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Research Article

The Impacts of the Applications of Artificial Intelligence in Maritime Logistics

Batin Latif Aylak

Turkish-German University, Faculty of Engineering, Department of Industrial Engineering, İstanbul, Turkey, (ORCID: 0000-0003-0067-1835), batin.latif@tau.edu.tr

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Abstract

This study aims to identify current approaches in the usage of Artificial Intelligence (AI) methods for solving shipping problems. Recent advances in AI are being examined, and the way it is adapted to maritime logistics is reviewed. In this study, 66 papers dealing with AI in the maritime industry are reviewed bibliometrically. Research data were primarily sourced from databases of IEEE Xplore, Web of Science, ScienceDirect (Elsevier), Sciences Citation Index, Google Scholar, Springer, and journals. Selected papers are categorized and classified, and the outcomes of some noteworthy publications are discussed in detail. A comprehensive assessment is also presented, which highlights research gaps and forecasts future research orientations. Two possible areas in the maritime industry are proposed for further research using AI capabilities. Predictive analysis is the first domain, followed by energy efficiency optimization. In addition, Machine Learning (ML) and Operations Research (OR) have fostered a growing interest in automating the learning of heuristics to solve optimization problems to avoid the need for expensive and inefficient human labour to create highly specialized heuristics. Future research can take advantage of these new ML approaches to address Maritime Logistics problems utilizing the ever-increasing amount of data available. Future research on maritime logistics can also develop learning models based on the identified gaps.

Keywords: Artificial Intelligence, Automated Information System, Literature Review, Machine Learning, Maritime Logistics

Deniz Lojistiğinde Yapay Zeka Uygulamalarının Etkileri

Öz

Bu çalışma, deniz taşımacılığı problemlerini çözmek için Yapay Zeka yöntemlerinin kullanımındaki güncel yaklaşımları belirlemeyi amaçlamaktadır. Yapay zekadaki son gelişmeler incelenerek deniz lojistiğine uyarlanma şekli gözden geçirilmektedir. Bu çalışmada denizcilik endüstrisinde yapay zeka ile ilgili 66 makale bibliyometrik olarak incelenmiştir. Araştırma verileri öncelikle IEEE Xplore, Web of Science, ScienceDirect (Elsevier), Sciences Citation Index, Google Scholar, Springer ve ilgili dergilerin veritabanlarından elde edilmiştir. Seçilen makaleler kategorize edilerek tasnif edilmiş ve bazı önemli yayınların sonuçları ayrıntılı olarak tartışılmıştır. Araştırma boşluklarını vurgulayan ve gelecekteki araştırma yönelimlerini tahmin eden kapsamlı bir değerlendirme de sunulmaktadır. Yapay zeka kullanan daha fazla araştırma için denizcilik endüstrisinde iki olası alan önerilmiştir. Tahmine dayalı analiz ilk alandır ve bunu enerji verimliliği optimizasyonu takip etmektedir. Buna ek olarak, Makine Öğrenmesi ve Yöneylem Araştırması yüksek düzeyde uzmanlaşmış buluşsal yöntemler oluşturmak için pahalı ve verimsiz insan emeğine duyulan ihtiyacı önlemek için optimizasyon sorunlarını çözmek için buluşsal yöntemlerin öğrenilmesini otomatikleştirmeye yönelik artan bir ilgiyi teşvik etmiştir. Gelecekteki araştırmalar, sürekli artan miktarda mevcut veriyi kullanarak Denizcilik Lojistiği sorunlarını ele almak için bu yeni makine öğrenmesi yaklaşımlarından yararlanabilir. Deniz lojistiği ile ilgili gelecekteki araştırmalar, belirlenen boşluklara dayalı öğrenme modelleri de geliştirebilir.

Anahtar Kelimeler: Yapay Zeka, Otomatik Bilgi Sistemi, Literatür Araştırması, Makine Öğrenmesi, Deniz Lojistiği

1. Introduction

Artificial intelligence (AI) currently occupies a prominent position in both research and practice. AI is a technology that allows computers to mimic human thinking abilities. Computers can be programmed to have fantastic searching, sorting, and arithmetic skills. But there are many things that computers are not capable of, such as thinking creatively, deciding what to do next, and speaking our own language. AI stands out in these areas; it tries to identify the necessary algorithms to meet these specifications (Millington & Funge, 2009). Today, AI has gradually established its ecological pattern. The field of AI has evolved to make it possible to be used as a popular means of solving business and societal problems. It is relatively straightforward that AI marks the next step in the evolution of things, just as companies today have adopted information technology to manage their processes more efficiently, which is a natural progression.

AI has become essential for data-driven decision-making across various industries (Liang & Liu, 2018). This technique can extract information from large datasets, including anomaly detection or photo recognition. Many traditional industries, such as the maritime industry, rely more on intuition than data because of the immense scale of network and planning problems (Brouer, Karsten, & Pisinger, 2017). Maritime Logistics plays a significant role in the logistics sector. According to United Nations Conference on Trade and Development (UNCTAD), over 11 million tons of containerized bulk and dry bulk were globally transported by ship in 2018, which explains why maritime transport is considered "the backbone of global trade" (Sirimanne et al., 2019). Thus, it is necessary to have fast, efficient, and reliable transportation. In the meantime, the growing amount of data and advancing digitalization are creating new prospects in the sector. Intelligent approaches to extract information can make data collected on ships usable.

In the beginning, research in AI tended to replicate human decision-making by utilizing large amounts of data. In the modern era, AI can accomplish things that were previously unthinkable. For instance, sophisticated AI systems can now design autonomous ships, which can operate without human interaction, and they have the lowest error rate compared to human-operated ships. With the use of AI, the traditional operational process of the maritime industry has been gradually transformed. Accordingly, a lot of research has been done on applying big data and AI in the maritime industry since 2012 (Liang & Liu, 2018). This trend inspires the development of new, data-centric innovative technologies and business models (Munim, 2019) that are reshaping the maritime industry and creating new opportunities for productivity, efficiency, and sustainability (Heilig, Lalla-Ruiz, & Voß, 2017).

This study is more extensive than previous studies in terms of the quality and diversity of the studies that used AI in the maritime context. Unlike previous reviews, the present study's literature search provided robust, transparent, and reproducible results. In this review, the author analyzes published studies that address AI applications in maritime contexts to identify future research directions. Considering this, the authors devised three research objectives. The initial aim is to identify the key journals in the field of interest. The second goal is to identify and investigate potential research clusters, and the end goal is to identify and present future research opportunities.

2. Literature Review Method and Structure

To provide a comprehensive overview of how AI technology has been applied to solve a wide range of maritime industry-related problems and to stimulate new thoughts about its application across the maritime industry, a systematic review of the use of AI technology as a solution technology is conducted in this paper. An in-depth literature search is performed during the review process by identifying relevant topics, methodologies, and trends, analyzing and synthesizing them to provide a holistic view of AI data studies.

Research data were primarily sourced from databases of IEEE Xplore, Web of Science, ScienceDirect (Elsevier), Sciences Citation Index, Google Scholar, Springer, and journals, such as Applied Sciences, Sensors, International Journal of Embedded Systems, Transportation Research Part E: Logistics and Transportation Review, Business and Information Systems Engineering, Journal of Advanced Transportation, Journal of Marine Science and Engineering, Journal of Intelligent & Fuzzy Systems. The keywords included maritime, ship, digitalization, ship automation, artificial intelligence, and artificial neural networks. The sources for the literature were selected according to three factors: the innovation involved in the scientific work carried out by the authors, scientific methods followed, and the relevance of the research.

3. Results of Literature Review

The methodology described in Section 2 yielded 357 publications related to the study area. The publication titles were then reviewed as a starting point for classification, and those that had no relevance to the application of Al in the maritime industries were eliminated. Furthermore, only papers published in the previous three years were considered, yielding 66 papers that were then thoroughly reviewed. Each source was read and evaluated against the quality criteria outlined in the methodology section as part of this thorough review.

Thus, the study included 66 articles, including 59 journal papers, 6 conference papers, and 1 technical report, all published within the previous three years. According to the database search results, the top 5 journals that have published at least two articles on AI applications in the maritime industry are presented in Table 1. Among the journals published during the initial periods (before 2019), papers mainly were published in those specializing in navigation safety, ship behaviour analysis, and the marine environment. During the last three years, the distribution of journals has been the most diverse, suggesting a broadening of research interests.

AI has applications in every aspect of maritime logistics. One such application field is ship route planning. For example, many publications use automated identification systems (AIS) data to

Table 1. Top journals on AI applications in the maritime industry

Journal	2021	2020	2019	Total
Applied Sciences (Switzerland)	1	6		7
Sensors (Switzerland)		3	2	5
Transportation Research Part E: Logistics and Transportation Review		1	1	2
Journal of Marine Science and Engineering		1	1	2
IEEE Access		2		2

predict ship trajectories to avoid collisions or weather maps to avoid heavy storms (e.g. Liu and Shi (2020), Ozturk, Birbil, and Cicek (2019), T. Yang, Han, Qin, and Huang (2020)). In addition, some papers investigate the problem of Berth Allocation (H. Kim, Kim, Park, & Lee, 2020; Qiang & Bi-Guang, 2020).

There are numerous AI methods and algorithms that can solve problems in the maritime industry. Still, Decision Trees, Random Forest, and genetic algorithms constitute the majority. Four publications make use of Deep Learning (DL). Some papers employ Machine Learning (ML) approaches such as k-nearest-neighbour (KNN) and support vector machines (SVMs) (Ozturk et al., 2019; Peng, Liu, Li, Huang, & Wang, 2020; Juan J. Ruiz-Aguilar, Moscoso-López, Urda, González-Enrique, & Turias, 2020). Several methods are combined or compared in other articles (Du, Wang, Yang, & Niu, 2019; Peng et al., 2020; C.-H. Yang & Chang, 2020). To summarise, intelligent heuristics have dominated AI's application, which is why most publications use unsupervised algorithms. Table 2 provides a general overview of the papers examined, the AI methods employed, and their specific applications to the maritime industry.

4. In-Depth Analysis of Selected Papers

AIS data is used in the majority of studies reviewed to reveal important information about the maritime industry. This survey includes twelve literature review studies, and the work involved in these papers is summarised below.

A comprehensive literature review conducted by Anwar, Henesey, and Casalicchio (2019) investigated the application of digital technologies to the management of logistics operations at container terminals. According to the researchers, over 94% of relevant studies addressed AI, 29% discussed IoT and cloud computing and very little focused on Blockchain at container terminals. Ceyhun (2020) studies the current state of AI in maritime companies and the latest developments related to it. According to Ceyhun, using AI will contribute to the prevention of ship-related accidents by anticipating future cases by using pinpoint calculations. As Ceyhun explained, AI will help prevent ship-related accidents by anticipating them with pinpoint calculations. After investigating the effects of Industry 4.0 technologies on the maritime industry, , de la Peña Zarzuelo, Freire Soeane, and López Bermúdez (2020) concluded that each technology in Industry 4.0 has advantages and disadvantages and adoption of these technologies should be done after considering the indirect consequences. Dornemann, Rückert, Fischer, and Taraz, 2021 investigated current approaches for using AI in optimizing problems. The researchers found that there is growing interest in using ML to develop heuristics that automatically solve optimization problems.

Although they used big data in their keyword searches, Fruth and Teuteberg (2017) and Sanchez-Gonzalez, Díaz-Gutiérrez, Leo, and Núñez-Rivas (2019) explicitly addressed digitalization. While Fruth and Teuteberg paid no attention to AI applications in maritime domains, Sanchez-Gonzalez et al. conducted a literature search that is quite abstract and cannot be replicated. Both used the Systematic Literature Review (SLR) methodology in their literature review on the digitalization of maritime transport. Fruth and Teuteberg examined 124 studies on the digitalization of maritime logistics that were relevant to academia and practice. Sanchez-Gonzalez et al. take a more robust and comprehensive keyword search approach than Fruth and Teuteberg. The authors divide the emerging literature on digitalization in shipping into six broad categories (automation, big data, simulation and modelling, software, sustainable maritime transport, risks). Heilig et al. (2017) presented a summary of the current state of digitalization in seaports and its evolution. These studies show how big data and Internet of Things (IoT) are being used at ports like Hamburg's. Hu, Liu, Chen, Wang, and Wei (2020) developed a port and shipping data system based on information obtained from the Internet and commercial sources. Their investigations used web crawlers and long-term manual processing to preprocess data from maritime ports (6945 ports), terminals (more than 14322 terminals), and berths. They got the vessel profiles primarily via web crawlers; therefore, they might not be complete when compared to the real world's current ships.

Mekkaoui, Benabbou, and Berrado (2020) examined the contributions in applying ML to port operations in a SLR. They claim that ML isn't being used to solve critical port operations challenges, and only thirty papers were deemed valid. As a result, they argue that more research is needed in the seaside, yard, storage, transportation, port design, and safety and security. Munim et al., 2020 outlined how Blockchain and IoT can monitor port operations for sustainability by measuring economic and environmental factors. As detailed by Xiao, Fu, Zhang, and Goh (2020), pattern mining and traffic forecasting studies in marine traffic validate the relevance of advanced maritime traffic studies and demonstrate the significant potential in sea transport for adopting IoT, AI, knowledge engineering, and big data computing solutions. Yang et al. (2020) analyzed studies that only used AIS data. AIS data has been used widely for various research initiatives, including marine data mining, navigation safety, ship behaviour analysis, environmental assessment, trade analysis, and ship and port performance study (Štepec et al., 2020).

The extensive literature analysis of original papers is done by categorizing them into six separate groups based on the field of application of AI. These include maritime surveillance, energy efficiency optimization, ship routing and trajectory prediction, shipping demand and throughput forecasting, designing, and building ships, and other applications.

Table 2. Papers reviewed in this survey

Author	Year	Al procedure	Application area
Abebe, et al.	2020	Decision Tree (DTR), Gradient Boosting (GBR), Extreme Gradient Boosting (EGBR), Random Forest (RFR), and Extra Trees (ETR)	Predicting ship speed over the ground
Adi, et al.	2020	Deep Reinforcement Learning	Vessel traffic and route planning
Al Hajj Hassan, et al.	2020	Reinforcement Learning	Shipping demand forecasting
Chen, et al.	2020	Deep Separable (DS) - Visual Geometry Group (VGG) network and Adversarial Spatial Transformer Network (ASTN) - Faster Region-based Convolutional Neural Networks (R-CNN)	Shipping container recognition
Chen, et al.	2020	Convolutional Neural Network-Ship Movement Modes Classification (CNN-SMMC) algorithm	Vessel traffic and route planning
Du, Pei, et al.	2019	Novel hybrid learning method - Variational Mode Decomposition (VMD), Extreme Learning Machine (ELM), Butterfly Optimization Algorithm (BELM),	Container throughput forecasting
Fikioris, et al.	2020	Genetic Algorithm (GA)	Optimizing vessel trajectory compression
Filipiak, et al.	2020	GA with Spatial Partitioning, CUSUM (cumulative sum) algorithm	Vessel traffic and route planning
Gao, et al.	2019	Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN)	Container throughput forecasting
Han and Yang	2020	Big data-driven mathematical framework	Vessel traffic and route planning
Hoque and Sharma	2020	Ensembled Deep Learning Approach	Maritime anomaly detection
Ji and Lu	2020	DDBN-OCSVM framework	Maritime anomaly detection
Jimenez, et al.	2020	Computational artificial intelligence model	Predictive maintenance
Kamal, et al.	2020	RNN	Prediction of Baltic Dry Index
Kanamoto, et al.	2020	Regression analysis	Shipping demand forecasting
Kim, Hanguen, et al.	2020	Not specified	Ship berth allcoation
Kim and Lee	2019	Not specified	Maritime track monitoring services
Kontopoulos, et al.	2020	Density-Based Spatial Clustering Of Applications with Noise (DBSCAN) algorithm	Vessel traffic and route planning
Lee, et al.	2020	ETR, RFR, GBR and Bagging	Ship berth allcoation
Lee, et al.	2021	DBSCAN	Ship Trajectory Prediction
Li, et al.	2019	Kernel Extreme Learning Machine (KELM)	Container throughput forecasting
Liu, Dongdong, and Guoyou Shi	2020	Collision Detection Algorithm	Ship collision risk assessment
Man, et al.	2020	Not specified	Maritime energy-efficiency optimization
Murray and Perera	2020	Unsupervised Learning	Ship Trajectory Prediction
Ozturk, Ulku, et al.	2019	Semi-Supervised Support Vector Machines (S3VM)	Ship collision risk assessment
Peng, Yun, et al	2020	GBR, RFR, BP Network (BP), Liner Regression (LR) and K-Nearest Neighbor Regression (KNN)	Maritime energy-efficiency optimization
Qiang and Bi-Guang	2020	Artificial Neural Network (ANN) Algorithm	Ship berth allcoation
Ruiz-Aguilar, et al.	2020	ANN	Container throughput forecasting
Ruiz-Aguilar, et al.	2020	Support Vector Regression (SVR)	Container throughput forecasting
Santipantakis, et al.	2020	Not specified	Ship Trajectory Prediction
Shankar, et al.	2019	LSTM Networks	Container throughput forecasting
Shin, et al.	2020	A* algorithm using AIS	Vessel traffic and route planning
Song, et al.	2020	Bayesian Network (BN)	Fraud detection of cargo theft
Štepec, et al.	2020	GBR	Vessel traffic and route planning
Suo, et al.	2020	DBSCAN	Ship Trajectory Prediction
Tsaganos, et al.	2020	Ensemble methods	Maritime anomaly detection

Tsou	2019	DT	Ship collision risk assessment
Varlamis, et al.	2021	DBSCAN	Ship Trajectory Prediction
Wang, et al.	2020	Not Specified	Vessel traffic and route planning
Wang, et al.	2019	Multiple Hexagon-Based CNN (MH-CNN)	Ship Trajectory Prediction
Wang, et al.	2021	BN	Port State Control (PSC) inspection
Wen, et al.	2020	DBSCAN	Vessel traffic and route planning
Xu, et al.	2020	K-means clustering	Vessel traffic and route planning
Yan, et al.	2020	DTR, RFR	Maritime energy-efficiency optimization
Yang, Cheng-Hong, and Po-Yin Chang	2020	CNN, LSTM, RNN	Container throughput forecasting
Yang, Tingting, et al.	2020	K-Means algorithm, GA	Ship collision risk assessment
Zhang, et al.	2021	CRNN	Shipping container recognition
Zhong, et al.	2019	Bi-directional LSTM-RNN (BLSTM-RNNs)	Ship trajectory restoration
Zhou, et al. .	2020	CNN, LSTM, Bidirectional LSTM Network with a CNN (BDLSTM-CNN).	Ship Trajectory Prediction

4.1. Maritime Surveillance

Maritime policies such as maritime security, illicit bunkering, tracking of marine oil transit, and search and rescue all benefit from surveillance of the maritime environment. Wang et al. provided a new methodology for quantifying shipping volume along the Yangtze River under current speed regulations utilising big data from the AIS (L. Wang et al., 2020). The study emphasises the need to modify ship speed in small waterways to avoid excessive traffic congestion and reduce the risk of maritime accidents. Songs et al. employed BNs to investigate bulk cargo theft at ports, as well as feature rankings to identify key risk factors (Song et al., 2020). Kim et al. introduced an algorithm for automatically selecting maritime traffic stream data for the presentation from a vast quantity of data by utilising a ML technique to generate a decision tree. The proposed system appears to be capable of adapting information selection based on port conditions to assure safety and efficiency (Kim & Lee, 2019).

Some of the studies are concerned with anomaly detection. Hoque and Sharma employed an LSTM neural network to predict the ship paths and suppress anomalous AIS data (Hoque & Sharma, 2020). By using a hybrid single classification framework based on depth learning, Ji and Lu are able to accommodate real-time monitoring of abnormal data during ship driving (Ji & Lu, 2020). Anomaly detection was carried out using the DDBN-OCSVM framework and the single classification algorithm. As indicated in Tsaganos et al.'s work, the AdaBoost classifier was applied to improve fault detection in engines (Tsaganos et al., 2020). The authors concluded that the ensemble methods used in their study resulted in 96.5% accuracy and are an appropriate choice for engine fault detection.

Despite a well-developed literature on anomaly detection, future research should focus on real-time anomaly detection of vessels and the application of advanced ML techniques. Future research could apply available shipping route extraction methods for collision prevention and the environmental consequences of maritime oil transit.

4.2. Energy-Efficiency Optimization

A variety of studies have used AI to improve energy efficiency in maritime transport. While most of these studies focused on vessel speed optimization (Abebe et al., 2020; X. Yan, Wang, Yuan, Jiang, & Negenborn, 2018), others targeted optimizing ships' energy consumption in port (Man et al., 2020; Peng et al., 2020; R. Yan et al., 2020).

Abebe et al. used a decision tree regression model and four ensemble methods to predict ship speed. Finally, the model optimized the actual ship route (Abebe et al., 2020).. Yan et al. found the optimal speed of inland ships using the distributed parallel k-means clustering algorithm. Their proposed method contributes to lowering carbon dioxide emissions from vessels and decreasing energy consumption (Yan et al., 2018).

Peng et al. suggested strategies to reduce energy consumption in China's Jingtang port and proposed models to predict future energy consumption (Peng et al., 2020). Gradient boosting regression, random forest regression, BP network, linear regression, and KNN regression were used to analyze 15 inputs that were thought to affect ships' energy consumption. The analysis concluded that the four most important factors for predicting ships' energy consumption are net tonnage, deadweight tonnage, actual weight, and facility efficiency. Optimizing energy consumption is challenging because there is no practical analytical approach for evaluating ship performance. Big data analytics are needed to get an accurate picture of actual fuel consumption. Using an ethnographic approach, Man et al. highlighted operational issues associated with fuel monitoring systems (Man et al., 2020). The model developed by Yan et al. aims to forecast fuel consumption and reduction with the help of random forest regression (R. Yan et al., 2020). The model was then applied to optimize two voyages using data from random forest regression. The model can reduce fuel consumption by 2 - 7% by choosing the best route.

According to the authors' knowledge, there are just a few studies that employ ML and DL models to estimate ship fuel use or emissions in port areas. As a result, more research in this area is necessary.

4.3. Ship Routing and Trajectory Prediction

In shipping risk analysis, accurate ship trajectory prediction is critical, and AIS data mainly influences such prediction based on modern methodologies. The following studies show ML models for ship trajectory prediction currently being developed.

Fikioris et al. exhibited a way for fine-tuning the parameter value selection for the trajectory detection module they developed. Researchers added vessel type into the configuration to improve trajectory synopses in terms of both approximation error and compression ratio. A GA was utilized in the study to develop a suitable configuration for each vessel type. Empirical results indicate that the compression efficiency may be higher than with the default parametrization (Fikioris et al., 2020). Filipiak et al. described how to derive sea routes from AIS data using a parallel genetic algorithm coupled with KD-B trees (Filipiak et al., 2020). Based on historical AIS trajectories, Han and Yang derived the main channel of a particular sea area, constructed a topological channel network by preserving the channel's geometric characteristics, and found the route of the ships through a grid-channel network (Han & Yang, 2020).

Wen et al. applied the DBSCAN algorithm to extract the turning section of a ship's trajectory, and an automatic route design algorithm was developed (Wen et al., 2020). Kontopoulos et al. used historical AIS data and polynomial interpolation to extract shipping lanes. Modifying the DBSCAN algorithm achieved more coherent clusters of trajectory points, which are then assembled to form shipping lanes. The analysis of future vessel paths shows that most (i.e., more than 90%) of them fall into the extracted shipping lanes (Kontopoulos et al., 2021). According to the authors, future studies should examine dynamic constraints in real-time (such as water velocity), rather than static constraints, and use 3D information instead of 2D to plan shipping routes.

4.4. Demand and Throughput Forecasting

The economic development of ports relies on container throughput, and accurate forecasting of container throughput can improve container operation efficiency while catering to financial trading needs. Some of the relevant studies include those summarized below.

RL framework for freight demand forecasting is proposed by Hassan et al. for supporting operational planning (Al Hajj Hassan et al., 2020). Kanamoto et al. forecasted future shipping demand based on AIS data from dry bulk vessels using a logit model and RA (Kanamoto et al., 2021). Experimental results have shown the Base Optimization Algorithm (BOA) algorithm outperforms the ant lion optimizer (ALO) for container throughput forecasting in Du et al.'s (2019) study. Gao et al. demonstrated using LSTM that LSTM is more accurate than AutoRegressive Integrated Moving Average (ARIMA) or backpropagation neural networks at predicting daily volumes of containers entering a storage yard (Gao et al., 2019). Li et al. proposed a hybrid secondary decomposition learning strategy for monthly forecasting of container throughput. The sample entropy is a metric for determining the complexity of a data series, and different modes are forecasted using ELM and KELM. The suggested method is highly effective for predicting nonlinear and nonstationary container throughput (Li et al., 2019).

Demand forecasting plays a vital role in making informed business decisions by using historical data to predict future sales. However, little research has been conducted on demand forecasting in the maritime industry.

4.5. Ship Design and Building

Kim et al. (2012) investigated AI applications in ship design and shipbuilding using the Takagi-Sugeno fuzzy model to create a stabilization controller system for autonomous unmanned underwater vehicles (UnVs). Cheng et al. (2012) developed a GA for path planning in a UnV that, despite being first regarded as a less-than-optimal solution due to a lack of a complete grasp of the problem, delivered better solutions at a reduced cost. Zhao et al. (2014) developed an adaptive neural network control that was applied to the control problem of monitoring the desired trajectory for a fully operated marine surface vehicle while taking different output restrictions into account. This was considered the most recent application of AI in the design of autonomous UnV.

Kim and Moon (2006) estimated the ship's wake fields on the propeller plane using a neuro-fuzzy approach. This approach produces precise and safe estimates of wake distributions. As a result of this research, hull form designers may estimate ship wake distribution during the early design stage, leading to the enhancement and optimization of stern hull form. Sanders (2009) suggested a pattern recognition method for distinguishing shipbuilding parts based on ANN and Fourier descriptors. The system used shape contour data with size, translation, and rotation invariant. Fourier descriptors provided data, and neural networks generated shape assessments.

4.6. Other Applications

Ning Chen proposes a DL strategy for container target recognition and detection based on the Faster R-CNN framework. The DS-VGG network is intended to improve accuracy while decreasing network parameters for faster recognition. The adversarial spatial transformer network (ASTN) improves data variety and identification performance by allowing faster network training. Under comparison to Faster R-CNN, recognition performance improves dramatically in difficult settings like fog, rain, and darkness (N. Chen et al., 2020). Chen et al. analyzed the results of CNN for ship movement classification, comparing them with KNN, SVM, and DT. The study showed that CNN is more effective for AIS data classification than other methods (X. Chen et al., 2020). To improve the Baltic Dry Index (BDI) predictive performance, Kamal et al. constructed a deep ensemble recurrent network consisting of RNN, LSTM, and a gated rectified unit neural network (GRU). According to the findings, the ensemble strategy outperformed the solo DL approach (Kamal et al., 2020).

Kim et al. suggested a unique AI vision-based monitoring system (AVMS) for ship berthing. Because it has such a large field of view, the AVMS can measure the distance between ship and berth regardless of ship size. It also gives the pilot a real-time picture of the ship approaching the berth, allowing for safe berthing (H. Kim et al., 2020). A ML approach was used in Lee et al.'s analysis, which resulted in predictions based on berthing velocity data (Li et al., 2019). Predictive analytics in maritime research has many applications, from predicting ship propulsion failure to predicting hazardous coastal blooms. Jimenez et al. suggest that predictive algorithms are now being developed in maintenance prediction. The authors demonstrated an ML-based solution for predictive maintenance in the maritime industry using real-time monitoring data (Jimenez et al., 2020).

5. Conclusions

This study combines bibliometric analysis and systematized content analysis to present a comprehensive review of AI studies in the maritime domain. In the findings, the different uses of AI in Maritime Logistics are summarized, along with their various techniques and an overview of the current state of research.

Maritime Logistics employs ML primarily based on AIS data as their primary input due to their widespread availability of large datasets. Maritime Logistics applications in other aspects aside from routing vessels aren't adequately represented because of this. It would be more beneficial to apply ML at the intersection of Logistics at sea and Logistics on land (terminals and hinterland) if more data were available to create more possibilities for applications requiring large datasets.

Two potential domains have been identified that could be further investigated using AI capabilities in the maritime industry. The first domain is energy efficiency optimization, which includes optimizing marine vessel speed, fuel usage, and vessel route planning. The other is predictive analysis, which provides traffic monitoring, ship repair forecasting, collision risk assessment, and other issues. In addition, ML and Operations Research (OR) have also led to a growing interest in automating the learning of heuristics for optimization problems to avoid the need for humans to develop highly specialized heuristics that are costly and time-consuming. Future research can take advantage of these new approaches to ML to address problems in Maritime Logistics utilizing the ever-increasing amount of data available.

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