Machine Learning Methods for Marine Systems

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Abstract. Automation plays a key role in shipping industry and aims towards minimal operating staff. However, the effective automation relies on effective controlling at various levels starting from shipbuilding to navigation. The industry is currently focussing on autonomous shipping which actually requires precise controlling. Although many conventional methods are available for control and automation with regard to automation, Artificial Intelligence Schemes (AIS) are widely attracting the maritime sector because of their benefits. The AIS along with fuzzy logic systems are offering promising results. The emerging use of AIS in a variety of maritime applications can act as a reference wpont for new researchers. This paper aims to conduct a valid AIS study and to examine the various machine learning approaches used in various maritime applications. It is possible to achieve complete automation in the shipping industry by implementing a related technique.

Keywords: Automation, autonomous shipping, artificial intelligence, machine learning

1. Introduction

Presently the digital transformation is one of the inevitable happening in anybody’s life and this is quite true after the covid-19 pandemic. While everyone directly or indirectly undergo this digital transformation, a valid and promising technology is needed to accomplish the same. Artificial intelligence systems are one such technique and it applies to almost every industry at a faster rate. Various gadgets and elements incorporate the AIS features in our routine life. These schemes possess altered characteristics based on the device, which adds them or based on a particular application. The approaches and procedures that are followed in seafaring sector are unique and to apply the AIS technology, the distinctiveness of the industry must be appropriately accounted. The scale of the dataset, its authenticity, and the use of recurring key incidents all play a significant role in the success of AIS. This is especially true in the traditional shipping industry, where the transition to full automation is regarded as critical. As a result, a survey was carried out in the most commonly used applications of the maritime industry. The aim of this research is to identify the best area for using AIS and then scale it up to allow full automation. Artificial intelligence can be realized in this field in several facets [1-5].

Machine learning is a subset of artificial intelligence and is a probable way to accomplish AI. Machine learning is capable of dealing with minor to major datasets by means of inspecting and associating the data to get mutual arrays and learn the details. Artificial intelligence is a technology where computers/machines can be trained through a relevant learning algorithm to mimic human brain viz. recognition, remembrance, application, etc. Shipping firms these days have understood that financing in quicker communication offers numerous benefits. Most vessels go forward to remote
workplaces at sea, which may offer consistent Internet access, simulated/virtual set-ups, e-mail, route organizers and many supplementary schemes and uses. It is now essential for the shipping firms to plan for long-term growth by investing in novel growing technologies to standardize the vessel operation, CTC reduction and business optimization plans. The shipping sector moves towards automation and AI assists in accomplishing the same [16].

Automated / Unmanned systems do not require rest, they effortlessly do repetitive works, and AI development will deliver work with unstable environments. AI is fundamental for automated systems and effectively replaces the manned systems. AI may perhaps an opportunity for modern shippers. Optimization of maritime operations is of prime importance especially in vessel precision operations. There are various means to precisely make ETA/ETD, perfecting container routing & re-routing, fuel saving, etc. by means of a number of geographical data. These data may accurately be processed using suitable machine learning algorithms [17].

This review was inspired by the promise and prospective of the shipping industry necessitating AIS, as well as the popularity of AIS in other areas. This technique uses data, as an instrument for learning from the bygone events and helps in enhancing the future decision-making. Enhanced metrics for strategy making, scheduling, stability, intelligent traffic, and operational productivity are just a few of the exceptional benefits of AI in the freight sector.

This paper is presented under the following headings: literature analysis, developments in maritime transport, AIS summary, Artificial Intelligence in marine applications, and conclusion. This paper highlights a few applications/case studies pertaining to AI in shipping industry.

2. Literature Review
The use of machine learning in the shipping industry is very constrained since it analyses vast volumes of data to construct a particular logic. Yet, latest scholars have attempted to apply machine-learning practices in data analysis. Various machine-learning techniques viz. neural networks, Bayesian networks and support vector machines are used to explain the problem of maritime anomaly detection. It is pointed out that the AI data has provided a better level of perception in case of anomaly detection [1]. An enhancement to an existing learning-based maritime field knowledge scheme for forecasting potential vessel position using the experience of current vessel behaviour is discussed, and it is shown that such schemes produce better performance [2]. The AI technique is applied for possible prediction of motion of vessel using learning weights [3]. EmmeiTu et al. [4] surveyed AIS data sources and utilized data for safety of seagoing personnel in the areas of traffic irregularity finding, route assessment, collision forecast and path scheduling. Another literature addressed the trick of determining waypoints of marine routes, using the streaming AIS data [5]. Andrea Coraddu et al. have utilized the machine learning approaches for naval propulsion plants [6]. The various sensors used for effective propulsion and for improving the maintenance based on the condition are aptly administered through predictive algorithms for economic reasons. Artificial intelligence in maritime sector is the current survey by many researchers [7]. Deep sea connectivity is one of the most difficult issues in the marine industry. Underwater Wireless Sensor Networks (UWSNs) have seen extensive use in marine and military applications in the recent past. However, in order to outspread the network's survivability in UWSN, effective and truthful fault tolerance mechanisms are essential. The Energy-efficient Fault Detection and Recovery Management approach is recommended by A.Pransanth for the UWSN with reasonably enhanced network efficiency. To achieve effective fault detection across the entire network, the Hidden Poisson Markov model has been introduced into the suggested method. The network simulator (NS 3.26) framework is employed to replicate the performance effects. According to the simulator performance the suggested model outshines the existing evidence [27].

3. Trends in Maritime Transport
Digitalization is the method of integrating digital devices into structures and procedures in order to upgrade or replace traditional devices with electronic devices. The term automation refers to processes and structures, which are mechanical or electronic machines that are routinely computerised to execute
specific tasks without human interference but are frequently supervised by humans. The system is considered to be autonomous if it has control tasks and can use various alternatives to solve a certain class of problems [8].

3.1. Degrees of Autonomy for Ships
There exist a variety of definitions of autonomy levels based on the transport used and perspectives for their own systems. The definition of autonomy levels for merchant ships is listed in Table 1. A degree of autonomy is assigned to the system relative to the amount of labour that must be performed by manned operators in conjunction with an automated system.

Lloyd's Register has printed a guide for design of autonomous ships [12]. The guide encompasses a classification of autonomy levels as given in Table 2. Remote monitoring and controlling is not accounted in this taxonomy, except as a choice for shore based decision support [12].

3.2. Infrastructure Operation for Ships
In maritime sector, the infrastructure and control of the vessel operations shift on the way to operation centres that are integrated and interconnected, like fleet service centres, support hubs for marine shipping traffic, etc. These central/integrated activities – maybe for a geologically limited zone like a harbour or for broader capacities like inland waterways – necessitate a technological framework that gives situational information to the controllers that decide things remotely. Such centralized/integrated controlling schemes progress within a broad framework using modern plans to incorporate automated patterns, operating practises, and conventions to ensure maritime vessel protection, effectiveness, and prediction [9].

Table 1. Degree of Autonomy for Ships [8]

| Level                  | Description                                                                 |
|------------------------|-----------------------------------------------------------------------------|
| Direct control         | Management of the ship is exercised directly by the crew on the bridge; no decision assistance is provided. |
| Decision support       | On the bridge, decision support and guidance are given to the crew. The crew makes the final decision.        |
| Automatic bridge       | The operation is automated, but the crew is constantly monitoring it.         |
| Periodically unmanned  | Shore is constantly monitoring the situation. If required, send in reinforcements. |
| Remote control         | Unmanned, constant surveillance, & command and control from land.             |
| Automatic              | Unmanned and under automated supervision, with monitoring from shore.         |
| Constrained autonomous | Unmanned, semi-autonomous, and constantly supervised from shore.              |
| Fully autonomous       | It is unmanned and unsupervised.                                             |

Table 2. Classification of Autonomy Levels [12]
3.3. Infrastructure Operation for Ships
In maritime sector, the infrastructure and control of the vessel operations shift on the way to operation centres that are integrated and interconnected, like fleet service centres, support hubs for marine shipping traffic, etc. These central/integrated activities – maybe for a geologically limited zone like a harbour or for broader capacities like inland waterways – necessitate a technological framework that gives situational information to the controllers that decide things remotely. Such centralized/integrated controlling schemes progress within a broad framework using modern plans to incorporate automated patterns, operating practises, and conventions to ensure maritime vessel protection, effectiveness, and prediction [9].

3.4. Predictive Maintenance of Vehicles
A significant percentage of servicing tasks in marine shipping could be conducted by personnel who are no longer stationed on-board the vessel, but rather in centrally facilitated support centres. Safety checks, such as software upgrades, may be performed remotely from those centres or through highly trained teams stationed in support sites worldwide and sent to the location where maintenance service is requested. Recent advancements in sensor expertise plus genuine networking help to accomplish the same and permit to observe the condition of apparatus on-board vehicles keenly [10]. Future prognostic maintenance schemes will gradually use an extensive collection of large data points. This knowledge is collected not just from vessels and facilities, but rather from peripheral operational configurations that have an effect upon this particular container such as freight, tides, landscape, and climatic parameters along voyages. Predictions can indeed be improved by creating a visual replica of the vessels and their structures (a "digital twin") [11].

3.5. Automation of Vessels
Fresh and creative forms of robotics and automation can support ship crews, spanning from adaptive vehicle tasks, such as watch keeping, velocity monitoring, and propellant usage to automated driving operation, even without manual assistance. Regulation of vessel activities and facilities is moving toward cohesive and integrated operation centres, such as fleet activity and traffic management hubs for sea vehicles. Independent ships are expected to work in restricted trading areas and parts (Inland Rivers, territorial waters, including surrounding countries). Integrated operation centres will offer increased support and control, with experts moving from ship to shore [16].

For more than a decade, the development of digital, and automation have affected work in the navigational and motor departments of on-board ships, for instance, unmonitored engine areas and maritime “autopilots”. The next technological leap would be to reduce the number of crew members...
on board to provide remote assistance. Experts at shore-based service centres will perform more operations [14].

3.6. User Interfaces
Custom-made services are possible with the help of intelligent interfaces. These interfaces utilize the data mining approaches possibly by means of artificial intelligence. In some cases, robots may be offering the required services to the customers either by digital mode or else physically. The maintenance and repairing jobs on-board vessels may be carried out with the combination of humans and robots. Aerial and subaquatic drones may be employed to examine the parts of the ship that are not reachable or unsafe to reach. The experts may carefully observe the compound engines and other equipment inside the vessel from a distant location (shore). On-request maintenance greatly reduces the transport schedule of the vessel.

4. Overview of Artificial Intelligence
Machine training is a tier of algorithm that enables code algorithms to generate more reliable performance predictions instead of being physically coded. As all marine transports entail smart technology, implementing machine-learning tools can have the greatest benefit in terms of performance, resilience, and cost-cutting. Data is perhaps the major aspect of AI that will help to unlock the inconsistency and accelerate shipping. Currently, data collection on maritime transport is minimal. As a result, deployment of machine learning methods in sea industry is hampered in comparison to other industries. However, the use of machine learning in the maritime field is needed for autonomous shipping or ship automation [14].

Meanwhile, machine learning is a method of computer programming that uses vast quantities of data to boost output criterion [17]. According to the essence of training, it can be divided into 3 main classes. In this scenario, the reader should use the flow diagram below for applications of automated learning. There are 3 types of device training techniques: supervised learning, unsupervised learning, and reinforcement learning. Figure 1 depicts the flow diagram of a machine learning programme.

Figure 1. Flow Diagram of a Machine Learning Programme.

4.1. Supervised Learning
Supervised learning involves inputs, and the majority of machine learning approaches involve supervised learnings. The elementary description of methods can indeed be specified as input parameters \((x)\) and target parameters \((y)\) calculating an algorithm to know the function from input to output, as seen in formula below:

\[
y = f(x)
\]

The meaning is that for a set of input parameters \(x\), the target \(y\) can be found. This type can further be divided as (a) regression and (b) classification problems. In (a), the necessary target parameters are continuous. The above learning method is primarily used to achieve point predictions of target variables for given input data. The latter method, on the other hand, necessitates clustering/clumping of target values in a known source database. The widely used methods of supervised learning algorithms include random-forest for classification and regression problems, linear-regressions,
support-vector-machines for classification problems, and artificial neural networks for regression problems. Figure 2 displays the fundamental components of Artificial Neural Network (ANN).

![Elements of ANN](image)

**Figure 2.** Elements of ANN.

4.2. Unsupervised Learning

This scheme is applicable only when the input data is present. In this situation, none of output variables will be in hand. Unsupervised learning assists in modelling the main structure or allocating the input parameter to boost input learning. In the meanwhile, there is no true response or fix to this sort of problem, because there is no supervision. As a result, it is regarded as unsupervised learning [17]. The machine uses its own algorithm to evaluate and familiarise itself with the original structure in the data in this process. It can also be separated into clustering as well as association problems. The first method can identify inherent classes in data, while the next one is a rule learning problem in which the user is eager to decide distinguishing rules for a larger sample size. The prevalent methods of unsupervised learning rules are k-means for clustering and apriori algorithm for associations rule. One such example for k-clustering is presented in Figure 3.

![Unsupervised Learning with K-means](image)

**Figure 3.** Unsupervised Learning with K-means.

4.3. Reinforcement Learning

This approach is hardly seen in machine learning algorithms since it incorporates known actions to optimise reward in a given situation. While it is similar to supervised learning, there are significant
variations, such as the data collection for instruction and the sequence of contingent resolutions. This learning is a subset of artificial intelligence in which an agent chooses which action to take depending on its current state. Q-learning, which employs the bellman equation, and strategy repetition are the two common types [18]. Figure 4 portrays the reinforcement-learning algorithm.

Figure 4. Reinforced-Learning.

5. AI in Maritime Applications
The machine learning application can contribute to enhance shipping because data is one of the chief components in unravelling the uncertainty. It agrees to use savvy algorithms for data analysis and provides a pragmatic approach to maritime transportation problems. The use of such algorithms is profound mostly in the fields of maritime infrastructure scheduling, flight forecasting, ship planning processes, maintenance procedure, etc. The information/particulars of the marine applications facilitate to focus on proper algorithm. The pros and cons of AI in maritime industry is emphasized in Table 3.

Table 3. Pros and Cons of AI - Maritime Sector [15]

| Artificial Intelligence – Maritime Sector | Pros                                           | Cons                                         |
|------------------------------------------|-----------------------------------------------|----------------------------------------------|
|                                          | Cutting-edge Analytics                        | Reduced data-quality                         |
|                                          | Computerised Processes/Equipment              | Dearth of proper info                         |
|                                          | Safety/Value-added Security                   | Panic of occupation replacement              |
|                                          | Direction/path optimization                   | Absence of perfect approach                  |
|                                          | Performance guessing                          | Make over into trade is a lengthy course      |
|                                          | Cost cutbacks                                 |                                              |
|                                          | Boosting maintenance                          |                                              |

5.1. Autonomous Ships
Any automation starts with the replacement of conventional control by electronic/programmable controllers. Likewise, modern sensors and digital meters exchange the conventional meters. All these circuits are carefully connected through a network. Instead of writing coding that run through pages, a smart algorithm with machine learning technique may be adopted. Independent ships are not predictable ships minus crewmembers; rather, these are mostly a new category of vessel having fewer but highly qualified crewmembers who monitor a variety of organizational activities and services onboard, most likely through direct service stations. Self-directed vessels would not be likely to substitute standard freighters, potentially resulting in work losses for sailors. It is presumed that unmanned ships will be built as component of a constrained transportation infrastructure, creating new nautical routes as a replacement for other modes of transportation. While the daily fleet's "digitalization" accelerates, seafarers' roles will move further toward modern ones, especially in
operations testing and system management, and away from functional work. Practicing and preparation will be updated in order to provide seafarers with the requisite latest expertise. Many automated ship techniques can be projected as part of overall shipping, which may possibly eventuate over the near five years. Accordingly, the seafarers may be equipped for data fluency, data interpretation and analysis of huge data. They must be aware of and trained to operate the ships digitally.

5.2. Port Automation
Port operators are normally extra proactive in bringing automation as compared to shipping carriers with respect to the arrangement of autonomous ships. Nonetheless, shipping companies and port operators jointly trust that an integrated gateway may be built in a controlled region in one country, where it could be protected by the nation's national authority. In contrast, when it comes to programmed ships that traverse the waterways of several countries or travel at sea, all national laws and international treaties must be followed. The technology readiness level (TRL) is an indication of hi-tech maturity. Several market reports examine about port automation. In broad-spectrum, prevailing and future practices of computerization in ports will include levels of implementation, and technological maturity. The Artificial intelligence models are much useful in achieving the above.

5.3. Obstacle Prevention for Under-Actuated Unmanned Marine Vessels
The under-actuated unmanned marine vessel having indefinite dynamics of the environs is protected from obstacle using a deep reinforcement-learning algorithm. The foremost gain of the proposed algorithm is its brevity and extendibility; the usual analytic control rule is not essential for manoeuvring the vessel. The vessel takes actions based on the present observations, together with the detected results for obstacles, and the simple measurements of working states of the vessel by means of the proposed algorithm. Further, this architecture is extendible to other composite/intricate tasks [19].

5.4. Liner Shipping Route for Container Ships
Artificial Intelligence principle is useful in planning the best/ideal route to diminish the overall fuel prices. A cross-machine-learning technique that was first developed aids in the prediction of fuel usage for cargo vessels by learning the practical knowledge of an Asian fleet. The predictive results along with certain assumptions of a liner-shipping path initially utilized. It was joined with the asymmetrical travelling salesperson algorithm to create a prime route to curtail the fuel cost. Deep learning is a data-driven practise that is heavily reliant on the accuracy of the learning dataset [20].

5.5. Fault Detection for Ship Systems Operations
Innovative machine learning based expected behaviour modelling with relevant control charts are applied to ship systems for identifying the fault on system operations. The main objective of the study is to permit for anticipatory actions and scheduling, plummeting interruption and to increase the safety, energy competence and add-on routine watching of vessel progressions. The prompt finding of emerging errors will possibly lessen the suboptimal functions of the supervised system, protecting its energy efficient processes [21].

5.6. Ship Fuel Consumption on a Container Ship
Optimizing the fuel consumption of marine vessel will allow for greater productivity and cost-effectiveness in ship management, since fuel price covers majority of running cost. The estimation of vessel fuel usage is a difficult topic since the rate of fuel consumption is directly dependent upon multiple conditions, viz. the state of the primary engine, passenger load, ship draught, sea/ocean weather, meteorological conditions, and so on. Out of an analysis with many predictive models including Multiple-Linear-Regression, Ridge- and LASSO=Regression, Support-Vector-Regression, Tree-Based Algorithms, the Enhancement for a container ship is found to be promising with K-fold
cross-validation offering greater accuracy [22]. Another study helped to assess the fuel oil consumption in the main engine using multiple regression algorithms. The following restrictions were taken into account in this study: shipboard information techniques, mid-morning reports, and Automated Data Recording & Tracking schemes [23].

Various other studies on AI schemes include prediction of energy consumption ships in green port [24], Prognostic preservation for ballast pumps on ship-repairing yards [25] and ship collision prevention [26].

While AIS can be used in a variety of shipping applications, the most important application that may yield positive results is vessel location monitoring or detecting a certain vessel's sailing pattern. As a consequence, only the outcome of such an application is elaborated. The same is true for many other applications, depending on the scale of the dataset, the amount of learning and training results, and the data's validity. Table 4 compares vessel pattern tracking with the proposed approach with the other current technologies.

Table 4 Comparison of Vessel Pattern Tracking With Matching Pursuit-Fletcher Reeves (MPFR) [28]

| Author       | Title                                                                 | Reference | Interpretations |
|--------------|-----------------------------------------------------------------------|-----------|-----------------|
| Chen, Zet.al (2018) | Classification of vessel motion pattern in inland waterways based on Automatic identification System | [28]      | Objective: Creating reliable techniques for automated vessel movement pattern detection in sea routes. |
|              |                                                                      |           | Model Used: The Lp-minimization-based sparse representation classification (SRC) tool. |
|              |                                                                      |           | Process Created: Matching Pursuit - Fletcher Reeves (MPFR) |
|              |                                                                      |           | Datasets Employed: Wuhan-dataset (W) & Taizhou-dataset (T). |

**Other Details:** The Yangtze River sailing in relation to Wuhan and Taizhou Vessels is classified into five groups based on the pattern of their vessel motions. The relevant datasets are listed below.

| Class | Training Number | Test Number |
|-------|-----------------|-------------|
|       | Wuhan (W) | Taizhou (T) | Wuhan (W) | Taizhou (T) |
| C1    | 555        | 355        | 200       | 350        |
| C2    | 675        | 265        | 300       | 230        |
| C3    | 730        | 387        | 260       | 300        |
| C4    | 670        | 517        | 200       | 280        |
| C5    | 830        | 233        | 350       | 290        |

The obtained results are tabulated and compared to the existing approaches, which are mentioned below.

| Class | Support Vector Machine (%) | k-Nearest Neighbour (%) | SRC-L1 Norm (%) | SRC-L2 Norm (%) | SRC-Lp Norm (%) | MPFR (%) |
|-------|---------------------------|-------------------------|-----------------|-----------------|-----------------|-----------|
|       | W                         | T                       | W               | T               | W               | T         |
| C1    | 86.5                      | 85.7                    | 88.0            | 86.2            | 88.5            | 86.6      | 87.0       | 85.5       | 89.0       | 89.1       | 91.0       | 91.1       |
| C2    | 86.7                      | 81.7                    | 88.3            | 80.8            | 89.3            | 83.5      | 88.7       | 86.0       | 90.3       | 85.2       | 91.6       | 88.2       |
| C3    | 84.6                      | 83.7                    | 85.3            | 86.0            | 88.1            | 87.3      | 88.8       | 86.7       | 89.6       | 89.7       | 91.9       | 90.3       |
| C4    | 87.0                      | 82.1                    | 87.5            | 82.9            | 89.0            | 85.3      | 86.0       | 85.0       | 88.5       | 85.3       | 90.5       | 86.8       |
| C5    | 85.4                      | 86.2                    | 86.2            | 87.2            | 88.9            | 86.3      | 86.6       | 87.9       | 89.4       | 91.3       | 90.8       | 92.8       |
| Average | 86.0                    | 83.9                    | 87.1            | 84.6            | 88.8            | 86.8      | 87.4       | 86.2       | 89.3       | 88.1       | 91.2       | 89.8       |

**Inference:** It can be shown that the precision is determined by the type of dataset as well as the methodology used. On average, the proposed MPFR approach yields slightly higher results for both
the Wuhan and Taizhou datasets. This is true with all 5 classes. It also is worth noting that the average training numbers are higher in the Wuhan dataset than the Taizhou dataset, whereas the average test numbers are higher in the Taizhou dataset. It has been discovered that more training/learning fetches more reliable results.

Table 5 compares the results of vessel monitoring patterns produced by the Associative Learning (AL) and Predictive Associative Learning (PAL) methodologies.

| Author | Title | Reference | Interpretations |
|--------|-------|-----------|-----------------|
| 1. Bomberger, N et.al (2006) | 1. Associative Learning of Vessel Motion Patterns for Maritime Situation Awareness | [2] | Objectives: Use Associative learning (AL) to recognise the pattern of the Vessl motion [2]. |
| 2. Rhodes, B at.al (2007) | 2. Probabilistic associative learning of vessel motion patterns at multiple spatial scales for maritime situation awareness | [3] | To investigate the motion of a vessel using probabilistic associative learning (PAL) [3]. |

Other Details: A comparable research has been conducted in both of the preceding literatures by subtly changing the techniques. A standardised square grid is used to discretize vessel position based on vessel velocity over the region of interest surrounding the port of Miami. The zones are split into four westward and eastward zones based on grid positions. The predictions were based on d0 (direct hits/zero distance from predicted cell), d1 (near misses/one cell away from predicted cell), and d2 (two cells away from predicted cell). The output was evaluated using four metrics: recall, coverage, precision and accuracy. The following analyses are tabulated and compared:

| Zone Number(s) | Recall | Coverage | Precision | Accuracy |
|----------------|--------|----------|-----------|----------|
|                | AL     | PAL      | AL        | PAL      | AL       | PAL      |
| All            | 0.20   | 0.20     | 0.56      | 0.55     | 0.20     | 0.20     | 0.36     | 0.36     |
| 1 & 2 (d0,d1 & d2) | 0.35   | 0.31     | 0.83      | 0.66     | 0.23     | 0.28     | 0.41     | 0.47     |
| 3 & 4 (d2 only) | 0.07   | 0.08     | 0.30      | 0.44     | 0.13     | 0.09     | 0.22     | 0.17     |
| 3 (d2 only)    | 0.12   | 0.11     | 0.44      | 0.36     | 0.14     | 0.19     | 0.27     | 0.31     |
| 4 (d2 only)    | 0.03   | 0.06     | 0.21      | 0.47     | 0.11     | 0.06     | 0.15     | 0.13     |

Inference: The AL approach uses fixed threshold while the PAL approach uses incremental learning. By lookig over the above Table it is seen that the precision and accuracy are improved in zones 1 & 2 with PAL. The performance is almost same when we consider all zones together with regard to both AL and PAL. Other metrics are varying and depend on the learning rate. A
multi-scale approach to express spatial position that fits the spatial scale to the track activity in a given area will result in better prediction results. Spatial forecasts would be unnecessarily high if the spatial scale is too coarse to reflect local activities. More training data would be needed if the spatial scale is too wide to achieve reasonable prediction performance. As the spatial scale is properly configured incremental learning can run quite effectively and soon attain productive levels of efficiency as the system tends to track and evaluate vessel activity.

6. Conclusion
Even if machine learning has previously been included in abundant sections of the online-world, its application in maritime sector is still constrained. To reap the gains for viable conveyance, marine transports need smart software and machine-learning concepts. This paper addressed the different facets of machine learning, as well as their upsides and downsides. The upshot of artificial intelligence on the marine industry's future is also explored. The rigorous investigation reveals that the seafaring experts and investigators ought to focus mainly on apt/suitable algorithm, as the outcomes are different for different algorithms and for different situations. The prospective domains on which the artificial intelligence be applied entails autonomous shipping, port automation and management, route organizing and optimizing, obstacle prevention in underwater environment, fault detection in ship operations, forecasting the fuel usage, energy consumption and management. Rather than focusing on a single application, the approach analysed major and important implementations. In addition, the outcomes of one main application of Vessel path control are elaborated and tabulated.

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