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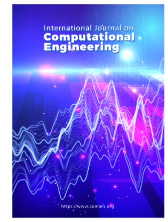

Anomaly Detection in Maritime Ship Trajectory Using a Deep Learning Approach: A Comprehensive Survey, State-of-the-Art and Future Perspective

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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 is particularly important 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-encoders, 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 helps identify research challenges in ship trajectory prediction and proposes corresponding remedies to guide future investigations. 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 plays a crucial part in enhancing the 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, passenger movements, and various vessel activities in the aquatic domain. The activities at sea continue to be vigorous, with a consistent rise in volumes. This mode of transportation remains a fundamental mechanism for conveying goods across the globe, particularly for different categories of cargo vessels. The escalating level of activity has been noted by the International Union of Marine Insurance (IUMI) in its annual report globally [1]. 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 [1]. 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).

Deep learning has been shown to be a powerful tool in anomaly detection, providing several advantages over traditional methods. One of the primary benefits is its ability to address unbalanced datasets, a common challenge in abnormality identification. Deep learning algorithms, such as autoencoders and convolutional neural networks, can effectively model complex, nonlinear relationships within data, making them suitable for detecting anomalies in various domains [2].

Anomalies in maritime ship trajectories refer to unusual or unexpected behaviors in ship movement that can be problematic and require further investigation. These anomalies can be detected using various techniques and methods, such as retrieving trajectory patterns and identifying anomalies. This approach emphasizes extracting diverse trajectory patterns for marine vessels and identifying anomalies based on their deviation from normal behavior [3].

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, and machine learning techniques. These techniques aim to recognize unusual vessel behaviors that could indicate illicit activities such as illegal fishing, environmental pollution, piracy, espionage, and smuggling. By analyzing ship trajectory characteristics and using various anomaly detection models, maritime authorities and enforcement agencies can improve maritime security and safety.

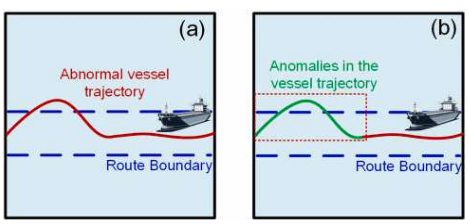

Fig. 1 Illustration of (a) abnormal vessel trajectory and (b) anomalies in vessel trajectory [4].

Maritime security is of growing importance due to the various non-conventional security challenges faced by the maritime sector. These challenges include marine crime, environmental issues, threats associated with technology and cyberspace, and socioeconomic and political difficulties [5]. The impact of maritime transport security on a country's economic growth is significant, as seen in the case of Indonesia. Stakeholder synergy plays a crucial role in creating a better maritime transport security ecosystem [6]. The ocean, being a global common, is governed by maritime legal systems, but it is also a source of international conflict due to national security concerns [7].

The contribution addresses challenges in satellite signal acquisition near hydraulic structures, increased vessel coordinate inaccuracies, and collision risks. We explore deep learning techniques and propose a taxonomy categorizing them into supervised, unsupervised, hybrid, and other types. We identify potential real-world applications to help developers and researchers understand deep learning better and outline future research directions for next-generation models.

II. MATERIALS AND METHOD

A deep learning model generally follows analogous processing phases to those observed in traditional machine learning methodologies. In Figure 2, we present a comprehensive deep learning workflow designed to address practical challenges, comprising three distinct processing stages: data comprehension and preprocessing, deep learning model construction and training, and validation and interpretation. However, unlike ML modeling [8], [9], feature extraction within deep learning models is executed automatically rather than manually. Techniques such as k-nearest neighbors, support vector machines, decision trees, random forests, naive Bayes classifiers, linear regression, association rule mining, and k-means clustering represent a selection of machine learning methodologies that are frequently employed across diverse application domains. [10]. Conversely, the deep learning (DL) paradigm encompasses convolutional neural networks, recurrent neural networks, auto-encoders, deep belief networks, among numerous others, and interdependencies of DL methodologies that must be considered prior to embarking on DL modeling for practical applications in the real world.

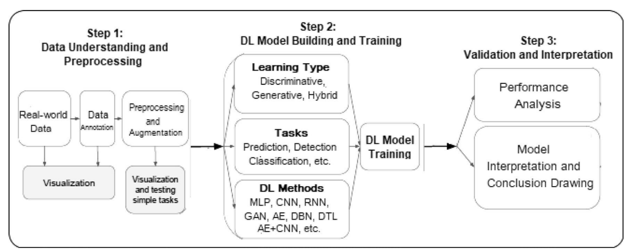

Fig. 2 A typical DL workflow to solve real-world problems, which consists of three sequential stages (i) data understanding and preprocessing (ii) DL model building and training (iii) validation and interpretation [11].

The 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. We investigate a range of prominent deep learning techniques and propose a comprehensive taxonomy that accounts for the diverse variations in deep learning tasks and their applications for distinct objectives. Within our taxonomy, we categorize these techniques into three principal classifications: deep networks designed for supervised or discriminative learning, unsupervised or generative learning, and deep networks facilitating hybrid learning, alongside other pertinent categories. We have synthesized several prospective real-world application domains of deep learning to aid both developers and researchers in expanding their understanding of deep learning techniques. We delineate prospective dimensions and research for advancing next-generation deep learning modeling, with a view toward guiding future research endeavors.

The survey is set up as follows:

- Describes the various traditional approaches to anomaly detection and the taxonomy.
- Focuses on deep learning architectures for the detection of maritime anomalies.
- Delves into maritime anomaly detection datasets used for trajectory prediction and various forms of data.
- Focuses on case studies highlighting successful implementations and lingering challenges, and prospects of anomaly detection in maritime ship trajectory and the deep learning application summary.
- Conclusion and summary of key findings are handled in the last part.

III. Results and Discussion

A. Traditional Approaches to Anomaly Detection

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.

1) Rule-Based Methods:

Rule-based techniques in anomaly detection depend on setting clear guidelines or cutoff points to spot abnormalities. These guidelines frequently draw from domain expertise and expert judgment, or specific business requirements. Anomaly detection in maritime ship trajectories 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 neural networks, convolutional neural networks, and autoencoders. Some studies have proposed ensemble deep learning approaches and physics-guided gap-aware anomaly detection tests. Anomaly detection can involve searching for erratic, unlawful, and other unusual appearances in vessel trajectory analysis-based trajectory data and abnormal vessel movement. These methods can be used with data from the Automatic Identification System (AIS), enabling real-world ship anomaly detection [12], [3], [13].

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 [14]. 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 readability of extracted granular rules while maintaining efficiency [15]. 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.

2) Statistical Methods:

Statistical methods for anomaly detection in maritime ship trajectories have been widely researched. Some notable approaches include finding anomalies using a ship's behavior trajectory: This method fits a statistical model that incorporates historical data on normal ship motion and detects anomalous 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 [16]. 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 [12]. Collective deep learning method for maritime anomaly detection. A technique for identifying anomalies in AIS trajectories using a kinematic interpolation method: This method focuses on AIS trajectory data and proposes an anomaly detection method that makes extensive use of the kinematic data concerning the vessel [13]. 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.

Traditional approaches to anomaly detection in maritime ship trajectories have domain-specific challenges. Maritime anomaly detection faces unique challenges, such as the lack of annotated data, diverse and variable vessel movement patterns, and the need for real-time detection of infrequent events [17].

B. Taxonomy of Deep Learning

1) Deep Networks for Supervised or Discriminative Learning:

This classification of deep learning methodologies is used to establish a discriminative function in supervised or classification contexts. Discriminative deep learning architectures are generally constructed to confer discriminative capabilities for pattern classification by characterizing posterior class distributions conditioned on observable data [18]. The primary types of discriminative architectures include Multi-Layer Perceptrons (MLP), Convolutional Neural Networks (CNN or ConvNet), and Recurrent Neural Networks (RNN), along with their respective variants. In the subsequent sections, we succinctly examined these methodologies.

2) Deep Networks for Generative or Unsupervised Learning:

This classification of deep learning methodologies is predominantly employed to delineate the high-order correlation characteristics or attributes pertinent to pattern analysis or synthesis, in addition to the joint statistical distributions of the observable data alongside their corresponding categories [18]. The fundamental premise of generative deep architectures posits that during the learning paradigm, precise supervisory data such as target class labels is not a focal concern. Consequently, the techniques encompassed within this classification are fundamentally utilized for unsupervised learning, as they are predominantly aimed at feature extraction or the generation and representation of data [19], [18]. Therefore, generative modeling can also serve as a preliminary step for supervised learning tasks, thereby enhancing the accuracy of the discriminative models. Frequently employed deep neural network methodologies for unsupervised or generative learning encompass Generative Adversarial Networks (GAN), Auto-encoders (AE), Restricted Boltzmann Machines (RBM), Self-Organizing Maps (SOM), and Deep Belief Networks (DBN), along with their respective variants.

3) Deep Networks for Hybrid Learning and Other Approaches

Alongside the aforementioned deep learning classifications, hybrid deep architectures and a multitude of alternative methodologies, including deep transfer learning (DTL) and deep reinforcement learning (DRL), have gained significant prominence.

Deep Transfer Learning (DTL)

Transfer learning is a methodological approach that facilitates the application of acquired model knowledge to address novel tasks with minimal training or fine-tuning requirements. In contrast to conventional machine learning methodologies [10], deep learning requires a substantial volume of training data.

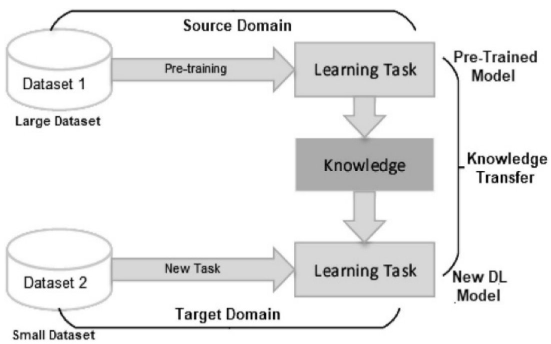

Fig. 3 A general structure of the transfer learning process, where knowledge from a pre-trained model is transferred into a new DL model [11]

Reinforcement Learning (DRL)

Reinforcement learning adopts a distinct methodology for addressing the sequential decision-making challenge compared to the other methodologies previously examined. In the context of reinforcement learning, the fundamental constructs of an environment and an agent are frequently introduced at the outset. The agent is capable of executing a succession of actions within the environment, each of which influences the state of the environment and may yield potential rewards (feedback) — “positive” rewards for favorable sequences of actions that culminate in a “desirable” state, and “negative” rewards for unfavorable sequences of actions that result in an “undesirable” state. The primary objective of reinforcement learning is to acquire effective action sequences through engagement with the environment, which is conventionally termed a policy.

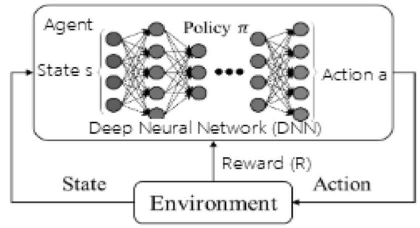

Fig. 4 Schematic structure of deep reinforcement learning (DRL) highlighting a deep neural network [11].

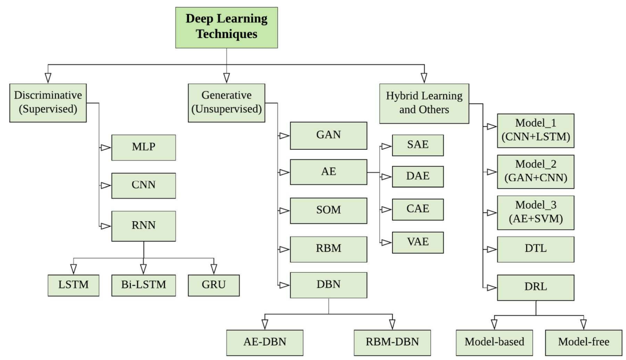

Fig. 5 A taxonomy of DL techniques, broadly divided into three major categories (i) deep networks for supervised or discriminative learning, (ii) deep networks for unsupervised or generative learning, and (ii) deep networks for hybrid learning [11].

C. Deep Learning Architectures for The Detection of Maritime Anomaly

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 [20]. Based on deep learning approaches have been suggested for vessel identification in recognition from space-borne optical imagery. Overall, deep learning frameworks have demonstrated promising results for maritime anomaly detection.

1) Recurrent Neural Networks (RNN):

RNNs are a class of artificial neural network architectures designed to handle information in sequence efficiently. In contrast to traditional neural networks, RNNs have a memory state that enables them to use a 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 areas and applications, including language modeling and text generation, speech recognition, machine translation, text summarization, video tagging, picture description generation, call center analysis, 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 Flipkart, 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 works 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 navigation, collecting data using the NMEA-0183 protocol and focusing on the previous vessel movement coordinates utilized in neural network training. The training used the Levenberg-Marquardt algorithm, which applies gradient reduction, with training accuracy measured by the mean square of the course error. Different activation functions were investigated to assess their potential 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 in 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 modeling 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 focused 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 the experiment included latitude and longitude, which are components of the vessel's position [21].

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 being performed using actual AIS information from the Tianjin port in China. 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 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, future research will focus on 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 among the features used in the experiment [12].

A recurrent neural network coordinate system is used to improve vessel trajectory prediction. The paper explores different trajectory calculation strategies for predicting a vessel's trajectory, including different coordinate systems, such as the Universal Transverse Mercator (UTM) 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 vessel coordinates, 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 a logarithmic scale. The resulting matrices are then separated into samples for network training and result comparison, 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 MAEH, which measures the total mean distance of the output, and regression measures to assess prediction accuracy 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 because AIS features with delta latitude and delta longitude are over 30% more accurate than those without them. The authors also compared the performance of different network architectures and found that using over 100 cells in the network configuration reduced error. The auto-encoder architecture showed the most minor and stable distribution of errors, while the bi-directional LSTM had the greatest distinction between the lowest and maximum error values. However, the paper focuses on predicting a vessel's trajectory using past data from the maritime industry and 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 applicable to other regions or vessel types. The study does not address missing vessel motion observations and does not explore methods for filling in data gaps. This could potentially impact the dependability and precision of trajectory forecasts; the paper focuses on short-term prediction. Position, COG, and SOG were the features used in the experiment [22].

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 models 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, [12] 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 the Sequence-to-Sequence (Seq2Seq) model 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 to evaluate overall performance, and Mean Distance Error (MDE) was used to evaluate prediction results. The suggested framework was contrasted with Bi-Attention-LSTM, a bidirectional LSTM-based attention model, and Seq2Seq models to confirm its efficacy. Experimental results showed that the proposed model achieved outstanding turning trajectory prediction ability, strong straight-line motion prediction accuracy, and higher prediction precision than the other two benchmark models. This paper does not provide specific details on the time frame of the ship trajectory prediction, whether it is for short-term or long-term [23].

3) Hybrid

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 performance and achieve better results in terms of velocity and precision [24]. A hybrid model is used to detect maritime anomalies to enhance performance and reliability. This model combines supervised and 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 a variational auto-encoder equipped with key performance indicators (KPIs) to achieve more reliable anomaly detection.

A Combinatorial Ship Clustering Model for Examining Patterns of Maritime Traffic in the Port Area. The paper proposes a mixed clustering approach for vessel trajectory analysis, combining the trajectory clustering DBSCAN algorithm with the K-Means algorithm. The methodology includes several steps: AIS pre-processing, extraction of ship trajectory features and assessment of dissimilarity, hybrid clustering method modeling, and examination of traffic parameters and identification of anomalous behavior. Ship trajectory attributes are built from actual ship trajectories, taking into account both static and dynamic attributes and the characteristics of motion parameter fluctuation. The hybrid clustering model uses the DBSCAN algorithm for characteristic classification and the K-Means approach for journey clustering within each group. The model evaluates differences between ship trajectories using both comprehensive and individual characteristic distances, considering different dissimilarity measures and weights. Zhanjiang Port is characterized using the suggested paradigm, demonstrating its effectiveness in clustering ship trajectories and detecting anomalies. The hybrid model effectively clusters ship trajectories and provides probabilistic ship traffic characterization and anomaly detection; the clustering results show differences in trajectory characteristics, such as length, destination, speed, course, and movement changes, which can be used 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 [25].

D. Maritime Anomaly Detection Datasets

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 [26]. Another dataset focuses on anomaly detection for maritime traffic surveillance within the framework of Vessel Movement of Traffic Service Facilities, utilizing communication and sensor technologies like AIS, radar, and radio communication [26].

Maritime anomaly detection relies on available datasets for surveillance and risk assessment. Various origins of maritime data, including information from AIS (Automatic Identification System), radar systems, and contextual information, are utilized for abnormality identification [26]. Modern and cutting-edge approaches, including neural net schemes and contrariness detection, are employed to capture complex patterns in vessel behavior and detect anomalies [27]. Additionally, analyzing 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.

1) Understanding Various Forms of Data:

As deep learning models acquire knowledge from datasets, a comprehensive understanding and representation of these datasets are crucial for building a data-driven intelligent system within a specific domain of application. In practical scenarios, data manifests in diverse formats, which are conventionally represented as follows for the purposes of deep learning modeling:

Sequential Data

Sequential data encompasses any form of data in which the sequence is of paramount importance, that is, a collection of ordered sequences. It is imperative to explicitly consider the sequential characteristics of the input data during the model development process. Instances of sequential data include text streams, audio segments, video sequences, and time-series data, among others.

Image or 2D Data:

A digital image is constituted by a matrix, which represents a rectangular configuration of numerical values, symbols, or expressions organized systematically in rows and columns within a two-dimensional array. The four fundamental attributes of a digital image are matrix, pixels, voxels, and bit depth.

Tabular Data:

A tabular dataset is fundamentally characterized by rows and columns. Consequently, tabular datasets present data in a columnar structure akin to that of a database table. Each column (field) is required to possess a designated name, and each column may exclusively contain data of a specified type. In summary, it represents a logical and methodical arrangement of data in rows and columns, based on the properties or features of the data. Deep learning models can effectively learn from tabular data, thereby facilitating the development of data-driven intelligent systems.

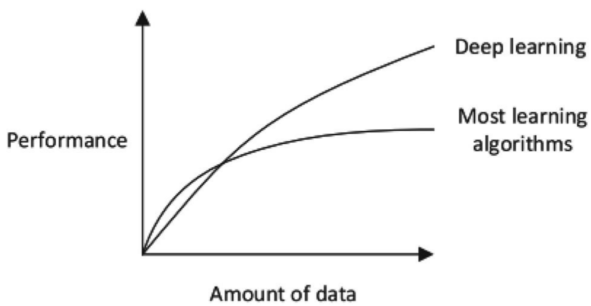

Fig. 6. An exemplar of the comparative analysis of performance between deep learning (DL) methodologies and alternative machine learning (ML) algorithms is presented, wherein DL modeling, leveraging extensive datasets, has the potential to enhance performance significantly; the aforementioned data forms are prevalent in the practical domains where deep learning is applied. Various classifications of DL techniques exhibit divergent performance outcomes contingent upon the inherent nature and characteristics of the data involved [11].

2) 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 homogeneous sequencing of the data. As proposed by [28]. An additional strategy is to apply a 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 [29]. 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.

3) Evaluation Metrics and Challenges

The field of anomaly detection in time series in maritime transportation systems (MTS) is always improving, and there are multiple approaches. However, there's not much consensus on the best evaluation measurements for specific scenarios and domains. Several papers provide a thorough rundown of the metrics used to assess time series anomaly detection techniques. They classify these metrics based on how they're computed and analyze twenty metrics in detail. These papers argue that the selection of assessment metrics must be carefully considered, keeping in mind the particular needs of the current work [30]. Another paper proposes an IoT trajectory anomaly detection approach based on transfer learning, which uses variational auto-encoders and a deep reinforcement learning algorithm [31].

4) Challenges in Evaluating Deep Learning Models

Deep learning models encounter difficulties because of several factors. Firstly, the intricacy of the space variables involved, including architectures, algorithms, and hyperparameters, makes it difficult to conduct controlled experiments and determine causal relationships between variables [32]. Second, the rapid advancement of training processes, along with the intrinsic unpredictability of machine learning technology, further complicates evaluation [33]. Additionally, the lack of specificity in defining the variables and treatments being applied in experiments raises doubts about the reliability of findings [34]. Furthermore, the time-consuming and expensive nature of training deep learning models, along with the need for large datasets, poses challenges in achieving better accuracy.

E. Case Studies Highlighting Successful Implementations

Several case studies and research findings highlight successful implementations in maritime anomaly detection. These studies demonstrate the efficiency of different techniques and technologies in detecting anomalous events in maritime traffic. Forty-four 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, most publications relied on confidential databases and struggled to obtain actual data for their assessment. The study highlighted the need for more comprehensive and publicly available datasets for evaluating anomaly detection algorithms [16].

Detecting Maritime Anomalies for Vessel Traffic Services: An investigation by [26] focused on anomaly detection within the framework of VTS's maritime traffic surveillance. The study found that AIS is the primary data source for anomaly detection, and five general anomaly types can be distinguished from the anomaly cases examined. 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 more sophisticated detection techniques to address the challenges of identifying anomalies in the maritime sector.

F. 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 [26]. 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.

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

Emerging trends in deep learning-based anomaly identification 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 clustering ship trajectories to establish a normal model and employing deep learning algorithms to detect anomalies [12]. 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 [35], [32]. These techniques help significantly improve maritime safety and autonomous shipping development

2) Potential 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 identify irregularities based on actions and fishing vessel characteristics by combining historical trajectory extraction with real-time anomaly detection. Finally, incorporating edge computing and the Internet of Things into 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. To address these issues, it is crucial to develop robust security measures, such as encryption, access controls, and threat monitoring systems, to protect data at the edge. Additionally, collaboration with trusted technology partners and following industry best practices is crucial for maintaining data security and privacy [36].

G. Deep Learning Application Summary

Over the past few years, deep learning methodologies have been adeptly utilized to address a plethora of challenges across diverse application domains. These domains encompass natural language processing, sentiment analysis, cyber-security, business analytics, virtual assistants, visual recognition, healthcare, robotics, among others. In the figure presented below, we have encapsulated several prospective real-world application domains pertinent to deep learning. A variety of deep learning methodologies, as delineated in our taxonomy illustrated in the figure above, which encompasses discriminative learning, generative learning, and hybrid models as previously articulated, are implemented within these application domains. Numerous deep learning tasks and methodologies are employed to tackle the associated challenges in various real-world application domains. In summary, as indicated in the figure below, one may infer that the future potential of deep learning models in real-world application domains is substantial, presenting numerous opportunities for exploration and development [11].

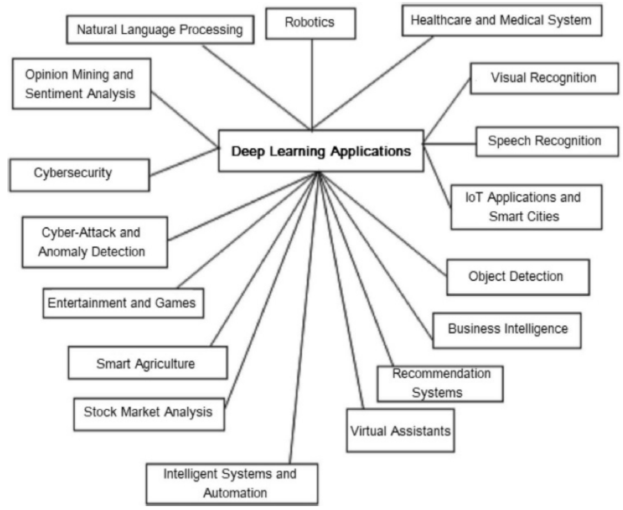

Fig. 7 Several potential real-world application areas of deep learning [11].

IV. Conclusion

In conclusion, anomaly detection in maritime plays a crucial part in enhancing the safety of marine traffic and security, leveraging advanced technologies and innovative approaches. Decision Support Tools (DST) in Vessel Traffic Services (VTS), [26] vessel kinematics data analysis for detecting suspicious activities [35], 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. Integrating anomaly detection techniques with cutting-edge technologies holds promise for ensuring the successful deployment and management of an IoT-empowered Maritime Transportation System. Some of the key findings in the papers reviewed include: poor prediction when the ship starts maneuvering. However, when a vessel is close to hydraulic systems, interference can cause issues with satellite transmission, increasing error in determining the vessel's coordinates [21]. In a similar research work, an expression for ship trajectory segmentation, based on repair of abnormalities in position, speed, and anomaly, as well as Ship behavior anomaly detection and spatiotemporal semantic analysis of the navigation environment correlation, is left to address [12]. In another study, the experimental findings indicate that the suggested model functions exceptionally well in predicting turning trajectories, with strong forecasting precision for linear motions. However, this is achieved 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) [24].

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 [37], anomaly detection systems can effectively identify abnormal reporting cases, assisting in marine traffic surveillance and mitigating hazardous behaviors that pose risks to ports, offshore structures, and the environment.

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