(Guo et al., 2021). The rule-based method has been a dominant approach in machine translation research for several decades and is still used in present-day MT systems. Rule-based methods are also used in other fields, such as artificial neural network training, where regulations that develop from genetic algorithms are used to determine the ideal time frame for training and initialization (Tsoulos et al., 2022). Rule-based methods have advantages in providing important features and their corresponding values, making them easy to understand for both technical practitioners and stakeholders. In the field of granular computing, rule-based methods are used for classification, with a focus on improving the extracted granular rules' readable quality while maintaining efficiency (Niu et al., 2022). In summary, while rules-based methods are useful for certain applications, they have limitations in adapting to evolving data patterns and can be time-consuming to maintain. Therefore, a mix of machine learning and rule-based methods is frequently recommended to achieve comprehensive anomaly detection.

B. Statistical Methods

Statistical methods for anomaly detection in maritime ship trajectories have been widely researched. Some notable approaches include: Finding anomalies using the trajectory of a ship's behavior: This method fits a statistical model that incorporates historical data on ship normal motion and detects anomalous ship behavior by comparing the observed data with the model. Identification of anomalies in marine AIS tracks: An analysis of 44 scholarly pieces focusing on detection of anomalies in maritime AIS trajectories has been conducted, highlighting the importance of this topic in maritime security and surveillance (Wolsing et al., 2022). Identifying unusual ship activity through utilization of grouping and a recurrent neural network in depth: This method uses ship trajectory data and employs clustering techniques to identify normal and anomalous ship behaviors (B. Zhang et al., 2023). Collective deep method of learning for maritime anomaly detection. A technique for identifying anomalies in AIS trajectories using kinematic interpolation method: This method focuses on AIS trajectory data and proposes an anomaly detection method that makes the extensive utilization of the kinematic data concerning the vessel (Guo et al., 2021). Anomalous behavior identification within maritime datasets through the utilization of geometric trajectory analysis: This approach analyzes ship trajectories from a geometrical perspective to detect anomalies in maritime data (Soleimani et al., 2015). These methods have shown promising results in detecting anomalies in maritime ship trajectories, helping to improve maritime security and surveillance. However, is essential to take into account the particular needs and constraints of each method when choosing the most suitable approach for a particular application.

C. Limitations and Challenges in Traditional Approaches

Traditional approaches to anomaly detection in maritime ship trajectories have several limitations and challenges. Some of these challenges include:

Data representation: The choice of representation can restrict the kinds of irregularities that are observable. For example, a chosen representation may not capture the complex behavior patterns of small sailboats, leading to a less accurate anomaly detection process (Auslander et al., 2011).

Data preparation: Aside from the techniques used, other variables that affect anomaly detection include data preparation. This can be challenging, especially when dealing with large amounts of data generated by various types of maritime vessels (Filipiak et al., 2018).

Anomaly detection algorithms: There are various anomaly detection algorithms based on statistical methods and nearest neighbor techniques. Still, the performance among these algorithms can change based on the type of maritime activity as well as the difficulty regarding the detection of anomalies tasks (Auslander et al., 2011). Domain-specific challenges: Maritime anomaly detection faces unique challenges, such as the lack of annotated data, diverse and variable movement patterns of vessels, and the need for real-time detection of infrequent events (Sadeghi & Matwin, 2023).

III. Result and Discussion

A. Deep Learning Architectures for The Detection of Maritime Anomaly

Identification of maritime anomalies is crucial task for ensuring maritime safety, security, and efficiency. Deep learning architectures have been proposed for vessel tracking with Automatic Identification System (AIS) streams of information (Nguyen et al., 2018). Algorithms for detecting anomalies have been split into two groups according to the learning properties of the models: geographical (map-dependent) model-based and statistical model-driven. A dataset of more than 2500 distinct vessels with numerous repeated images was employed to instruct a twin neural network-oriented vessel re-identification algorithm observations (Giona, et al., 2021). Based on deep learning approaches have been suggested for vessel identification in recognition from space-borne optical imagery (Giona, et al., 2021). Overall, deep learning frameworks have demonstrated promising results for maritime anomaly detection.

1) Neural Networks Recurrent (RNN)

RNNs is a class artificial neural network architectures that are intended to handle information in sequence efficiently. In contrast to traditional RNNs are neural networks with a memory state that enables them to use hidden state to process arbitrary sequences of inputs, which allows them to be used for tasks like speech recognition or connected handwriting recognition. RNNs are often utilized in various area and applications, including language modeling and text generation, speech recognition, machine translation, text summarization, video tagging, picture description generation, and call center analysis, and facial recognition and OCR software, and more. RNNs come in many variants, including fully recurrent neural networks (FRNN), Elman networks, Jordan networks, and LSTM networks. LSTM networks are among the most well-known and widely used machine translation applications, and they are used in various E-commerce platforms like Flip kart, Amazon, and eBay.

Several Studies have been carried out using RNN within the domain of maritime trajectory prediction by different researchers and below are some of the research work done by some researchers.

Ship Trajectory Prediction Using Neural Network Utilizing AIS Information. The paper discusses the use of artificial neural networks to develop a remedial mechanism for AIS data-based ship trajectory prediction. The research conducted an experiment on a ship in river navigations, collecting data using the NMEA-0183 protocol and focusing on the previous vessel movement coordinates utilized in neural network training. The training utilized the Levenberg-Marquardt algorithm which applies a concept of gradient reduction, with the training accuracy measured by the course error's mean square. Different activation functions of neural networks were investigated in order to assess their possibilities in solving the problem of restoring the ship's trajectory using previous AIS information. However, the precision of the information generated by the neural network for ship trajectory forecasting differed when the vessel was maneuvering, showing a large discrepancy from the real data. This limited neural network applications creating autopilots guaranteeing the safety of the vessel's motion. The neural network that was created was not appropriate for long-term use because the prediction quality is unstable. Simulation modelling showed that neural networks gave satisfactory results when the vessel moved along a straight trajectory but faced challenges when the ship started to maneuver and the focuses on Short-Term prediction. Position, COG, and SOG were not explicitly mentioned as features in the experiment. However, it is crucial to remember that the GGA-GPS information collected during experiment included latitude and longitude, which are components of the vessel's position (Volkova et al., 2021).

Ship Abnormal Activity Identification using Deep Neural Network with Recurrent Architecture and Clustering. Applications with Noise: Density-Based Spatial Clustering (DBSCAN) for ship trajectory clustering algorithm for identifying regular ship movement patterns. Better DTW (dynamic time warping) algorithm utilized to gauge how similar two things are to one another in ship paths. Gated Recurrent Unit in both directions (Bi-GRU) Using a recurrent neural network to forecast the course of real-time abnormality identification aboard ships. Data preprocessing to be able to raise a standard of unprocessed AIS information along with the experiments been performed using actual AIS information from the Chinese the Tianjin port. Comparison of trajectory Bi-GRU's prediction performance utilizing the Long-Term Memory Network with Gated Recurrent Unit models. The prototype also showed that the standard of raw AIS information is effectively improved by the data pre-processing procedure. However, the suggested ship technique for detecting anomalies is evaluated utilizing actual AIS information from the Chinese the Tianjin port, which may limit generalization of the outcomes to other maritime environments. The paper does not discuss the scalability of the proposed method to handle large scale AIS data or its performance in real-time scenarios with a high volume of ship trajectories. The paper does not offer a thorough examination of the findings on computational complexity and resource requirements of the proposed method, which could be important considerations for practical implementation. The comparison of the Bi-GRU model with the LSTM and GRU models is limited to trajectory prediction performance and anomaly detection accuracy, without considering other factors such as training time or model interpretability. Hence, the future research direction will be to repairing data that cannot reconcile static and dynamic data, and has fewer valid trajectory points to optimize the utilization of AIS information mining. Position, Course Over Ground (COG) and Speed Over Ground (SOG) were part in the features for the experiment (B. Zhang et al., 2023).

Utilizing coordinates system of recurrent neural networks are used for improving vascular trajectory prediction. The paper explores different trajectory calculation strategies for predicting the trajectory of a vessel, including the use of different coordinate systems the Universal Transverse Mercator (UTM), for example and polar coordinate systems. The authors employ three recurrent network architectures for model calculations: Auto-encoder Gated Recurrent Unit Networks, Bi-directional Long Short-Term Memory, and Long Short-Term Memory. Feature engineering techniques are applied to transform the coordinates of the vessel, including regular polar coordinate system transformations, transformation of azimuth angle and haversine distance, as well as polar transformation into Cartesian (UTM) projection. The available data is cut into equal-length segments, normalized and transformed using logarithmic scale. The resulting matrices are then separated into samples for network training and result comparison that are used for validation, testing, and training. The paper presents the results of training different recurrent network architectures using accurate AIS data and various trajectory calculation strategies. The models were evaluated using the role of MAEH, which measures the total means distance of output, and regression measures to assess the accuracy of the predictions in terms of geographic coordinates. The study found that using rotation angles and subtracted distances to train recurrent neural networks, as well as utilizing UTM projection to transform coordinates into two-dimensional space, yielded better outcomes compared to using polar coordinates alone. Significantly, the UTM transformation improved the forecast accuracy, utilizing a 1.141km minimum error. This was AIS features with delta latitude and delta longitude are over 30% more accurate than those without them. The authors also compared performance of different network architectures and found that utilizing over 100 cells in the network configuration reduced error in the architecture. The auto-encoder architecture showed the most minor and stable distribution of errors, while LSTM that is bi-directional had the greatest distinction between the lowest and maximum error values. However, the paper focuses on predicting a vessel's trajectory with past data from the maritime industry, automated identification systems (AIS) transport domain and is limited to cargo vessel type trajectories. The experiments and methodology described in the paper are based on a specific dataset and may not be directly application to other regions or vessel types. The study does not address the issue of missing vessel motion observations and does not explore methods for filling in the gaps in the data. This could potentially impact the dependability and precision of trajectory forecasts, the paper focuses on short-term prediction. The position, COG, SOG were path of the features in the experiment (Jurkus et al., 2023).

2) Long Short-Term Memory Networks (LSTM).

An example of a recurrent neural network (RNN) architecture is Long Short-Term Memory (LSTM) commonly employed in maritime anomaly detection. LSTM moles are effective in obtaining long-term temporal relations with spatial trends in sequential observations of vessel movement. They have been applied in various studies for track association and anomaly detection in marine surveillance. For example, (B. Zhang et al., 2023) suggested a technique that uses vessel trajectory clustering and a Gated Recurrent Unit in both directions (Bi-GRU) LSTM model for real-time ship anomaly detection.

An Integrated Method for Predicting Ship Trajectories Using Conv.-LSTM- Sequence-to-Sequence model. The paper created a model for predicting trajectories that incorporates the Convolutional LSTM (Conv.-LSTM) and models of Sequence to Sequence (Seq2Seq) to extract Ship trajectories' temporal and spatial characteristics and improve prediction precision. The paths were preprocessed to improve training data quality using Applications with Noise: Hierarchical Density-Based Spatial Clustering of Applications (HDBSCAN) and kinematic-based anomaly removal. The Square Root Error (RMSE) was used for the model's performance to be evaluated assess overall performance and Mean Distance Error (MDE) to evaluate prediction results. The suggested framework was contrasted the Bi-Attention-LSTM, a bidirectional LSTM based on an attention mechanism models with Seq2Seq models in order to confirm its efficacy. Experiment outcomes showed that the suggested model achieved outstanding turning trajectory prediction ability, strong straight line motion prediction accuracy, and a higher an increase in the precision of predictions when compared to the other two benchmark models and these paper does not provide specific details on the time frame of the ship trajectory prediction, whether it is for short-term or long-term (Wu et al., 2023).

3) Hybrib

Hybrid refers to the combination or integration of different elements or technologies. In the context of algorithms, hybrid algorithms combine the benefits of different algorithms to improve search engine algorithms and achieve better results regarding velocity and precision (Kumar, 2022). A hybrid model is used in detection of maritime anomalies to enhance performance and reliability. These model combines supervised with unsupervised machine learning methods to identify anomalies within ship traffic and behavior. One variant of the hybrid model involves using a supervised model to detect normal samples. The system combines an LSTM, or long short-term memory with variational auto- encoder equipped with key performance indicators (KPI) to achieve more reliable anomaly detection.

A Combinatorial Ship Clustering Model Paths for Examining Patterns of Maritime Traffic in the Port Area. The paper proposes model of mixed clustering for vessel trajectory analysis, which combines the trajectory clustering DBSCAN algorithm with the K-Means algorithm. The methodology includes several step, AIS pre-processing, extraction of ship trajectory features and assessment of dissimilarity, hybrid clustering method modelling, and examination of traffic parameters and identification of anomalous behavior. Ship trajectories attributes are built from actual ship trajectories, taking into account both static and dynamic attributes and the characteristics of motion parameter fluctuation. The model of hybrid clustering uses the DBSCAN algorithm for characteristic classification and the K-Means approach for journey clustering within every group. The model evaluates the differences between ship trajectories determined by both comprehensive and individual characteristic distances, considering different dissimilarity and weights. The Zhanjiang Port is characterized using the suggested paradigm, demonstrating its effectiveness in clustering ship trajectories and detecting anomalies. The clustering of hybrids model effectively clusters ship trajectories and provides probabilistic ship traffic characterization and anomaly detection and the clustering results show differences in trajectory characteristics, such as length, destination, speed, course and movement changes, which can be utilized to divide the trajectories. However, the paper does not consider the starting and finishing points of trajectories in the K-Means clustering process, which may limit the accuracy of trajectory clustering. The Position, COG and SOG are part of the features (Liu et al., 2022).

B. Maritime Anomaly Detection Datasets

Maritime anomaly detection datasets are used to train models for detecting abnormal behavior in maritime surveillance. One such dataset is the data openness has a significant part in the field of Maritime Surveillance for a purpose of detecting anomalies, which was developed by the Swedish Coastguard and uses Timetables for vessel traffic, AIS data, and vessel characteristic information to spot irregularities such as vessel destination changes, arrival time mismatches, and unusual trip pattern (Abghari, 2012). One dataset, collected from Sanduao Harbor in China, includes visible light remote sensing images for maritime targeting offshore such as places with raft culture, fish row cage culture, and ships (Stach et al., 2023). Another dataset focuses on anomaly detection for maritime traffic surveillance within the framework of Vessel Movement of Traffic Service Facilities for utilizing communication and sensor technologies like AIS, radar, and radio communication (Hu et al., 2023) .

1) Overview of Available Datasets

Maritime anomaly detection relies on available datasets for surveillance and risk assessment. Various origins of maritime data, information AIS, or Automatic Identification System, for example, radar systems, contextual information, are utilized for abnormality identification (Stach et al., 2023). Modern and cutting edge approaches, including neural net schemes and contrario detection, are employed to capture complex patterns in vessel behavior and detect anomalies (Nguyen et al., 2021). Additionally, the analysis of NMEA messages carrying sensor data can help detect anomalies and potential cyber-attacks in navigational functions. Overall, the availability and analysis of these datasets play a vital part in maritime anomaly detection and risk assessment.

2) Publicly Available Datasets

Publicly available datasets for maritime anomaly detection include Maritime Benchmark and dataset for autonomous surface automobiles for vessel identification (N. Wang et al., 2024). An ODADS, or open anomaly detection system for data which is intended for traffic observation and has been used in the sea security and maritime area awareness (Abghari, 2012). The Marine Traffic Vessels Database, which provides real-time data on vessel positions and movements (Wolsing et al., 2022). These datasets can be accessed through the sources provided in the search results.

Data Integrity and Authenticity, the system for automatic recognition (AIS) is the primary source of data for the maritime industry anomaly detection, but there are concern about data falsification, spoofing, and errors (Iphar et al., 2020). Data Volume and complexity, with the increasing volume of data generated by AIS and other sources, that's challenging to perform and evaluate the data in the present, especially for big data approaches (Filipiak et al., 2018). Data Quality and Completeness, the quality of data is crucial for accurate anomaly detection. Missing or incomplete data can lead to false negatives, while data with errors or falsification can lead to false positives. Domain Knowledge and Expertise, maritime anomaly detection requires a deep understanding of maritime domain knowledge and expertise to interpret the data and identify anomalies (Iphar et al., 2020)(Iphar et al., 2022).

3) Pre-Processing Techniques for Maritime Ship Trajectory Data

Preprocessing techniques for maritime ship trajectory data involve various approaches. One method is to prior to analysis, utilize time adjustment to imitate the homogenous sequencing data. As proposed by (J. Zhang et al., 2023). An additional strategy is to apply deep learning model that takes into account any possible link among different Variables and temporal features, such as the CNN-LSTM-SE model proposed by (X. Wang & Xiao, 2023). Additionally, the use of the transformer model has been shown to improve prediction accuracy. Furthermore, a preprocessing model based on time series data, trajectory extraction, and trajectory similarity evaluation has been developed, followed by a temporal sequence prediction model derived from Attention as well as LSTM.

C. Case Studies Highlighting Successful Implementations

There are several case studies and research findings that highlight successful implementations in maritime anomaly detection. These studies demonstrate the efficiency of different techniques and technologies in detecting anomalous events in maritime traffic. Visual Analytics for Maritime Anomaly Detection: A study by (Riveiro et al., 2011) investigated the application within visual analytics concepts to facilitate identification of unusual ship activity for marine transportation. The research resulted in a visual and interactive analysis tool for detecting abnormalities in behavior seen in statistics on maritime transportation. The model revealed that those who employed the visualization of the data were able to identify anomalous behavior more effectively, potentially reducing reaction time and increasing trust and comprehensibility in the system (Riveiro et al., 2011).

Identification of Anomalies in Maritime AIS Tracks: An Overview 44 studies on the identification of irregularities in marine AIS monitors found that route deviation was the most common anomaly type. Most detectors focused on a specific region and required re-training to be used in different areas. Additionally, the majority of publications referred to confidential databases and struggled to get actual data for their assessment. The study highlighted the need for more comprehensive and publicly available datasets for evaluating anomaly detection algorithms (Wolsing et al., 2022).

Detecting Maritime Anomalies for Vessel Traffic Services: An investigation by (Stach et al., 2023), focused on anomaly detection within the framework of VTS's maritime traffic surveillance. The study found that the primary data source for anomaly detection is AIS, and five general anomaly kinds can be distinguished from the served anomaly cases. The authors highlighted the importance of considering various anomaly types and the need for more sophisticated detection techniques.

These case studies and research findings demonstrate the progress made in maritime anomaly detection and the potential for further advancements in this field. However, there is still a need for more comprehensive and publicly available datasets, as well as the development of more sophisticated detection techniques to take note of the challenges of identifying anomalies in the maritime sector.

1) Future Perspectives

Future perspectives in maritime anomaly detection involve leveraging advanced technologies like Automatic identification Systems (AIS), radars, and Decision Support Tools (DST) to enhance surveillance capabilities and ensure maritime traffic safety (Stach et al., 2023). Addressing false-positive rates and the need for context-specific anomaly detection methods are key areas for future research, aiming to develop robust models that can adapt to new challenges while retaining past knowledge.

2) Emerging Trends In-Depth Education for Maritime Identification of Anomalies

Emerging trends utilizing deep learning to identify anomalies extend across various domains. In the maritime sector, where anomaly detection is crucial for ensuring operational safety, deep learning models are gaining traction. Machine learning algorithms detect anomalies in maritime data collected via AIS by utilizing various techniques. One approach involves using clustering of ship trajectory to establish a normal model and employing deep learning algorithms for detection of anomalies (B. Zhang et al., 2023). Furthermore, The IoT, or the Internet of Things and Systems for Maritime Transportation (MTS) have come together to produce the development of anomaly detection strategies like Transfer Learning based Trajectory Anomaly Detection (TLTAD), which leverage variational auto-encoders and deep reinforcement learning algorithms to accurately detect anomalies in ship trajectories while reducing model training times (Ribeiro et al., 2023)(Hu et al., 2023). These techniques help significantly to improving maritime safety and autonomous shipping development

3) Potenetial Integration with IoT and Edge Computing

Potential combination with IoT and edge computing in maritime anomaly detection can provide significant benefits, such as real-time data processing and analysis, improved accuracy, and enhanced security. However, it also presents challenges, such as data security and privacy concerns, infrastructure requirements, and integration complexities. The search results provide insights into the potential benefits and challenges of implementing edge computing and IoT in maritime anomaly detection. An edge computing-based Model for real-time anomaly detection (RADM) has been proposed for fishing boats, which can find irregularities based on the actions in fishing vessel characteristics with combine Extraction of historical trajectories via real-time anomaly detection. Finally, the incorporation of edge computing and Internet of Things in maritime anomaly detection can provide significant benefits, but it also presents challenges that need to be addressed. By recognizing and proactively addressing these challenges, companies can ensure a successful and smooth transition to edge computing technologies, revolutionizing the marine business landscape and promoting sustainability in the maritime industry.

IV. CONCLUSION

In conclusion, anomaly detection in maritime performs a crucial part in enhancing safety of marine traffic and security leveraging advanced technologies and innovative approaches. Decision Support Tools (DST) in Vessel Traffic Services (VTS), (Stach et al., 2023) vessel kinematics data analysis for detecting suspicious activities (Ribeiro et al., 2023), and IoT Trajectory Finding Anomalies with Transfer of Learning

These approaches contribute to improving detection performance, reducing false alarms, and anticipating proper actions in response to anomalous behaviors, ultimately enhancing maritime situational awareness and operational efficiency in complex maritime environments. The integration of anomaly detection techniques with cutting-edge technologies holds promise for ensuring the successful deployment and management of IoT-empowered Maritime Transportation System.

Some of the key findings in the papers reviewed include: poor prediction when the ship start maneuvering. But in the event that a vessel is close to hydraulic systems, interference will cause issues along with receiving a satellite transmission, increasing the error in determining the vessel's coordinates (Volkova et al., 2021). In a similar research work expression for ship trajectory segmentation, based repair of abnormalities in position, speed, and anomaly, as well as Ship behavior anomaly detection and spatiotemporal semantic analysis of the navigation environment correlation are left on address (B. Zhang et al., 2023). In another research conducted the experiment findings indicate that the suggested model functions exceptionally good in predicting turning trajectories with strong forecasting precision for linear motions. However, this is achieves with only longitude and latitude considered in the experiment, which should have included features such as, both Course Over Ground (COG) and Source Over Ground (SOG) (Wu et al., 2023).

The advancement of abnormality identification in maritime security holds significant implications for enhancing the safety of vessels and maritime operations. By leveraging rule-based methods for data integrity assessment (Kishore et al., 2022), anomaly detection systems can effectively identify abnormal reporting cases, assisting in marine traffic surveillance and mitigating hazardous behaviors that pose risks to ports, off-shore structures, and the environment.

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