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## An insight into the Application of AI in maritime and Logistics toward Sustainable Transportation

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**Abstract**— This review article looks at the developing field of artificial intelligence and machine learning in maritime and marine environment management. The marine industry is increasingly interested in applying advanced AI and ML technologies to solve sustainability, efficiency, and regulatory compliance issues. This paper examines maritime and marine AI and ML applications using a deep literature review and case study analysis. Modeling ship fuel consumption, which impacts the environment and operating expenses, is a top responsibility. The study demonstrates that ML approaches such as Random Forest and Tweedie models can estimate ship fuel use. Statistical analysis demonstrates that the Random Forest model beats the Tweedie model regarding accuracy and consistency. For the training and testing datasets, the Random Forest model has high R2 values of 0.9997 and 0.9926, indicating a solid match. Low Root Mean Square Error (RMSE) and average absolute relative deviation (AARD) suggest that the model accurately reflects fuel use variability. While still performing well, the Tweedie model has lower R2 values and higher RMSE and AARD values, suggesting reduced accuracy and precision in fuel consumption prediction. These findings provide light on the potential applications of artificial intelligence and machine learning in maritime and marine environment management. Advanced analytics enables decision-makers to analyze fuel consumption patterns better, increase operational efficiency, and decrease environmental impact, thus improving maritime sustainability.

**Keywords**— Machine learning; sustainability; marine transport; marine logistics; Tweedie; random forest.

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### I. INTRODUCTION

As reported, over 80% of the world's goods commerce is carried out by sea, and the maritime field plays a vital role in shipping goods in the world [1], [2]. Thus, it is acknowledged as the cornerstone of the manufacturing supply chain and international trade. A nation's economic structure also heavily depends on the maritime transport sector, which imports and exports resources and generates employment [3]–[5]. The principal hubs in the marine transportation network are seaports, sometimes called ports, which are connected by shipping lanes. Comparably, ports in the modern conception of the global supply chain have developed from traditional

hubs for loading, unloading, and storing goods to significant nodes that coordinate the whole supply chain [6], [7]. As demonstrated by the emergence of the container idea, which unifies international trade and fosters linkages between diverse modes of transportation, this expansion has dramatically raised port demand in the past few decades [8], [9]. Additionally, the majority of the major ports across the world are physically constrained by cities that encircle them. Ports must thus increase their internal and external efficiency to reduce overall logistics costs [10], [11].

The maritime and logistics industries are essential to the functioning of the global economy since they serve as the basis for international trade and commerce [12], [13]. These industries encompass various activities associated with

transporting goods, raw materials, and passengers across oceans, seas, and land. In their most fundamental form, these industries are intricately intertwined, with sea transportation playing a significant role in enabling the flow of products inside and between nations [14]–[17]. It is essential to have a sound understanding of the intricacies and dynamics of these industries to comprehend their role in the construction of the modern world [18], [19]. The marine sector, often called the maritime industry, encompasses all aspects of marine transportation, including shipping, shipbuilding, port operations, and maritime services [20]–[23]. Shipping, in particular, is an essential component of this business since it involves the movement of goods and products using vessels such as ships and boats [24], [25]. The term encompasses various vessels, ranging from container ships and bulk carriers to tankers and specialized boats like ferries and cruise liners, among other vessels. The maritime industry is supported by a network of companies that work together to ensure the effective movement of goods across global supply networks. These include shipping companies, shipbuilders, port authorities, and marine service providers [7], [26].

The maritime industry is distinguished by its global reach, which enables goods to be carried to virtually any area on the earth [27], [28]. This is one of the sector's distinctive characteristics. International trade is made possible by this extensive network of maritime trade routes, which significantly contributes to the economy's expansion and development. In addition, sea transportation is typically the most cost-effective and energy-efficient method of transporting large quantities of goods across long distances, which is why it is a crucial mode of transportation for international trade [29]–[31]. In the same vein, the logistics business is essential to ensure that the flow of goods from suppliers to consumers is uninterrupted. The logistics process includes several components: transportation, warehousing, inventory management, and distribution chain optimization. Logistics companies accomplish the efficient movement of goods along the supply chain by utilizing a wide range of modes of transportation, such as ships, trucks, trains, and airplanes [32]–[34]. As a result of the proliferation of e-commerce and globalization, there has been a growth in the need for sophisticated logistics solutions, which has led to an increase in the industry's level of innovation and technical advancement [35], [36].

In modern supply chain management, one of the most critical components is the integration of operations involving the maritime and logistics sectors [37], [38]. Ports are essential nodes in the global logistics network, serving as hubs that facilitate the movement of goods between different modes of transportation, including ships, trucks, and trains, among others [39], [40]. Efficient port operations are essential for reducing the time it takes for goods to travel, saving money, and enhancing the overall efficiency of supply chain activities [41][42]. To further emphasize the need for faultless coordination among maritime carriers, logistics providers, and other stakeholders, optimizing shipping routes and solving any potential logistical challenges is essential. In recent years, the maritime and logistics industries have emphasized the need for sustainability measures [43][44]. Other factors have prompted players in the sector to adopt more sustainable practices, including environmental concerns,

legal requirements, and altering customer preferences. Changes in business practices and the promotion of innovation in environmentally responsible transportation systems are being brought about due to efforts to minimize carbon emissions, promote clean energy solutions, and lessen environmental impact. The maritime and logistics sectors are actively researching strategies to decrease their environmental impact and contribute to a more sustainable future. These efforts include the construction of environmentally friendly boats as well as the execution of green logistics initiatives.

The maritime and logistics sectors play crucial roles in facilitating global trade and commerce, connecting economies, and promoting economic growth [45]. These industries are well-positioned to tackle the problems and opportunities of a world becoming increasingly interconnected because of their extensive communication networks, cutting-edge technology, and commitment to environmental preservation. Through an understanding of the complexities and dynamics of maritime and logistics operations, stakeholders can successfully navigate the ever-evolving landscape of international commerce and make significant contributions to the development of a global supply chain ecosystem that is more efficient, resilient, and sustainable. Sustainability in marine transportation plays a crucial role in influencing the environment, economy, and society on a large scale. Marine shipping is a vital component of global transportation, which is pivotal in enabling international trade and commerce [46]–[48]. Nevertheless, the impact of maritime operations on the environment, such as greenhouse gas emissions, oil spills, and marine pollution, presents notable obstacles to sustainability [49]–[51]. One of the main drivers for focusing on sustainability in marine transportation is the environmental consequences of shipping activities. Maritime vessels play a significant role in air and water pollution by releasing harmful pollutants like sulfur oxides (SO<sub>x</sub>), nitrogen oxides (NO<sub>x</sub>), and particulate matter (PM) [52]–[55]. These emissions hurt air quality, climate change, and ocean acidification, putting marine ecosystems and biodiversity at risk. Moreover, the discharge of ballast water and the release of dangerous chemicals present risks to marine habitats and coastal communities [56], [57]. Moreover, the financial viability of marine transportation is intricately connected to environmental factors. Environmental damage and pollution cleanup expenses can be significant, resulting in financial setbacks for shipping companies and port operators. Furthermore, adhering to international conventions like the International Maritime Organization's (IMO) MARPOL Convention and the Ballast Water Management Convention involves extra costs for vessel owners and operators. Embracing sustainable practices in marine transportation can help lower these expenses and improve the long-term sustainability of the shipping sector. In addition to environmental and economic considerations, sustainability in marine transportation also carries social implications [58]. Coastal communities and vulnerable populations bear the brunt of the adverse effects of marine pollution and habitat degradation. Furthermore, using fossil fuels for maritime propulsion leads to energy insecurity and geopolitical tensions. The maritime industry can advance social equity, boost public health, and strengthen global energy security by adopting cleaner and more sustainable fuels and technologies.

Machine learning is crucial in tackling sustainability issues in marine transport, providing creative solutions to boost efficiency, cut emissions, and lessen environmental harm. Utilizing machine learning algorithms to examine extensive

data from maritime activities, such as vessel performance metrics, weather patterns, and environmental conditions, can enhance different facets of shipping operations [59]–[62].

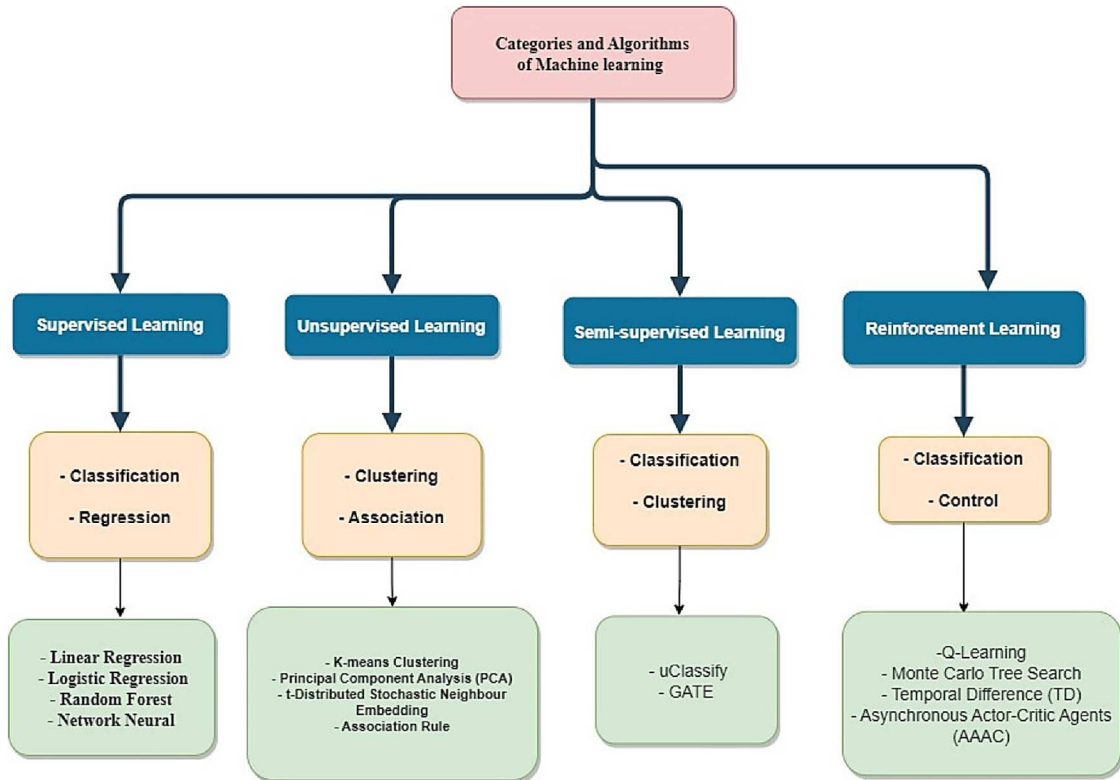


Fig. 1 An overview of ML techniques [63]

One important use of machine learning in promoting marine transport sustainability is through predictive maintenance. The classification of main ML techniques is depicted in Fig. 1. By analyzing historical data on vessel maintenance records and equipment performance, machine learning models can forecast potential failures and suggest proactive maintenance strategies [64]–[67]. This can help decrease downtime and lower the

chances of mechanical breakdowns while at sea. In addition, machine learning algorithms can be used to optimize vessel routing and speed profiles by utilizing real-time data on fuel [68]–[71], weather forecasts, and traffic patterns [72]–[76], leading to a decrease in fuel consumption, greenhouse gas emissions, and operating costs. A typical application spectrum is depicted in Fig. 2.

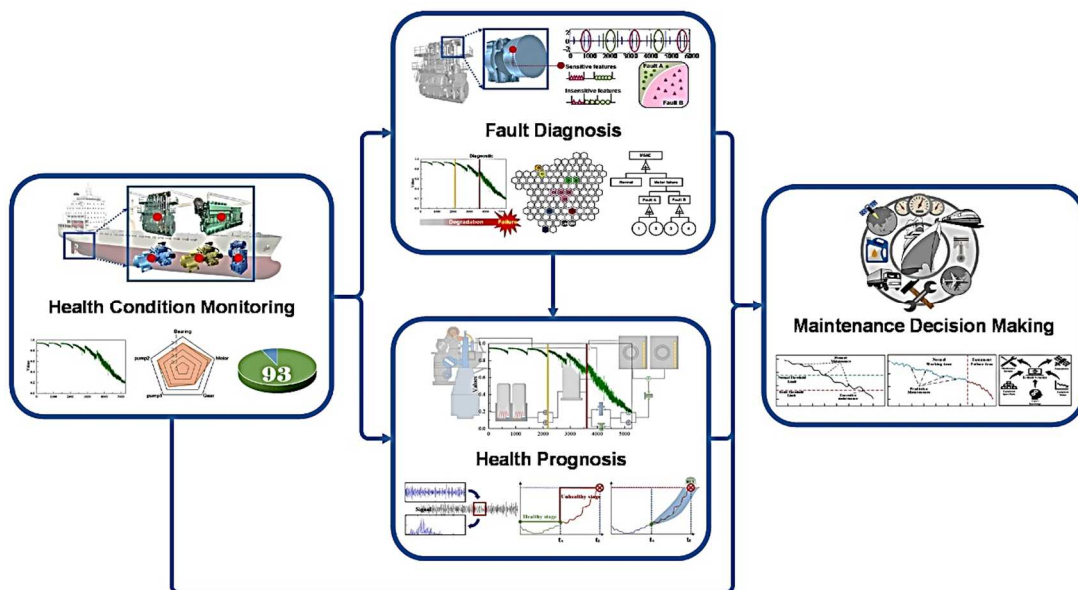


Fig. 2 Application of AI & ML in marine transport [77]

Furthermore, machine learning methods can enhance decision-making in port operations and logistics management, increasing efficiency and decreasing congestion. Through data analysis related to port activities, cargo flows, and supply chain dynamics, machine learning models can enhance berth scheduling, container handling operations, and inventory management [78]–[80]. This optimization can reduce turnaround times, decrease emissions, and enhance port performance. Machine learning can transform sustainable practices in marine transport through data-driven decision-making, resource allocation optimization, and operational efficiency enhancement in the maritime sector [81]–[83]. With the rapid advancement of technology, incorporating machine learning into maritime operations is essential for creating a more sustainable and resilient marine transportation system [84], [85].

#### A. Literature review

Autonomous shipping and navigation constitute a new frontier in the maritime sector, with the potential to change vessel operations and navigation procedures [86], [87]. ML is critical in enabling the development and deployment of autonomous systems, allowing ships to operate with minimum human interaction while maintaining safety, efficiency, and compliance with maritime rules [88]. ML algorithms help autonomous boats see and understand their environment correctly. ML models can recognize and categorize items in the area of a vessel by analyzing sensor data from radar, lidar, cameras, and other onboard sensors, such as other ships, navigational hazards, and maritime infrastructure [89]. This real-time situational awareness enables autonomous ships to make intelligent judgments about navigation, collision avoidance, and route planning, lowering the likelihood of accidents and boosting overall maritime safety. Furthermore, machine learning-based predictive analytics improve ships' autonomous navigation capabilities by anticipating environmental variables, sea states, and vessel behavior. Autonomous warships can predict changes in weather patterns, sea prevailing currents, and traffic patterns using historical data and machine learning algorithms, allowing for proactive modifications to navigation routes and speed profiles to improve fuel efficiency and trip performance.

##### 1) Autonomous navigation and shipping

In autonomous shipping and navigation, machine learning extends beyond the realm of real-time vision and decision-making to encompass a wide range of essential assignments and capabilities. When designing better control systems that enable autonomous vessels to negotiate challenging marine scenarios with precision and efficiency, machine learning is one area in which it excels [90]–[92]. It is possible to optimize control approaches for autonomous ships by utilizing machine learning algorithms that consider vessel dynamics, environmental factors, and operational limits [93], [94]. Machine learning models have the potential to modify steering, propulsion, and maneuvering motions by analyzing data on ship performance, propulsion systems, and environmental factors. This would allow for optimizing

energy efficiency, reducing fuel consumption, and reducing emissions while the ship is in transit. The International Maritime Organization (IMO) defines four degrees of autonomy (DoA) for maritime autonomous surface ships (MASS), as given in Table I. MASSs can have varying levels of autonomy throughout a single journey [95].

TABLE I  
THE LEVEL OF AUTONOMY ALLOWED FOR MASS [95]

Degree of autonomy	Description
DoA 1	Ship with automated procedures and decision support, wherein seafarers are on board to operate and control shipboard systems and functions.
DoA 2	A remote-controlled ship with seamen on board. The vessel is managed and controlled from another place while sailors remain on board.
DoA 3	A ship that is managed remotely and does not have any sailors aboard. The ship is operated remotely. There are no seafarers aboard.
DoA 4	A fully autonomous ship is one whose operating system can make decisions and take actions.

In addition, machine learning techniques substantially contribute to the resilience and robustness of autonomous navigation systems. Reinforcement learning and adaptive control are two approaches that autonomous boats may employ to learn from their experiences and dynamically adjust their navigation strategies in response to unanticipated events such as malfunctioning equipment, adverse weather conditions, or collisions with other vessels. Autonomous ships can navigate in a manner that is safe and effective in the face of dynamic and unexpected maritime conditions if they can adapt and alter in real-time. In addition, the application of machine learning techniques assists in optimizing collision avoidance strategies for autonomous aircraft. Machine learning algorithms can foresee likely collision situations by analyzing data on vessel trajectories, traffic patterns, and collision risk variables [96], [97]. These algorithms may prescribe evasive tactics to avoid accidents and ensure safe passage. This proactive collision avoidance technique increases the safety and reliability of autonomous shipping operations, reducing the risk of maritime accidents and decreasing the potential for adverse effects on the environment and the economy. One such arrangement of autonomous navigation is depicted in Fig. 3.

A wide range of capabilities, such as perception, decision-making, control, and collision avoidance, are acquired through machine learning in the context of autonomous shipping and navigation. By employing the power of machine learning to analyze data, gain knowledge from experience, and adjust to changing circumstances, autonomous boats have the potential to revolutionize the maritime industry [87], [99]. This would usher in a new era of shipping operations that are safer, more efficient, and more environmentally friendly. It is anticipated that the introduction of machine learning into autonomous navigation systems will play a significant role in shaping the future of maritime transportation and opening up new options for innovation and growth as technology continues to improve.

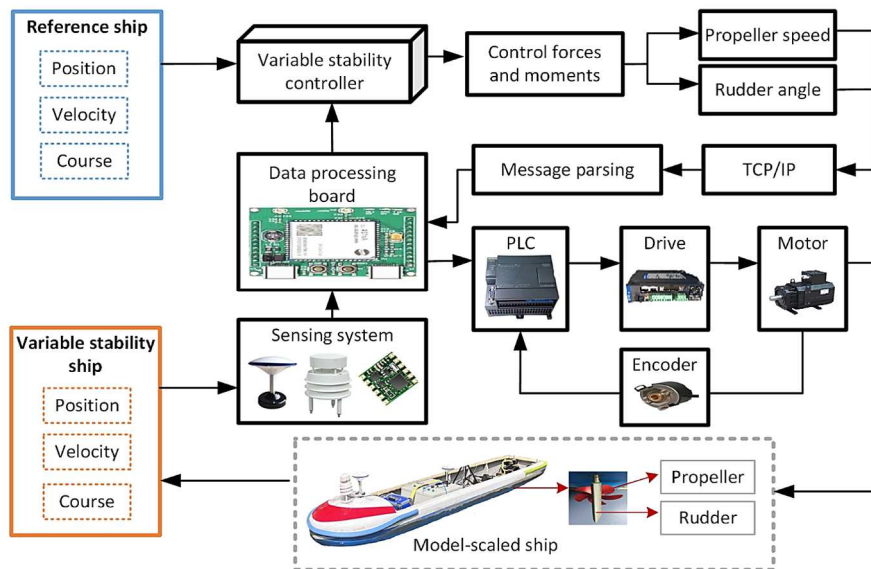


Fig. 3 Hardware arrangement for variable stability control system [98]

### 2) Predictive maintenance and condition monitoring

Predictive maintenance and condition monitoring, which employ machine learning, are regarded as revolutionary in the marine industry. These methods are anticipated to significantly improve vessel dependability, operational efficiency, and cost-effectiveness [100], [101]. Machine learning empowers ship operators to detect and rectify potential equipment malfunctions proactively. This reduces vessel downtime, decreases maintenance expenses, and enhances vessel performance. To achieve machine learning, sophisticated analytics, and predictive algorithms are implemented. One of the foremost benefits of predictive maintenance, powered by machine learning, is its ability to analyze vast quantities of data gathered from onboard sensors, equipment reports, and historical maintenance records. By conducting this analysis, it becomes possible to detect patterns, trends, and anomalies that serve as indicators of impending failures. By employing machine learning algorithms, subtle alterations in equipment behavior and performance metrics, including vibration levels, temperature fluctuations, and fluid pressures, can be identified. It is possible to identify underlying issues or deterioration using these measurements. In addition, machine learning-based predictive maintenance models can provide actionable and precise insights regarding the state and functionality of critical apparatus and systems situated aboard vessels [102], [103]. Proactive scheduling of maintenance operations, efficient management of spare parts inventories, and resource allocation are all achievable for ship operators who can forecast equipment failure probabilities and estimate the equipment's remaining useful life [104]. This enables them to optimize asset utilization while minimizing unforeseen periods of inactivity. Furthermore, machine learning methodologies enable condition monitoring systems to identify and acquire knowledge from data streams in real-time, thereby facilitating the continuous enhancement and improvement of forecast models [105], [106]. Machine learning algorithms can enhance the precision and dependability of predictive maintenance forecasts by integrating feedback loops and supplementary data sources,

including personnel feedback, environmental conditions, and operational parameters. Such outcomes may result in enhanced risk mitigation strategies and improved decision-making [107], [108].

Predictive maintenance prompted by machine learning enhances equipment dependability and operational efficiency and has significant environmental consequences for the marine sector, ensuring its continued sustainability. By minimizing the risk of equipment malfunctions, vessel operators can reduce the likelihood of ecological problems, accidents, and pollution. Preserving maritime ecosystems and enhancing safety standards will be the outcomes of this initiative.

### 3) Optimization of cargo handling

Machine learning (ML) to optimize cargo handling has considerable prospects for enhancing marine logistics efficiency, productivity, and safety. ML algorithms may enhance cargo handling procedures at ports and terminals by analyzing data from various sources, such as cargo manifests, vessel schedules, port infrastructure, and historical performance indicators [109]. One important ML use in cargo handling optimization is the automated scheduling and prioritizing of loading and unloading processes [110]. Machine learning models may develop optimum loading and unloading strategies that decrease turnaround times and congestion and increase throughput by assessing real-time data on vessel arrivals, cargo quantities, berth availability, and equipment capacity.

ML approaches also offer predictive analytics and forecasting, improving the precision of cargo handling activities. By examining past data and trends, ML algorithms can forecast changes in cargo demand, vessel arrivals, and port usage, allowing operators to allocate resources, modify workforce levels, and improve workflow operations in response to shifting demand patterns. Furthermore, ML-based optimization algorithms can increase equipment use and resource allocation in cargo handling operations. ML models may improve crane scheduling, container stacking, and yard management procedures by assessing equipment performance

data and operating factors. This will result in more effective resource use and shorter idle times for handling equipment.

### *B. Objectives*

The prime objective is to investigate the value addition owing to the application of modern artificial intelligence technology to sustainable business models in the shipping industry. To examine how businesses utilize and may deploy AI-based solutions to add value to their operations by boosting economic and environmental sustainability, the present work will combine a literature review with a case study research methodology. This will be achieved by combining the two research methods. Further, it will investigate whether or not the marine industry can implement solutions based on artificial intelligence. The purpose of the study is to review the literature on the efficient exploitation of AI techniques to enhance financial savings and lessen adverse environmental effects.

## II. MATERIAL AND METHOD

### *A. Review Approach*

As we search for publications relevant to our review on "AI and ML for maritime and marine environment management," we realize the importance of using boolean operators to refine our search criteria. We aim to refine our search results by utilizing boolean operators to ensure they are both practical and relevant, closely aligned with our review article's subject matter and goals.

When attempting to condense the extensive material on the topic, we used boolean operators in our search strategy. Utilizing boolean operators helps filter out irrelevant information and focus on papers exploring overlapping fields. This is crucial as research in artificial intelligence, machine learning, and maritime and marine environment management grows. By merging terms like "artificial intelligence," "machine learning," "maritime," "marine," and "environment management," we aim to engage a broad audience while staying relevant to our analysis.

Moreover, incorporating precise terms related to the central theme of our review, such as "sustainability," "environmental monitoring," "pollution control," and "marine biodiversity," assists in narrowing down our search and guaranteeing that we cover literature that deals with the crucial issues and obstacles in the management of maritime and marine environments. These terms provide a comprehensive understanding of our search, allowing us to explore the application of artificial intelligence and machine learning in addressing sustainability issues, monitoring environmental conditions, and mitigating human impact on marine ecosystems. Using Boolean operators, the authors could adjust the search queries to filter out irrelevant papers for our review topic. These papers might cover issues related to healthcare or finance. With this specialized method, we can quickly find top-notch literature. This literature offers valuable insights and contributions to artificial intelligence and machine learning applications in managing maritime and marine environments.

Ultimately, integrating Boolean operators into our search approach is crucial for narrowing down our search parameters, guaranteeing the relevance of our search outcomes, and

efficiently pinpointing literature on the convergence of artificial intelligence, machine learning, and maritime and marine environment management. By utilizing this method, the objective was to conduct a thorough and insightful analysis that would significantly enhance the current knowledge on this topic.

### *B. Data Collection in Marine Transportation*

The maritime sector may undergo significant transformations due to artificial intelligence (AI) and automatic identification systems (AIS). The Automatic Identification System (AIS) mandates that boats send real-time data about their speed, position, and other parameters to improve marine traffic safety. This is because the law demands bigger ships to comply with this requirement [111]. It is possible to handle and analyze vast volumes of AIS data using AI algorithms and machine learning techniques, which can lead to the discovery of significant insights and patterns. Effective decision-making, situational awareness, and control of vessel traffic are all made possible due to this. Improving route planning, strengthening communication and coordination between ships and authorities, and revolutionizing how ships operate are potential benefits that might result from combining artificial intelligence with AIS in the shipping sector.

#### *1) Density-Based Spatial Clustering of Applications with Noise*

The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) approach is reliable for gathering data from marine settings. It is particularly well-suited to marine environments' complex and ever-changing nature [112]. This clustering approach can successfully capture the underlying patterns and structures in marine datasets by identifying geographical groupings of data points based on density. Even in the face of noisy data, which is common in maritime settings due to sensor faults and ambient variation, DBSCAN can give robust clustering because of its ability to differentiate between core points, dense regions, and noise points, sparse regions. In addition, because DBSCAN can identify clusters of varying shapes and sizes, it is an excellent tool for marine data, which may contain spatial patterns with irregular shapes or fluctuate substantially in size. Because of the scalability of the DBSCAN parameters, it is possible to modify them based on the characteristics of the marine dataset [113]. This allows for effectively capturing clusters with varied densities and geographical dispersion. In addition, the processing efficiency of DBSCAN makes it possible to do real-time analysis of streaming marine data, which is beneficial for applications such as environmental monitoring, habitat mapping, and offshore resource exploration. In general, DBSCAN is a powerful and versatile approach for gathering data from the ocean. It enables the identification of spatial patterns and the formulation of well-informed decisions in the context of oceanographic research, preservation operations, and the management of marine resources.

#### *2) Integration of AI and AIS*

The integration of artificial intelligence with automatic identification systems (AIS) is a rapidly expanding area of study and innovation in the maritime industry [114], [115]. Because of the sheer volume and complexity of the data



obtained via AIS, it is challenging to extract valuable insights from the data. At this point, the application of artificial intelligence becomes relevant. Integrating artificial intelligence with artificial intelligence systems (AIS) requires using complex algorithms and machine learning strategies to analyze, assess, and extract usable information from AIS data. Artificial intelligence can determine the vast data that automatic identification systems (AIS) provides, including vessel positions, speeds, directions, and other contextual information. This allows AI to recognize patterns, trends, and anomalies that human operators could miss. When it comes to enhancing efficiency, safety, and sustainability in maritime operations, the utilization of Artificial Intelligence (AI) and Automatic Identification System (AIS) technologies for data collection in this sector represents a significant step forward [116]. Ships are provided real-time position and navigational information via the Automatic Identification System (AIS), primarily developed to avoid collisions and monitor vessels. Many opportunities for improving many aspects of sea transportation are made available when artificial intelligence (AI) technologies are combined with automatic identification system (AIS) data collection.

The optimization of routes and the performance of predictive analytics are two major applications of the combination of AI and AIS. These artificial intelligence systems can forecast appropriate vessel routes by using historical data from the Automatic Identification System (AIS) and environmental elements such as weather, sea currents, and traffic patterns. Furthermore, artificial intelligence can dynamically adjust real-time routes in reaction to changing conditions, increasing safety and efficiency. Furthermore, artificial intelligence-powered predictive maintenance systems may use Automatic Identification System (AIS) data to monitor the status and functioning of onboard machinery and equipment. By examining data supplied by the Automatic Identification System (AIS) on vessels' speed, direction, and engine health, artificial intelligence systems can uncover anomalies that may suggest potential issues or the need for repair. Reduced downtime, increased reliability, and a longer lifespan for essential pieces of equipment are all outcomes of this preventative maintenance strategy.

Moreover, artificial intelligence can enhance environmental monitoring and compliance in the maritime transportation sector. Artificial intelligence systems can use AIS data with satellite photos and sensor data to identify environmental hazards such as oil spills, maritime pollution, and illegal fishing. Being able to enforce norms efficiently, limit ecological damage, and maintain naval habitats are all made possible by this talent. Additionally, decision support systems powered by artificial intelligence may leverage AIS data to improve port operations and logistical management efficiency. By analyzing vessel traffic patterns and congestion levels, artificial intelligence algorithms can potentially enhance berth scheduling, cargo handling, and the utilization of port infrastructure. This might lead to reduced wait times and improved throughput efficiency outcomes. Within the maritime sector, integrating artificial intelligence with automatic identification systems (AIS) for data collection in sea transportation has tremendous potential to improve efficiency, safety, and sustainability. Stakeholders may use AI-driven insights from AIS data to optimize route planning,

improve maintenance practices, monitor environmental effects, and improve port operations. This will ultimately result in a marine transportation system that is more efficient, resilient, and environmentally sustainable.

### *C. Machine Learning in Marine Logistics*

In the field of international freight transportation management (IFTM), machine learning (ML) is a promising avenue because of its ability to harness the power of data that is becoming more accessible to researchers and practitioners in the field of freight transportation. When we talk about international freight transportation, we refer to the actual transfer of goods from one country to another, whether via ship, air, rail, truck, pipeline, or multimodal systems. During an international freight transit, there may be a significant number of participants involved. These participants may simultaneously include one or more shippers, carriers, forwarders, third-party logistics providers, and the customs authorities of two or more nations [117]. When compared to the movement of domestic goods, international freight transportation is distinguished by more significant volumes (for example, transported by containerships with a capacity of more than 10,000 TEU) and greater distances (for example, intercontinental), the utilization of large vehicles (for example, ocean-going ships) and infrastructure (for example, seaports), and the presence of border-crossing checks. These factors contribute to the high complexity of managing international freight transport. Because of the complexity, assessing the relationships between the different inputs, outputs, and decisions involved in international freight transportation networks is more complicated. The research difficulties associated with managing international freight transportation are more difficult to address. These problems range from the forecasting of demand to the planning of operations, as well as the maintenance of assets and the prediction of timely delivery [118], [119].

Machine learning (ML) has the potential to significantly transform maritime logistics by improving efficiency, safety, and sustainability across a variety of supply chain components. This technology has the potential to revolutionize naval logistics. Following are some of the ways that machine learning might help enhance maritime logistics:

#### *1) Predictive Maintenance*

- Machine learning algorithms can analyze vast amounts of sensor data from onboard machinery and equipment to recognize trends that could foreshadow future malfunctions or performance deterioration [120], [121].
- Using predictive maintenance models, maritime operators efficiently schedule maintenance work in advance, minimizing downtime and preventing costly repairs [121], [122].
- Machine learning can also improve spare parts management by predicting the possibility that particular components will need to be replaced. This helps ensure that essential components are readily available whenever required [120], [121].

#### *2) Route Optimization*

- Machine learning models can use historical data on shipping routes, weather, sea currents, and traffic trends to optimize vessel routing and scheduling [123].

- Using the information gathered in real-time by sensors and satellite photographs, dynamic changes to routes can be made to avoid severe weather or roads already in use [124].
- Route optimization reduces fuel use and travel time and enhances safety by avoiding regions prone to piracy or other dangers [124], [125].

### 3) Port Operations Optimization

- Machine learning-powered analytics can enhance port operations by enabling the prediction of vessel arrivals, the estimation of berthing times, and the streamlining of cargo processing procedures.
- Machine learning models can potentially enhance berth allocation, crane scheduling, and container handling by analyzing data obtained from IoT devices such as RFID tags and sensors.
- Predictive analytics can increase total port throughput and decrease vessel wait times. This can help port authorities anticipate congestion and facilitate more efficient resource management.

### 4) Cargo Forecasting and Demand Prediction

- To estimate the demand for particular types of cargo and places, machine learning algorithms can use historical shipping data, economic considerations, and market trends.
- Improved cargo allocation, elimination of empty container transfers, and reduction of stockouts are all possible outcomes for marine businesses that can accurately foresee variations in demand.
- To provide more accurate demand forecasting, more advanced machine learning algorithms, such as deep learning, may be utilized to analyze unstructured data sources such as satellite images, social media, and news articles.

### 5) Environmental Impact Reduction

- Machine learning approaches can assist maritime firms in reducing their harmful environmental impact by optimizing fuel usage, emissions, and waste handling processes.
- Machine learning algorithms can analyze data on vessel performance, engine efficiency, and fuel usage patterns to identify potential fuel savings and emissions reductions.
- Machine learning-powered optimization algorithms can recommend environmentally friendly route options, alternative propulsion systems, and sustainable behaviors to reduce harmful environmental effects while preserving operating efficiency.

### 6) Enhanced Safety and Risk Aversion

- With the help of machine learning algorithms, marine data may be analyzed to determine potential safety dangers, security threats, and operational risks.
- By incorporating information from various sources, including the Automatic Identification System (AIS), weather forecasts, and nautical charts, machine learning models can provide real-time risk assessments and make recommendations regarding necessary preventative measures.

- Anomaly detection that is enabled by machine learning may recognize deviations from typical operating conditions, such as unusual vessel behavior or equipment faults. This allows prompt action to avert accidents or environmental incidents from occurring.
- Finally, the incorporation of machine learning into maritime logistics operations has the potential to dramatically improve efficiency, safety, and sustainability compared to traditional methods. Suppose marine firms can leverage the potential of data analytics and predictive modeling. In that case, they may be able to optimize their operations, reduce their costs, and better manage risks in the increasingly complex and competitive global shipping industry.

## D. Machine Learning

### 1) Tweedie Regression

In machine learning (ML), the term "Tweedie regression" refers to using regression techniques to model data with a Tweedie distribution characteristic. In machine learning, Tweedie regression is a technique that has proven to be wildly successful in dealing with data that contains excess zeros, skewness, and heteroscedasticity. These characteristics are frequently encountered in a wide range of engineering applications. In machine learning, Tweedie regression is an attempt to develop a predictive model that can forecast the conditional mean of the response variable based on the predictor variables. This model must consider the specific properties of the Tweedie distribution, such as the connection between the mean and the variance and the presence of excess zeros. In the field of machine learning, Tweedie regression is often performed through the utilization of algorithms and techniques that are comparable to those utilized in standard regression modeling. These methodologies and algorithms include linear regression, generalized linear models (GLMs), or Tweedie regression-specific algorithms mainly built for this purpose. The mathematical expression for Tweedie regression is as follows:

Let  $Y$  be the response variable, and  $X$  be a matrix of predictor variables.

Two parameters define the Tweedie distribution. The mean-variance power parameter,  $p$ , ranges from 1 to 2.

The dispersion parameter,  $\phi$ , is a positive constant. In Tweedie regression, using a logarithmic function, the response variable's conditional mean ( $\mu$ ) is linked to the predictor variables ( $X$ ). Therefore, we have:

$$g(\mu) = X\beta \quad (1)$$

herein,  $g(\cdot)$  denotes the link function while a beta represents the vector of coefficient regression.

The link between conditional variance  $\sigma^2$  of output variable and its mean  $\mu$  employing the Tweedie variance function as:

$$Var(Y) = \phi \cdot E(Y)^{p-1} \quad (2)$$

Combining the formulae for the dependent mean and variance yields:

$$E(Y) = g^{-1} \cdot (X\beta) \quad (3)$$

$$Var(Y) = \phi \cdot [E(Y)]^{p-1} \quad (4)$$



The likelihood function for Tweedie regression is then built using the probability density function (pdf) for the Tweedie distribution, which can be represented as:

$$f(y; \mu, \phi, p) = \frac{1}{\phi \cdot B\left(\frac{2-p}{p}, 1-\frac{p}{2}\right)} \cdot \exp\left(\frac{y \cdot \mu^{1-p}}{\phi(1-p)}\right) \cdot \left(\frac{y}{\mu}\right)^{\frac{1-p}{p}} \quad (5)$$

The parameters  $\beta$  and  $\phi$  are calculated by maximizing the likelihood function using numerical optimization techniques like maximum likelihood estimation (MLE). After estimating the parameters, use statistical inference on regression coefficients to evaluate predictor variables and generate predictions for future data.

The ML method to Tweedie regression consists of the following steps:

- **Data Preprocessing:** Prepare the dataset by addressing missing values, encoding categorical variables, and scaling features as needed.
- **Model Selection:** Select a regression algorithm or approach suited for Tweedie regression. This might include GLMs with Tweedie distributions, as the Tweedie GLM in R or the TweedieRegressor in Python's scikit-learn module.
- **Model Training:** Apply the selected model to the training data, calculating the parameters that best represent the connection between the predictor variables and the response variable.
- **Model Evaluation:** Assess the trained model's performance using appropriate metrics, such as mean squared error (MSE), mean absolute error (MAE), or others relevant to the application.
- **Model Interpretation:** Analyze the model coefficients to determine the relevance of predictor factors in forecasting the response variable.
- **Prediction:** Using the trained model, make predictions on incoming data by estimating the conditional mean of the outcome variable according to the predictor variables.

Tweedie regression in machine learning is often performed using algorithms and approaches comparable to those used in standard regression modelling, such as linear regression, generalized linear models (GLMs), or customized algorithms created expressly for Tweedie regression.

## 2) Random Forest

The Random Forest Regressor (RFR) is a sophisticated machine-learning method commonly used for regression problems. It is flexible, durable, and has high prediction accuracy. It is part of the ensemble learning family, which involves training many decision trees individually and then aggregating their predictions to create final predictions.

Let's denote our training dataset as

$$D = \{(x_1, y_1), (x_2, y_2), \dots, \dots, \dots, \llbracket(x) \rrbracket_n, y_n(n)\} \quad (6)$$

Herein  $x_i$  represents the feature vector for the data point  $i_{th}$  and  $y_i$  represents the corresponding target variable. Regression involves a continuous numerical number

The Random Forest Regressor works by building numerous decision trees, each trained on a random part of the training data and employing a random subset of characteristics at each node split. The randomization included into the training

process helps to decorrelate individual trees and decrease overfitting, resulting in more robust and generalizable models. The forecasts of separate decision trees are then combined to form the final prediction. In regression, this aggregation often includes taking the average of each tree's predictions:

$$\hat{y} = \frac{1}{n} \cdot \sum_{i=1}^N y_i \quad (7)$$

Where  $\hat{y}$  is the anticipated target variable and  $N$  is the number of decision trees in the random forest. One of the most significant advantages of Random Forest Regressor is its capacity to handle big datasets with high-dimensional feature spaces without requiring considerable preprocessing or feature selection. Furthermore, it is less sensitive to outliers and noise than other regression methods, making it suited for a variety of real-world applications.

The hyperparameters of the Random Forest Regressor, such as the number of trees (`n_estimators`), the maximum depth of each tree (`max_depth`), and the number of features considered for each split (`max_features`), can be tuned to optimize model performance using techniques such as grid search or randomized search. Overall, Random Forest Regressor is a useful and effective tool for regression problems, providing a good combination of predictive effectiveness and computational economy.

## 3) ML-based models evaluation criteria

Statistical tests were used to validate the Tweedie Regression and RFR models, including coefficient of determination ( $r^2$ ), reduced chi-square ( $\chi^2$ ), root mean square error (RMSE), and average absolute relative deviation (AARD). The typically utilized parameters were computed.

$$\chi^2 = \frac{\sum_{i=1}^N (x_{exp,i} - x_{pre,i})}{N-n} \quad (8)$$

$$RMSE = \frac{1}{N} \cdot \left[ \sum_{i=1}^N (x_{pre,i} - x_{exp,i})^2 \right]^{0.5} \quad (9)$$

$$AARD = \frac{1}{N} \cdot \sum_{i=1}^N \left| \frac{(x_{exp,i} - x_{pre,i})}{x_{exp,i}} \right| \quad (10)$$

## E. A case study

A case study was conducted to show the applicability of ML in this domain. It is a typical case in which the fuel consumption of a test logistic ship was conducted. Using both Diesel Oil (DO) and Low-Fuel Oil (LFO) in the same trip, often known as fuel swapping or mixing, serves several operational and regulatory objectives for ships. This strategy enables boats to comply with environmental rules, especially in locations or routes where emissions control areas (ECAs) require the use of low-sulfur fuels such as LFO to fulfill severe sulfur oxide (SOx) emissions limits. By switching to DO while entering certain designated zones and utilizing LFO for the remainder of the journey, ships may assure regulatory compliance while minimizing fuel expenditures, as LFO is often less expensive than DO due to its reduced sulfur content. Furthermore, converting between fuel types is beneficial for vessels equipped with engines that can run on several fuels, providing flexibility in fuel choices based on considerations such as availability, cost, and emissions standards. Furthermore, using fuel switching tactics, ships can minimize SOx, nitrogen oxides (NOx), and particulate matter emissions, contributing to environmental sustainability, especially in

vulnerable coastal areas or heavily inhabited regions. Combining DO and LFO on the same voyage allows ship operators to manage the complicated world of regulatory compliance, financial efficiency, and environmental responsibility while maximizing fuel use and reducing emissions. In the present study, a novel approach to using their ratio in the form of L/D was investigated for modeling. The comprehensive dataset from the ship register for 100 trips was employed in this study.

### III. RESULTS AND DISCUSSION

As mentioned in the previous section, data regarding the distance travelled and time taken in each trip were collected from the ship's register, and the fuel switching ratio between diesel and low-sulfur fuel was calculated from fuel

consumption data. This data was employed to develop a machine learning model.

#### A. Data analysis and correlation heatmap

The data was employed to plot the correlation heatmap as depicted in Fig. 4a. The correlation values are listed in Table II. It was observed that there is some redundancy in feature selection since the correlation values are almost similar in the case of low sulfur oil (LSO) fuel and D/L ratio. At the same time, the correlation values of diesel were not significant. Hence, the feature selection was conducted using correlational data, the diesel and LSO were removed, and only the D/L ratio was kept in the next stage. A new correlation heatmap diagram was plotted to keep the worthiest features in model development. The updated correlation heatmap is shown in Fig. 4b, and updated correlation coefficient values are listed in Table III.

TABLE II  
CORRELATION VALUES

	Distance, nm	Travel duration, Hours	Diesel, Gallons	Low Sulfur Fuel, Gallons	L/D ratio
Distance, nm	1	0.9667	-0.1879	0.8858	0.2239
Travel duration, Hours	0.966779	1	-0.1768	0.909847	0.2877
Diesel, Gallons	-0.18785	-0.1768	1	0.0445	-0.3914
Low Sulfur Fuel, Gallons	0.885867	0.9098	0.0446	1	0.0862
D/L ratio	0.223862	0.28774	-0.3914	0.0862	1

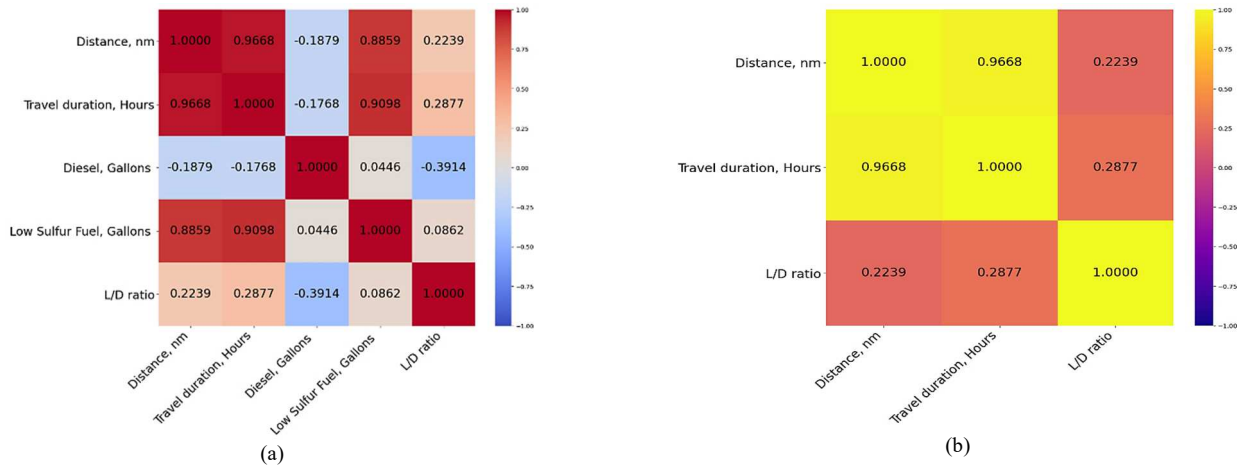


Fig. 4 Correlation heatmap for (a) all features; (b) most important features.

TABLE III  
CORRELATION VALUES BETWEEN THE MOST IMPORTANT FEATURES

	Distance, nm	Travel duration, Hours	L/D ratio
Distance, nm	1	0.9668	0.2239
Travel duration, Hours	0.9668	1	0.2877
D/L ratio	0.2239	0.2877	1

#### B. Model Development and Testing

The third part of the research focused on creating predictive models specially tailored to anticipate the Low Sulfur Oil (L/D) to Diesel Oil (DO) ratio. This challenge was handled using two sophisticated ML techniques: Random Forest Regressor (RFR) and Tweedie Regressor. These approaches were chosen because of their resilience and capacity to handle complicated, nonlinear data patterns, making them perfect for modeling the intricate interaction between marine fuels. The

dataset used for this purpose is carefully partitioned employing a random split, with 70% put aside for model training and the remaining 30% retained for testing. This split technique guaranteed that the models were trained on a sizable amount of data, helping them to understand the underlying patterns and correlations efficiently. Meanwhile, the test set allowed for objectively evaluating the models' performance on previously unstudied data, essential to determining their generalizability and predictability.

Once trained, the models were applied to the whole test dataset to predict the L/D ratio. This stage was essential because it allowed the researchers to assess the models' ability to make accurate predictions across an extensive range of data points, imitating real-world settings where the ratio of low-sulfur oil to diesel oil varies dramatically. Using these powerful machine learning algorithms, the study aims to develop a dependable tool for estimating fuel ratios, which is critical for managing fuel usage and conforming to

environmental standards in marine operations. It can be observed that the RF-based model performed superior to the

Tweedie-based model both in the case of training as well as testing, as depicted in Fig. 5.

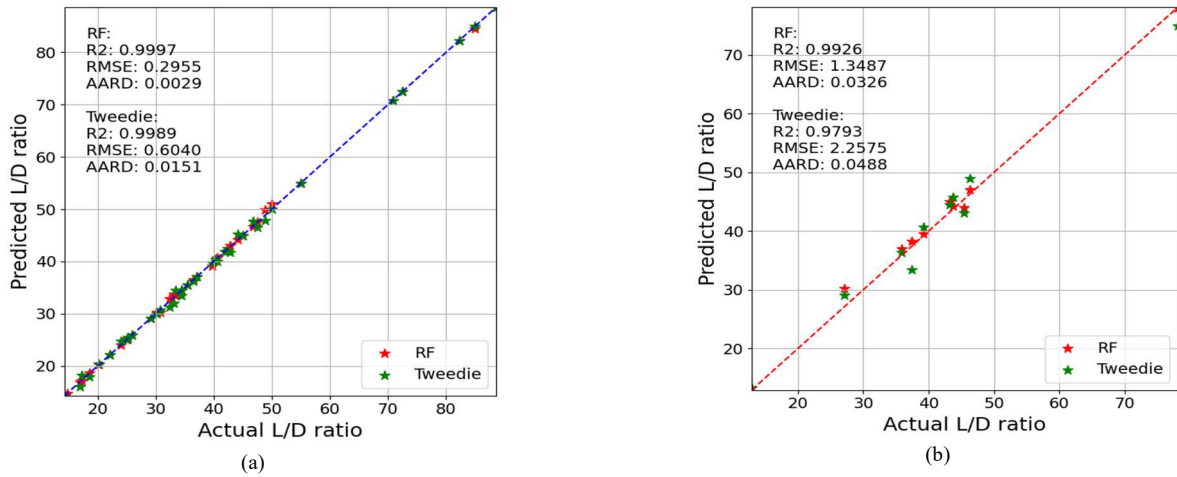


Fig. 5 Model prediction results during model (a) Training; (b) Testing

### C. Statistical Evaluation

The statistical assessment findings in the table compare the performance metrics of two distinct models, Random Forest and Tweedie, in forecasting ship fuel consumption. These models were assessed using training and testing datasets and outcomes listed in Table IV. The Random Forest model's coefficient of determination ( $R^2$ ) for the training dataset is 0.9997, suggesting that the model fits the data almost perfectly. Similarly, the  $R^2$  score for the testing dataset is strong but somewhat lower at 0.9926, indicating that the model generalizes well to new data.

The Random Forest model has a root mean square error (RMSE) of 0.2955 on the training dataset, indicating that the model's predictions differ by just 0.2955 units from the actual values in the training data. However, the RMSE rises to 1.3487 on the testing data, demonstrating significantly larger prediction errors on unknown data than on the training data. The Random Forest model's average absolute relative deviation (AARD) is astonishingly low, at 0.0029 for the training dataset and somewhat higher at 0.0326 for the testing dataset. This measure represents the average relative difference between the model's predictions and the actual values, with smaller values indicating higher predictive accuracy.

Moving on to the Tweedie model, the  $R^2$  value for the training dataset is 0.9989, indicating that the model fits the data well but somewhat less so than the Random Forest model. Similarly, the testing dataset has an  $R^2$  value of 0.9793, showing high generalization performance. The Tweedie model has an RMSE of 0.604 on the training dataset and 2.2575 on the testing dataset. This rise in RMSE between training and testing datasets implies that the Tweedie model somewhat overfits the training data, resulting in more significant prediction errors on unknown data. Finally, the Tweedie model has an AARD of 0.0151 for the training dataset and 0.0488 for the testing dataset. These numbers represent the model's average relative deviation from fundamental values, with larger values indicating worse predictive accuracy than the Random Forest model. In summary, both models perform well on the training dataset,

with the Random Forest model marginally outperforming  $R^2$  and AARD. However, the Random Forest model outperforms the Tweedie model on the testing dataset, as indicated by lower RMSE and AARD values.

TABLE IV  
STATISTICAL EVALUATION OF DEVELOPED MODELS

		Training	Testing
Random forest	$R^2$	0.9997	0.9926
	RMSE	0.2955	1.3487
	AARD	0.0029	0.0326
Tweedie	$R^2$	0.9989	0.9793
	RMSE	0.604	2.2575
	AARD	0.0151	0.0488

### D. Comparison with Taylor's diagram

The comparison with Taylor's diagram visually depicts the statistical assessment findings produced from the Random Forest and Tweedie models for predicting ship fuel consumption. As depicted in Fig. 6, Taylor's diagram provides insights into the link between the standard deviation ratio and the correlation coefficient, which aids in determining the models' prediction performance and dependability. Beginning with the Random Forest model, the Taylor diagram shows a significant connection between anticipated and actual fuel consumption figures, as indicated by the data points near alignment around the reference circle. The comparatively low standard deviation ratio and strong correlation coefficient show that the model correctly captures the variability in the data and makes consistent predictions. This is consistent with the high  $R^2$  and low RMSE values reported from the statistical assessment, demonstrating a solid fit of the Random Forest model to training and testing datasets.

On the other hand, the Tweedie model's Taylor diagram shows a somewhat more excellent dispersion of data points than the Random Forest model, indicating that the predictions are slightly more variable. While the correlation between anticipated and actual values remains outstanding, the increased standard deviation ratio suggests that the model's predictions are significantly less precise. This is consistent with the statistical evaluation's lower  $R^2$  and higher RMSE

values, showing that the model fits the training dataset well but performs somewhat worse on the testing dataset.

Overall, Taylor's diagram enhances the statistical evaluation findings by giving a graphical picture of the

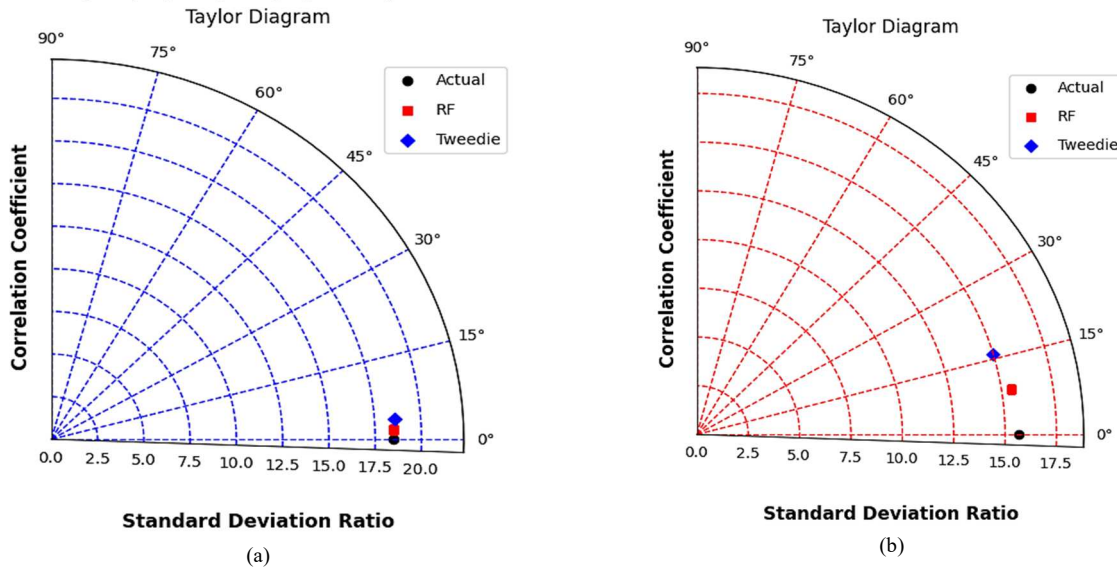


Fig. 6 Taylor's diagram for model comparison during model (a) Training; (b) Testing

### E. Challenges, Opportunities, and Future Directions

#### 1) Regulatory considerations and safety concerns

To successfully incorporate machine learning (ML) technology into maritime transportation operations, it is necessary to consider regulatory and safety problems seriously. To ensure that marine boats continue to operate in a safe and compliant manner, it is essential to address the legal frameworks and safety concerns associated with using machine learning algorithms. These algorithms are increasingly utilized for predictive maintenance, route optimization, and autonomous vessel navigation. Here is a rundown of the factors to consider:

International, regional, and national maritime bodies oversee the complex regulatory system that controls marine transportation. This framework is responsible for ensuring compliance with regulations. Machine learning applications must adhere to the most recent norms, regulations, and recommendations to guarantee legal compliance and operational safety. This includes laws that regulate vessel design, equipment requirements, personnel qualifications, navigation rules, environmental protection, and other topics. To ensure that machine learning algorithms are in compliance with regulations and certified for use in maritime applications, maritime stakeholders and machine learning developers must collaborate.

**Data privacy and security:** The algorithms that power machine learning heavily depend on the vast amounts of data gathered from sensors, cameras, and other sources located onboard boats. Guaranteeing the privacy and security of data is essential to preserve sensitive information and prevent unauthorized access or utilization. Compliance with data protection regulations, such as the General Data Protection Regulation (GDPR), is paramount. This requires the implementation of robust data encryption, access limitations,

models' prediction performance. It emphasizes the Random Forest model's higher accuracy and dependability in estimating ship fuel usage over the Tweedie model, validating the statistical assessment results.

data anonymization techniques, and secure data transit protocols.

Safety assurance is the highest priority in the marine transportation industry. Machine learning applications must go through stringent safety assessments and validation processes to ensure that they do not put the safety of the vessel, its crew, passengers, or the environment in jeopardy under any circumstances. Among these are testing machine learning algorithms in various operational settings, modeling real-world scenarios, and evaluating their reliability, precision, and resistance to errors or anomalies. Safety-critical systems must comply with stringent safety regulations, such as those outlined in the criteria established by the International Maritime Organization (IMO) for the operation of autonomous ships.

**Man-Machine Interaction:** Automation and autonomy allowed by machine learning bring new dynamics to the interaction between humans and machines onboard ships. Crew members need to be adequately educated to grasp machine learning systems, examine the outputs of those systems, and intervene as required. To facilitate smooth communication and collaboration between people and machine learning algorithms, efficient human-machine interfaces (HMIs) must be created. This will enable crew members to monitor, regulate, and override automated activities as necessary.

Some ethical considerations include that machine learning algorithms might unintentionally propagate biases, discrimination, or unfair practices if they are not created and controlled appropriately. Ethical considerations need to be taken into account while developing and using machine learning technologies in the maritime transportation sector to guarantee fairness, transparency, and accountability. To accomplish this, algorithmic biases must be eliminated, diversity and inclusion in data collection guaranteed, and

mechanisms for algorithmic responsibility and explanation established.

In conclusion, addressing issues regarding safety and regulations is essential for the appropriate application of machine learning in maritime transportation. To build robust frameworks, standards, and best practices that support the safe, efficient, and ethical use of machine learning technologies in naval operations, machine learning developers, stakeholders in the marine sector, regulatory organizations, and safety authorities must collaborate.

### 2) *Integration challenges with existing infrastructure*

Machine learning in marine transport has significant integration challenges with the present infrastructure that must be addressed to realize AI's promise fully. Data Integration: Integrating machine learning algorithms with data infrastructure is complex. Marine transportation operations generate vast amounts of data from sensors, IoT devices, marine databases, and legacy systems [126], [127]. Combining this data into a framework machine learning algorithms can understand is difficult. Siloed, unstructured, or incompatible data requires extensive preparation and purification [128], [129].

Legacy Systems Compatibility: Marine transport companies use legacy systems and software. These technologies may not work with modern machine learning systems, making AI integration challenging. Retrofitting obsolete systems with machine learning while retaining compatibility and data integrity is tough. Machine learning models in marine transport applications often require real-time data processing to improve decision-making [127], [130]. However, existing infrastructure may struggle to handle real-time data streams' volume, velocity, and variety. Implementing scalable, low-latency data processing pipelines for real-time data intake, preprocessing, and model inference is crucial yet complex.

Integrating machine learning algorithms with existing infrastructure poses cybersecurity risks, especially in the maritime sector, where vessels are increasingly connected to digital networks. Protecting sensitive data, networks, and communication channels against malware, ransomware, and unauthorized access is crucial. Maintaining data privacy, confidentiality, and integrity while maintaining operational continuity is difficult.

The marine sector must follow strict safety, security, and environmental regulations. Implementing machine learning technology in infrastructure must comply with IMO, SOLAS, and classification society regulations. Legal and compliance knowledge is needed to use AI technology successfully and comply with regulations. Integrating machine learning systems into maritime operations requires consideration of human-machine interaction. Crew, shore-based workers, and stakeholders must use AI-powered tools, dashboards, and interfaces. User acceptance, training, and change management help integrate and use machine learning technologies. The marine industry, technology vendors, regulatory agencies, and cybersecurity experts must work together to solve these integration issues. Developing robust data integration techniques, upgrading aging systems, enhancing cybersecurity, and fostering an inventive and

digital transformation culture are essential to successfully using machine learning in marine transportation.

### 3) *Future trends and recommendations for sustainable AI adoption*

Future trends and recommendations for sustainable AI adoption in marine transport machine learning relate to efficiency, environmental impact, and safety. AI in Vessel Operations: As AI technologies advance, vessel operations will incorporate more AI-driven solutions. Machine learning algorithms optimize route planning, speed management, and fuel usage, lowering emissions and operational costs. Weather, traffic density, and fuel efficiency may be used to recommend routes, making sea travel more sustainable. Real-time vessel performance monitoring and machinery and equipment anomaly detection by AI-powered predictive maintenance solutions can change fleet management. Machine learning models may anticipate problems and plan maintenance using past data and sensor readings, lowering downtime, operational efficiency, accidents, and environmental issues.

Advanced navigation aids, collision avoidance systems, and risk assessment tools from AI-based systems can improve sea transport safety. Deep learning algorithms trained on massive maritime data can increase ship captains' situational awareness and offer early warning warnings for possible risks, minimizing accidents and improving crew, passenger, and cargo safety. Sustainable AI adoption uses machine learning for environmental monitoring and regulatory compliance. AI algorithms can evaluate satellite pictures, sensor data, and oceanographic data to assess ecological consequences, monitor pollution, and comply with IMO's MARPOL emissions restrictions. AI technology can assist marine operations in reducing their environmental impact and shift to cleaner, more sustainable shipping practices by promoting proactive ecological stewardship.

Continued research and development are needed to maximize AI's potential in marine transport. Collaboration between academics, industry players, and government agencies can advance maritime-specific AI technology. This involves developing specialized machine learning models, data-driven decision support tools, and autonomous shipping solutions to improve marine supply chain efficiency, safety, and sustainability. Finally, sustainable AI adoption in machine learning for marine transport offers viable solutions to maritime sector difficulties while encouraging environmental responsibility and operational excellence. By adopting AI-driven technologies and data-driven decision-making best practices, stakeholders may improve marine operations' efficiency, safety, and sustainability.

## IV. CONCLUSIONS

This article explores the rapidly growing topic of Artificial Intelligence (AI) and Machine Learning (ML) applications in maritime and marine environmental management. As the marine sector faces more complex difficulties in terms of sustainability, efficiency, and regulatory compliance, there is a rising interest in using sophisticated AI and machine learning approaches to solve these concerns successfully.



- This article, based on a comprehensive literature review and case study analysis, provides insights into the many uses of AI and ML in maritime and marine settings.
- Particular emphasis is placed on modeling ship fuel consumption, an essential component of vessel operation with significant consequences for environmental impact and operating expenses.
- The study shows that ML approaches, such as Random Forest and Tweedie models, effectively forecast ship fuel usage trends.
- The statistical examination of the created models reveals notable performance measures, with the Random Forest model outperforming the Tweedie model in accuracy and consistency.
- Specifically, the Random Forest model gets excellent R<sup>2</sup> values of 0.9997 and 0.9926 for the training and testing datasets, respectively, demonstrating a good match with the data.
- Furthermore, the model has low RMSE and AARD, indicating its ability to capture fuel consumption fluctuations properly.
- In comparison, while still performing well, the Tweedie model has somewhat lower R<sup>2</sup> values and higher RMSE and AARD values, indicating a lower level of accuracy and precision in forecasting fuel consumption patterns.

These findings provide important insights into applying AI and machine learning techniques in maritime and marine environmental management. By leveraging sophisticated analytics, decision-makers may get more visibility into fuel consumption patterns, maximize operational efficiency, and reduce environmental impact, eventually furthering the marine industry's sustainability goal.

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