Physics Infused LSTM Network for Track Association Based on Marine Vessel Automatic Identification System Data

Tasmiah Haque
West Virginia University, th00027@mix.wvu.edu

Follow this and additional works at: https://researchrepository.wvu.edu/etd

Part of the Industrial Engineering Commons

Recommended Citation
https://researchrepository.wvu.edu/etd/11819

This Thesis is protected by copyright and/or related rights. It has been brought to you by the The Research Repository @ WVU with permission from the rights-holder(s). You are free to use this Thesis in any way that is permitted by the copyright and related rights legislation that applies to your use. For other uses you must obtain permission from the rights-holder(s) directly, unless additional rights are indicated by a Creative Commons license in the record and/or on the work itself. This Thesis has been accepted for inclusion in WVU Graduate Theses, Dissertations, and Problem Reports collection by an authorized administrator of The Research Repository @ WVU. For more information, please contact researchrepository@mail.wvu.edu.
Physics Infused LSTM Network for Track Association Based on Marine Vessel Automatic Identification System Data

Tasmiah Haque

Thesis submitted to the
College of Engineering and Mineral Resources at
West Virginia University
in partial fulfilment of the requirements for the degree of
Master of Science in
Industrial Engineering

Imtiaz Ahmed, Ph.D., Chair
Alan McKendall, Ph.D.
Zeyu Liu, Ph.D.

Department of Industrial and Management Systems Engineering
Morgantown, West Virginia
2023

Keywords: AIS, track association, LSTM, physics-based model
Copyright 2023 Tasmiah Haque
ABSTRACT

Physics Infused LSTM Network for Track Association Based on Marine Vessel Automatic Identification System Data

Tasmiah Haque

In marine surveillance, a crucial task is distinguishing between normal and abnormal vessel movements to timely identify potential threats. Subsequently, the vessels need to be monitored and tracked until necessary action can be taken. To achieve this, a track association problem is formulated where multiple vessels’ unlabeled geographic and motion parameters are associated with their true labels. These parameters are typically obtained from the Automatic Identification System (AIS) database, which enables real-time tracking of marine vessels equipped with AIS. The parameters are time-stamped and collected over a long period, and therefore, modeling the inherent temporal patterns in the data is crucial for successful track association. The problem is further complicated by infrequent data collection (time gap) and track overlaps.

Traditionally, physics-based models and Kalman-filtering algorithms are used for tracking problems. However, the performance of Kalman filtering is limited in the presence of time-gap and overlapping tracks, while physics-based models are unable to model temporal patterns. To address these limitations, this work employs LSTM, a special neural network architecture, for marine vessel track association. LSTM is capable of modeling long-term temporal patterns and associating a data point with its true track. The performance of LSTM is investigated, and its strengths and limitations are identified. To further improve the performance of LSTM, an integration of the physics-based model and LSTM is proposed. The performance of the joint model is evaluated on multiple AIS datasets with varying characteristics.

According to the findings, the physics-based model performs better when there is very little or no time gap in the dataset. However, when there are time gaps and multiple overlapping tracks, LSTM outperforms the physics-based model. Additionally, LSTM is more effective with larger datasets as it can learn the historical patterns of the features. Nevertheless, the joint model consistently outperforms the individual models by leveraging the strengths of both approaches. Given that the AIS dataset commonly provides a long stretch of historical information with frequent time gaps, the combined model should improve the accuracy of vessel tracking.
# TABLE OF CONTENTS

ABSTRACT ........................................................................................................................................... ii
LIST OF TABLES .................................................................................................................................... iii
LIST OF FIGURES ............................................................................................................................... iv

1. INTRODUCTION ............................................................................................................................ 1
   1.1 Motivation ..................................................................................................................................... 1
   1.2 Problem Background .................................................................................................................... 4

2. DATA DESCRIPTION .......................................................................................................................... 5

3. LITERATURE REVIEW ...................................................................................................................... 8
   3.1 Research Works Using Conventional Method On AIS Data .......................................................... 8
   3.2 Research Works Using Neural Networks On AIS Data ............................................................... 9
   3.3 Research Works On Physics Infused Neural Network ................................................................. 11

4. METHODOLOGY ............................................................................................................................... 14
   4.1 Long Short-Term Memory (LSTM) ............................................................................................. 14
   4.2 Physics-Based Model ................................................................................................................... 16
   4.3 Integration Of Physics-Based Model and LSTM ........................................................................... 18

5. THE PROPOSED TRACK ASSOCIATION ALGORITHM ................................................................. 18
   5.1 Track Association Using LSTM .................................................................................................. 18
   5.2 Track Association Using Physics Infused LSTM ........................................................................ 20
   5.3 Performance Evaluation Metrics ............................................................................................... 23

6. RESULT ANALYSIS .......................................................................................................................... 24
   6.1 Performance Evaluation .............................................................................................................. 24
      6.1.1 AIS Data Without Time Gaps And Lower No. Of Observations .............................................. 24
      6.1.2 AIS Data With Time Gaps And Lower No. Of Observations ............................................... 27
      6.1.3 AIS Data Without Time Gaps And Higher No. Of Observations ......................................... 35
      6.1.4 AIS Data With Time Gaps And Lower No. Of Observations ............................................... 38
   6.2 Impact Of Dataset Characteristics On Algorithm’s Performance ............................................... 42
      6.2.1 Impact Of Dataset Characteristics On LSTM Model Performance ..................................... 43
      6.2.2 Impact Of Dataset Characteristics On Physics-Based Model Performance ..................... 44
      6.2.3 Impact Of Dataset Characteristics On Physics Infused LSTM Model Performance ............. 45

7. CONCLUSION ..................................................................................................................................... 48

8. REFERENCES ...................................................................................................................................... 48
LIST OF TABLES

Table 1. Characteristics of the datasets................................................................. 7
Table 2. Layout of Confusion Matrix ...................................................................... 23
Table 3. Results of ANOVA analysis for LSTM model performance..................... 43
Table 4. Results of ANOVA analysis for physics-based model performance ........... 45
Table 5. Overall accuracy of the individual models and the proposed hybrid model .. 46
Table 6. Results of ANOVA analysis for physics infused LSTM model performance .... 46
Table 7. Results of ANOVA analysis for analyzing the significance of selected model .................. 47
Table 8: Results of ANOVA analysis for the comparison of LSTM model and physics infused LSTM model with respect to physics-based model ........................................................................................................... 47
Table 9. Performance comparison of physics infused LSTM and physics infused BiLSTM models ...... 47
LIST OF FIGURES

Figure 1. Illustration of the track association problem ................................................................. 4
Figure 2. A snapshot of AIS dataset .................................................................................................. 6
Figure 3. Sample tracks for 20 vessels in Norfolk, Virginia during 1400-1800 UTC .......................... 6
Figure 4. Summary of the literature review .................................................................................... 13
Figure 5. Visual illustration of the structure of LSTM ................................................................. 14
Figure 5.1 Forget Gate .................................................................................................................. 15
Figure 5.2 Input Gate .................................................................................................................. 16
Figure 5.3 Output Gate ................................................................................................................ 16
Figure 6. Illustration of predicting new node location using geodesic path .................................... 17
Figure 7. A schematic diagram of physics infused LSTM architecture ......................................... 19
Figure 8. A block diagram to summarize the proposed framework ................................................ 21
Figure 9. A process flow diagram of implementing Physics Infused LSTM for track association .... 22
Figure 10. A block diagram to summarize the proposed framework ............................................. 22
Figure 11. Performance of LSTM model on dataset-1 ................................................................. 25
Figure 12. Performance of physics-based model on dataset-1 ....................................................... 26
Figure 13. Training loss and validation loss curves for the applied models on dataset-1 ............... 26
Figure 14. Performance of physics infused LSTM model on dataset-1 ........................................ 27
Figure 15. Performance of LSTM model on dataset-2 .............................................................. 28
Figure 16. Performance of physics-based model on dataset-2 ..................................................... 29
Figure 17. Training loss and validation loss curves for the applied models on dataset-2 ............... 30
Figure 18. Performance of physics infused LSTM model on dataset-2 ........................................ 31
Figure 19. Performance of LSTM model on dataset-3 ............................................................... 32
Figure 20. Performance of physics-based model on dataset-3 ..................................................... 33
Figure 21. Training loss and validation loss curves for the applied models on dataset-3 ............... 34
Figure 22. Performance of physics infused LSTM model on dataset-3 ........................................ 34
Figure 23. Performance of LSTM model on dataset-4 ............................................................... 35
Figure 24. Performance of physics-based model on dataset-4 ..................................................... 36
Figure 25. Training loss and validation loss curves for the applied models on dataset-4 ............... 37
Figure 26. Performance of physics infused LSTM model on dataset-4 ........................................ 38
Figure 27. Performance of LSTM model on dataset-5 ............................................................... 39
Figure 28. Performance of physics-based model on dataset-5 ..................................................... 40
Figure 29. Training loss and validation loss curves for the applied models on dataset-5 ............... 41
Figure 30. Performance of physics infused LSTM model on dataset-5 ........................................ 42
Figure 31. Summary of the impact of dataset characteristics on LSTM model performance ........ 44
Figure 32. Summary of the impact of dataset characteristics on physics infused LSTM model performance .................................................................................................................. 45
1. INTRODUCTION

Detecting potential security risks and monitoring unusual movement patterns in marine vessels require accurate tracking, which is facilitated by track association, the process of associating signals from unknown vessels to their correct tracks. Since maritime tracking involves sequential and spatiotemporal data, an effective track association algorithm should consider these properties. Machine learning algorithms rely on historical data sequences to uncover hidden patterns, while physics-based models focus on modeling the underlying mechanics of the process and do not necessarily require large datasets. However, physics-based models tend to underperform when presented with irregular data, while machine learning models struggle with low observation numbers. In this thesis, the performance of standalone machine learning and physics-based models under varying complexity scenarios are investigated and their respective strengths and weaknesses are identified. Then a physics-infused machine learning model is proposed to capitalize on the advantages of both approaches. This section lays out the motivation for this study, highlights the objectives, and discusses the background of the problem.

1.1 Motivation

In recent years, the issue of maritime safety has gained significant attention due to the rise in incidents involving human trafficking and smuggling. To address this concern, coastal authorities have deployed tracking devices that enable the real-time monitoring of vessel locations. However, a reliable algorithm is crucial for accurately associating tracks in scenarios where signal reception from the vessels is disrupted. Ongoing research aims to develop an algorithm for tracking marine vessels in situations where the system fails or a vessel deliberately stops sending signals.

The process of accurately assigning unlabeled moving objects to their corresponding true tracks is known as track association [1]. To ensure maritime security, sophisticated position tracking systems are used to transmit the positions and movements of multiple objects in real-time. The Automatic Identification System (AIS) is a vessel monitoring system that enables ships to self-report their positions and is defined as a ship and shore broadcast system based on wireless information by the International Maritime Organization (IMO). AIS was introduced in 2000 and is installed in most ocean-going commercial ships. To enhance maritime traffic management, the AIS network is constructed with several AIS base shore stations. According to the IMO 2002 convention, AIS installation is mandatory for all passenger ships regardless of size, cargo ships of 500 and more tonnage, and international voyaging ships of 300 or more gross tonnage [1]. Since 2015, studies on vessel position prediction have used AIS as a historical data source for vessel information [10]. AIS provides a significant data source for large cooperating ships, and the temporal resolution of the received AIS signal is commonly improved through marine radar and correlated with raw sensor data [2]. AIS transmits a ship's static and voyage-related information data, such as the IMO number, ship name, Maritime Mobile Service Identity (MMSI) number, size, type of vessel, location coordinates (longitude and latitude), speed, heading direction, etc. to coastal maritime authorities and other ships [25, 23]. AIS enables the tracking of a ship's movement and behavior patterns, which helps with maritime traffic management and ensures navigational
safety. Although AIS was initially adopted to avoid collisions among ships, it is now increasingly used as a monitoring system.

AIS equipment consists of [24]:

a) One VHF transmitter and two VHF receiver  
b) A DCS transceiver  
c) A GPS receiver  
d) A CPU with software and RS-232 or RS-422 ports  
e) A Minimum Keyboard and Display unit capable of displaying the vessel’s position, alarms and indications, AIS data of other vessels, and manual input of maritime safety related messages.

Extracting reliable trajectory features from the original AIS data can be challenging for coastal authorities as it contains redundant information [4]. To analyze shipping route knowledge, ongoing research for several years has been focused on developing an appropriate algorithm. These research works can be classified into categories such as trajectory clustering, route prediction, anomaly detection, and others [1]. Research on the application of AIS data has so far been carried out in five fronts, with collision avoidance and anomaly detection being the most common applications [4].

In 2019, the National Geospatial Intelligence Agency (NGA) partnered with the National Science Foundation (NSF) for the Algorithm for Threat Detection (ATD) program to launch data association challenges. The aim was to develop algorithms for large spatiotemporal datasets with applications to human dynamics, which could accurately identify regular activities based on limited data and detect anomalies when necessary. In national security and surveillance systems, tracking multiple moving objects and monitoring their anomalous trajectory patterns is crucial. To assess the algorithms, the team designed a set of challenge problems using AIS data, which was chosen for its wide-ranging and spatiotemporal nature. Each node in the AIS data file contains timestamps for signal reception, coordinates, speed, direction, and a vessel identification (VID) number. Each ship is assigned a unique MMSI number, and its track is defined by the collective time-sequenced nodes. The challenge was to develop an algorithm that could accurately associate each node with a vessel’s track based on other AIS data information in cases where the vessel ID is missing. Vessels may suddenly stop transmitting signals due to equipment failure or a deliberate attempt to conceal their location. To simulate this scenario, the dataset included time gaps and withheld vessel IDs.

Although the data challenge competition concluded in 2020, the need for an optimal association algorithm persists and served as a driving force for this thesis. Before this competition, multi-object trackers (MOT) were commonly recommended for this type of tracking problem. These methods utilize noisy information from multiple sensors to estimate the future positions of moving objects. Two well-known MOT algorithms are the Global Nearest Neighbor (GNN) and Joint Probabilistic Data Association (JPDA). Nevertheless, their performance on the challenge datasets
was dismal for various reasons. Firstly, MOTs depend on the Kalman filter for estimating dynamic states, which does not perform well on nonlinear data patterns. Secondly, they cannot manage the complex data patterns found in the AIS datasets, which were intentionally created to challenge the state of the art. Finally, the AIS data is free of clutter and noise, providing no extra benefits to Kalman filter-based approaches [1].

To handle the complexities of the challenge datasets, the current state of the art is to employ a physics-based model for track association, as described in [1]. This model utilizes Vincenty’s geodesic distance framework along with a heuristic to account for the spatiotemporal nature of vessel data. During association, the model only uses the last known location to predict the vessel's next position, which can result in inaccurate predictions due to the model's memoryless property. Additionally, if one prediction is incorrect, it can compromise all future associations. One way to improve prediction accuracy is to consider a small sequence of nodes instead of a single node.

Another approach involves mining the historical sequences of vessels using a neural network. Recurrent Neural Network (RNN) is a well-established method for modeling sequential and time series data, such as language translations and auto-completion in emails. LSTM is a widely-used form of RNN that can memorize information for longer periods and predict future data based on the characteristics of a series of prior data. However, data-driven machine learning (ML) models alone cannot capture real-world phenomena as they do not consider underlying physical principles [11]. These models also require large amounts of data for training, which is typically not available.

The individual models discussed earlier are unable to achieve the desired level of accuracy when applied to AIS data due to their unique characteristics. However, by combining these models, it is possible to generate better results. This study aims to develop an integrated model and compare its performance with the standalone models. The proposed algorithm has several strengths. First, it can analyze the historical pattern of prior events and capture the underlying long-term pattern using an LSTM-based neural network. Second, it can model the underlying physics of vessel movements using a physics-based approach. Third, it is capable of tracking vessels even in the presence of time gaps in the AIS signals and can handle complicated vessel trajectories. The objectives of this research are thus given below:

a) To develop a variant of the LSTM method and apply it to the AIS datasets to observe the performance for predicting locations and tracking vessels.

b) To develop a physics-infused LSTM framework where a physics-based model will be integrated with an LSTM model.

c) To compare the performance of the joint framework with the individual models.

d) To evaluate the sensitivity of these competing models with respect to dataset characteristics.
1.2 Problem Background
To illustrate the underlying research question and tracking task, two hypothetical scenarios are created in Figure 1; one in the presence of vessel ID information for each vessel and another one without this information. If the vessel ID is present and valid, a monitoring officer can use it to identify the received AIS information belonging to a single, unique vessel.

![Diagram](image)

(a) Visual depiction of AIS data with VID  
(b) Grouping the nodes that belong to the same VIDs

(c) Visual depiction of AIS data in absence of VID  
(d) Grouping the nodes that belong to the same vessels when VID is missing

Figure 1. Illustration of the track association problem [1]
Figure 1(a) depicts situations when vessel ID is available. Each letter and color correspond to a particular vessel and the number indicates the order of the nodes. For instance, "A1" signifies the starting position of vessel A, followed by its positions at "A2" and "A3". A successful tracking algorithm will group nodes "A1", "A2" and "A3" together. To group the vessel nodes, corresponding latitude, longitude, speed, and direction can be utilized. The arrow width and direction denote the vessel's speed and heading direction, respectively. Figure 1(b) demonstrates how the nodes of an individual letter and color can be easily grouped together if the vessel ID is present. However, in Figure 1(c), the letter and color are removed to illustrate the case where the vessel ID is missing, and the nodes need to be associated with their true tracks using other available variables only. In this case, the nodes are labeled with the time they were generated, with "1" representing the earliest and "14" representing the latest signal. The challenge is to design a tracking algorithm that can determine the trajectory of each vessel and group them as shown in Figure 1(d) in the absence of the actual vessel ID. Additionally, multiple receivers connected to the network can cause irregular and redundant data, making the problem more challenging.

To apply our proposed algorithm to AIS datasets, certain assumptions have been made as follows:

i. The number of vessels is fixed.
ii. The training data points of each vessel are known.
iii. In the test set, the identities of all of the vessels are unknown.

The rest of the report has been divided into sections as follows. The data format and the characteristics of the problem and dataset are described in Section 2. Section 3 has highlighted the literature review based on research works related to AIS data, LSTM, and physics-based neural network models. In Section 4, the methodologies considered for this work are described. Section 5 explains the steps of our proposed integrated approach. The analysis of results is presented in Section 6 and finally, the paper is summarized in Section 7.

2. DATA DESCRIPTION

The AIS datasets used for the research work are described in this section. The data is collected from the United States Coast Guard’s historical database of the Automatic Identification System which covers the area around Norfolk, Virginia for the first three datasets. The large dataset is collected from an open-source AIS database [30]. Data files are in CSV (Comma Separated Values) format. A snapshot is shown in Figure 2. The variables provided for track association are:

a) Object ID: It represents the order of the generated node according to the signal receiving time.
b) VID: It is the vessel identification number which is a representative number of the MMSI number of the vessel.
c) Timestamp: The time the signal is received is represented in hh:mm:ss format where hh is hours, mm is minutes and ss is seconds.
d) Latitude: The latitude position of the vessel is given in degrees at that corresponding time.

e) Longitude: The longitude position of the vessel is given in degrees at that corresponding time.

f) Speed: The speed of the vessel is given in tenths of knots at that corresponding time.

g) Course of direction: The heading direction or the angle of the vessel is given in tenths of degrees at that corresponding time.

<table>
<thead>
<tr>
<th>OBJECT_ID</th>
<th>VID</th>
<th>SEQUENCE</th>
<th>LAT</th>
<th>LON</th>
<th>SPEED_OVER_GROUND</th>
<th>COURSE_OVER_GROUND</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100008</td>
<td>14:00:00</td>
<td>36.90685</td>
<td>-76.089</td>
<td>1</td>
<td>1641</td>
</tr>
<tr>
<td>2</td>
<td>100015</td>
<td>14:00:00</td>
<td>36.95</td>
<td>-76.0268</td>
<td>11</td>
<td>2815</td>
</tr>
<tr>
<td>3</td>
<td>100016</td>
<td>14:00:00</td>
<td>36.90678</td>
<td>-76.0891</td>
<td>0</td>
<td>2632</td>
</tr>
<tr>
<td>4</td>
<td>100019</td>
<td>14:00:00</td>
<td>37.003</td>
<td>-76.2832</td>
<td>148</td>
<td>2460</td>
</tr>
<tr>
<td>5</td>
<td>100016</td>
<td>14:00:01</td>
<td>36.90678</td>
<td>-76.0891</td>
<td>0</td>
<td>2632</td>
</tr>
<tr>
<td>6</td>
<td>100005</td>
<td>14:00:01</td>
<td>36.90682</td>
<td>-76.0888</td>
<td>1</td>
<td>1740</td>
</tr>
<tr>
<td>7</td>
<td>100006</td>
<td>14:00:01</td>
<td>36.90689</td>
<td>-76.0893</td>
<td>0</td>
<td>1440</td>
</tr>
<tr>
<td>8</td>
<td>100008</td>
<td>14:00:02</td>
<td>36.90685</td>
<td>-76.089</td>
<td>1</td>
<td>1641</td>
</tr>
<tr>
<td>9</td>
<td>100015</td>
<td>14:00:03</td>
<td>36.95</td>
<td>-76.0268</td>
<td>11</td>
<td>2770</td>
</tr>
<tr>
<td>10</td>
<td>100013</td>
<td>14:00:03</td>
<td>36.97197</td>
<td>-75.9811</td>
<td>91</td>
<td>2626</td>
</tr>
<tr>
<td>11</td>
<td>100017</td>
<td>14:00:03</td>
<td>36.96196</td>
<td>-76.0654</td>
<td>144</td>
<td>1080</td>
</tr>
<tr>
<td>12</td>
<td>100015</td>
<td>14:00:05</td>
<td>36.95</td>
<td>-76.0268</td>
<td>9</td>
<td>2771</td>
</tr>
<tr>
<td>13</td>
<td>100019</td>
<td>14:00:06</td>
<td>37.00283</td>
<td>-76.2837</td>
<td>149</td>
<td>2450</td>
</tr>
<tr>
<td>14</td>
<td>100004</td>
<td>14:00:06</td>
<td>36.95373</td>
<td>-76.1661</td>
<td>24</td>
<td>929</td>
</tr>
<tr>
<td>15</td>
<td>100007</td>
<td>14:00:06</td>
<td>36.90687</td>
<td>-76.0888</td>
<td>0</td>
<td>1475</td>
</tr>
<tr>
<td>16</td>
<td>100008</td>
<td>14:00:09</td>
<td>36.90685</td>
<td>-76.0891</td>
<td>0</td>
<td>2521</td>
</tr>
<tr>
<td>17</td>
<td>100016</td>
<td>14:00:09</td>
<td>36.90678</td>
<td>-76.0891</td>
<td>0</td>
<td>1440</td>
</tr>
<tr>
<td>18</td>
<td>100020</td>
<td>14:00:09</td>
<td>36.90905</td>
<td>-76.327</td>
<td>1</td>
<td>2798</td>
</tr>
<tr>
<td>19</td>
<td>100015</td>
<td>14:00:10</td>
<td>36.95</td>
<td>-76.0268</td>
<td>11</td>
<td>1651</td>
</tr>
</tbody>
</table>

Figure 2. A snapshot of AIS dataset

Figure 3. Sample tracks for 20 vessels in Norfolk, Virginia during 1400-1800 UTC [1]
For this research, five datasets are used which are ordered in the increasing order of size, time gap and complexities. The number of vessels and the number of total observations are in the range of 20-25 and 15000-25000 respectively for the first three datasets. The fourth and fifth datasets are larger datasets containing 327 vessels and 324203 observations. Since a neural network requires enough datapoints for training, a threshold of 500 observations is set for the smaller datasets and a threshold of 1000 observations is set for the larger datasets. The pattern of the vessel movements of a dataset is demonstrated in Figure 3.

To simulate real-world challenging tracking scenarios, various complex characteristics are incorporated as described below [1]:

- Vessels may pass each other at a perilously close distance and cross paths multiple times.
- Multiple vessels’ information can be generated simultaneously, but the frequency of incoming data fluctuates during the information collection period.
- To introduce time gaps in the AIS data, some of the timestamps have intentionally been omitted. In the second dataset, gaps are selectively introduced in the data for certain track subsets and in the third dataset, gaps are created for all tracks at two fixed timestamps. However, the competing algorithms do not know for which tracks or at what timestamps the gaps have been created.
- Time gaps have been created for the 1-hour period at three random timestamps in the larger dataset (dataset-5) which means no data has been reported from any of the vessels for 1-hour duration after these three timestamps, maintaining track continuity across each data gap. The purpose of creating these gaps is to assess the algorithm’s performance in situations where data gaps are present within a larger dataset.
- During the time gap period, a vessel can abruptly change its speed or direction which may result in a huge difference in location coordinates between the start and end of the time gap.

The characteristics of the datasets are summarized in Table I.

<table>
<thead>
<tr>
<th>Problem Set</th>
<th>No. of vessels</th>
<th>AIS Data Duration</th>
<th>No. of observations for each vessel</th>
<th>Data gap</th>
<th>Complicated trajectories</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>6</td>
<td>4 hours</td>
<td>1000-2000</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>02</td>
<td>7</td>
<td>4 hours</td>
<td>1000-2000</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>03</td>
<td>8</td>
<td>4 hours</td>
<td>1000-3000</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>04</td>
<td>18</td>
<td>24 hours</td>
<td>1000-7000</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>05</td>
<td>18</td>
<td>24 hours</td>
<td>1000-7000</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Since we are dealing with three characteristics (data gap, complicated trajectories, and size of the dataset), in total eight combinations \(2^3\) are possible for analysis. However, these datasets are
open-source and we did not have any control over the collection process. Therefore, some combinations could not be considered in this study.

3. LITERATURE REVIEW

This section is divided into three subsections, where the first subsection is about research works related to AIS data using conventional methods. There are various directions where researchers have walked to extract knowledge from AIS and applied those to multi-object tracking, trajectory clustering, route prediction etc. In the next subsection, some research works are discussed where neural network methods are implemented to process AIS data. The last subsection explains the use of LSTM in various fields and how the integration of physics-based models with neural networks has contributed to other applications.

3.1 Research Works Using Conventional Methods On AIS Data

Over the years, a significant amount of research has been conducted based on AIS datasets due to their vastness and the scope of analysis they offer. One area that has received considerable attention is trajectory clustering, which is closely related to track association. This subsection will therefore discuss some papers that focused on track association and trajectory clustering.

In [1], researchers developed a spatiotemporal framework for track association using AIS data. Their two-step approach involved online track association and post hoc merging. In the first step, each node appearing in the process is associated with a track. A new track is opened using the first data point, and after receiving the next data point, the future locations of existing tracks are predicted. They then compare the actual values of unassigned data points with the predicted measurements using haversine distance and angular change of direction over time, generating a dissimilarity score. If the score is higher than a threshold value, a new track is opened; otherwise, the data point is assigned to the track with the lowest dissimilarity score. Post hoc merging handles issues related to time gaps and abrupt changes in directions.

The researchers compared their algorithm's continuity score and completeness score with those produced by a sample algorithm and some MOT approaches. In most of the test sets, their score was 100%, whereas the sample algorithm and the MOT approaches performed below their level. The researchers concluded that their proposed approach could be used for threat detection by tracking multiple moving objects. They recommended that future research should incorporate a sequence of prior nodes to predict future data instead of relying solely on the features of the last node. This thesis considers their suggestion and aims to investigate the potential of a neural network-based approach that can leverage sequential information.

In [2], a trajectory mapping and clustering algorithm was proposed that combined the Merge Distance (MD), Multidimensional Scaling (MDS), and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithms to identify conventional and abnormal shipping
routes. The algorithm first measures trajectory similarity using MD and constructs a distance matrix. MDS is then used to map the trajectory data to a low-dimensional representation and generate spatial point expressions, which are clustered using DBSCAN. Results showed that the proposed algorithm outperformed other clustering algorithms in terms of accuracy and time complexity. Future studies were recommended to use larger datasets and discern the parameters in DBSCAN according to the differences in point distances.

In [3], a model was proposed for analyzing vessel traffic patterns using a trajectory clustering approach. The model involves preprocessing AIS data, measuring trajectory similarity using spatial, directional, and speed distance metrics, clustering using DBSCAN, creating representative trajectories for each cluster using the sweeping line approach, and representing clustered trajectories by their average speed values. Results showed the effective performance of the algorithm and future studies were recommended to incorporate more AIS data and find better methods for preprocessing the data.

In [4], a multi-step trajectory clustering method was proposed that uses Dynamic Time Warping (DTW) for similarity measurement, Principal Component Analysis (PCA) for distance matrix decomposition, and an improved center clustering algorithm for final AIS trajectory clustering results. Results showed the superior performance of the proposed algorithm for clustering analysis and future studies were recommended to study the selection of the improved center algorithm based on the distance between different trajectories.

The authors of [5] introduced a vessel tracking method integrating an AIS calibration technology with dual frequency High-Frequency Surface Wave Radar (HFSWR). The vessels were tracked using a JPDA-UKF (Kalman Filter) algorithm. Their results showed that the fusion method generates higher tracking accuracy compared to the tracking process with a single frequency.

A survey and summary of the research status, new developments, and the challenges that exist in moving object clustering algorithms were presented in [6]. One of the challenges they identified is that most of the algorithms do not fully integrate the features of trajectories including time and space dimensions. Additionally, these algorithms have low general applicability.

### 3.2 Research Works Using Neural Networks On AIS Data

Along with applying conventional methods, researchers used neural network methods for trajectory clustering since research over the years revealed that the distance between the target trajectory and the most similar trajectory does not remain constant. This section presents a discussion of some representative papers related to developing neural network models for analyzing AIS data.

In [7], three innovative models were introduced that utilize similarity search for predicting vessel trajectories. The first model adopts a point-based similarity search to find the most similar vessel to the target vessel and then predicts its next location based on spatial, course, and speed distances between historical points in the dataset. The second model utilizes trajectory-based similarity
search by measuring the similarity between the target vessel's trajectory and other vessel trajectories using DTW, and then applies the same location prediction method as the first model. The third model uses LSTM and takes as input the longitudinal and latitudinal distances between the most similar trajectory point and the last point of trajectory to predict future spatial distances and the next location point at each time interval. The results demonstrated that the third model performs more accurately in long-term prediction. For future research, the authors recommended considering environmental factors such as wind, waves, weather, etc. since these factors have an impact on the movement of vessels.

In [8], a multistage method has been proposed for automatic vessel detection using image processing techniques and convolutional neural networks that integrate satellite optical imagery and AIS data. The method involves downloading a sentinel-2 image of an area, masking out coastline geometries, and dividing the image into tiles for individual processing. Otsu and Yen filters are applied to differentiate image background from features using thresholding. For each feature at the pixel level, metrics are calculated, and a trained Convolutional Neural Network (CNN) is utilized to classify the features. This model can identify whether a feature in the satellite image is a vessel or not, and the accuracy of the model is greater than 95%.

A sequence-to-sequence recurrent neural network has been proposed in [9] to predict vessel trajectories. They explored an LSTM encoder-decoder architecture, and it demonstrated better performance compared to other methods.

Some end-to-end deep learning (DL) models are used in [10] for long term ship position prediction. They built three DL models: Multilayer Perceptron (MLP) model, RNN model and LSTM model. Each model was built with the same input, output and validation split. Their results were compared with some motion-based straightforward methods. The DL models generated more accurate results and they can predict the movements of ships near port. The authors recommended incorporating longer time intervals in the dataset for long term prediction.

The authors of [11] have proposed Artificial Neural Network (ANN) to detect and track multiple vessels and an Extended Kalman Filter (EKF) for vessel state estimation and navigational trajectory prediction. They recommend to use ANN approaches for vessel classification and identification for future works.

A framework is developed in [12] using Variational Recurrent Neural Network (VRNN) for abnormal behavior detection, trajectory reconstruction and vessel type identification. The authors concluded with the recommendation of considering weather and wave effects to analyze the behavior of vessels.

These neural network-based approaches can utilize the large AIS datasets. However, they do not scale well in the presence of a low amount of training data. Also, they do not consider the underlying motion characteristics. These often challenge the accuracy of the tracking process.
3.3 Research Works On Physics Infused Neural Network Models

Although the combination of physics-based models and neural network methods has not yet been applied to AIS data, the success of this approach in other applications suggests its potential for analyzing spatiotemporal time series datasets. Several papers have reported satisfactory results using this combination, as discussed below.

In [13], a fusion model that integrates a physics-based model and an LSTM was presented as a solution to overcome the limitations of using these models separately in complex dynamic systems. The authors used both the integrated model and the data-driven model separately in the inverted pendulum and tumor growth problems. They combined the sensor data and the output generated by the physics-based model as inputs to the LSTM model. The authors observed that the hybrid model outperformed the individual models in both cases and concluded that the effectiveness of the physics-based model significantly affects the accuracy of the hybrid model.

System dynamics with machine learning models were integrated in [14] using physics-informed long short-term memory networks (PhyLSTM) and physics-informed neural networks (PhyNN). In the evaporative cooling process, the time-dependent relationship between control input and system response was determined by these physics-informed networks. Their proposed PhyLSTM provided less than 2% error. For future research, they intended to explore the networks’ performance for multiple input and multiple output systems.

In [15], a hybrid approach combining physics-based modeling and neural networks was proposed for predicting streamflow and flood production. The methodology utilized a physics-guided neural network modeling framework that extracts simulation information and meteorological forcing information from a process-based model, VIC-CaMa-Flood, using the LSTM network. To evaluate the performance of the hybrid approach, both the data-driven LSTM model and the process-based VIC-CaMa-Flood model were applied separately and compared with the hybrid model. The findings suggested that integrating physical regularization in data-driven modeling and observation-informed bias correction in process-based modeling are necessary for accurate predictions.

A digital twin model was presented in [16] combining both physics-based model and neural network model by assigning weights to each of the models. The PhysiNet model showed lower error than the neural network model and the physics-based model at the beginning and end of the life cycle of the digital twin respectively. Future studies were suggested for developing models for problems beyond regression problems.

In [17], the fusion of a physics-based model and neural network for prognostics aims to minimize the weaknesses of each of the individual methods and leverage their advantages. They applied the algorithm to predict the remaining useful lifetime (RUL) and observed that the proposed algorithm’s performance surpassed purely data-driven approaches and it is less sensitive to the limited characteristics of the dataset.
In [18], a physics-guided neural network is introduced for transient simulation. A physics-guided loss function is utilized in the training process of the neural network to enforce fairness in prediction.

Based on the discussions above, it is evident that combining physics-based models with neural network approaches can result in better outcomes and improved accuracy. According to a survey conducted [19] on integrating physics-based modeling with machine learning, combined models have the potential to establish promising algorithms in diverse fields. However, no studies have been reported yet that apply this approach to track association in AIS data. This study aims to fill this gap in the literature. The following is a summary of the literature review for better understanding:
### Figure 4: Summary of the literature review

#### Conventional Methods

<table>
<thead>
<tr>
<th>Works on AIS data</th>
<th>Neural Network-Based Approaches</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Improved center clustering algorithm for trajectory clustering</strong> (Li et al., 2017)</td>
<td><strong>ANN approaches combined with Extended Kalman Filter for vessel state estimation and vessel trajectory prediction</strong> (Perera et al., 2012)</td>
</tr>
<tr>
<td><strong>A survey and summary of trajectory clustering algorithm</strong> (Yuan et al., 2017)</td>
<td><strong>Variational RNN for multi-task setting using AIS data</strong> (Nguyen et al., 2018)</td>
</tr>
<tr>
<td><strong>DBSCAN algorithm to identify abnormal trajectories</strong> (Li et al., 2018)</td>
<td><strong>LSTM encoder-decoder architecture to predict vessel trajectories</strong> (Forti et al., 2020)</td>
</tr>
<tr>
<td><strong>DBSCAN algorithm to extract shipping route pattern</strong> (Sheng &amp; Yin, 2018)</td>
<td><strong>Image processing techniques and convolutional neural networks for automatic vessel detection</strong> (Bereta &amp; Zisssis, 2020)</td>
</tr>
<tr>
<td><strong>Vessel tracking algorithm using Joint Probabilistic Data Association-Kalman Filter</strong> (Zhang et al., 2018)</td>
<td><strong>Trajectory-based similarity search prediction using LSTM model to predict vessel trajectories</strong> (Alizadeh &amp; Sharif, 2021)</td>
</tr>
<tr>
<td><strong>Spatiotemporal algorithm for multiple moving object track association</strong> (Ahmed et al., 2022)</td>
<td><strong>Multilayer perceptron model, RNN model and LSTM model for long term ship position prediction</strong> (Hamada et al., 2021)</td>
</tr>
</tbody>
</table>

#### Physics Infused Neural Network Approaches

<table>
<thead>
<tr>
<th>Works on areas other than AIS data</th>
<th>Physics Infused Neural Network Approaches</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Integrating physics-based model and LSTM for prediction in complex dynamics systems</strong> (Singh et al., 2019)</td>
<td><strong>Physics guided neural network for transient simulation</strong> (Meethal &amp; Kondamadugula, 2021)</td>
</tr>
<tr>
<td><strong>A survey on integrating physics-based model with machine learning</strong> (Willard et al., 2020)</td>
<td><strong>Physics informed LSTM to determine the time dependent relationship between control input and system response</strong> (Lahariya et al., 2022)</td>
</tr>
<tr>
<td><strong>Physics guided neural network for streamflow simulation and flood prediction</strong> (Liu et al., 2022)</td>
<td><strong>Physics guided neural network to improve prediction accuracy of the life cycle for developing a digital twin system</strong> (Sun &amp; Shi, 2022)</td>
</tr>
<tr>
<td><strong>Physics-based model and neural network are integrated to predict remaining useful lifetime of complex safety-critical system</strong> (Chao et al., 2022)</td>
<td><strong>Physics-based model and neural network are integrated to predict remaining useful lifetime of complex safety-critical system</strong> (Chao et al., 2022)</td>
</tr>
</tbody>
</table>
4. METHODOLOGY

In this research, two distinct methods have been considered: a conventional recurrent neural network, specifically the LSTM model, and a physics-based model. The operational mechanisms of these methods are elaborated in the subsections below.

4.1 Long Short-Term Memory (LSTM)

A Recurrent Neural Network (RNN) is a type of neural network that can handle inputs of variable sequence lengths and uses previous outputs as inputs. The recurrent hidden state is a special memory that allows the RNN to retain information from previous inputs in the sequence [20] and make predictions about future inputs. However, RNNs may suffer from the "Vanishing Gradient" problem, which occurs when information about the input or gradient is lost as it passes through multiple layers, leading to difficulty in capturing long-term dependencies and preventing further learning [21].

To overcome this problem, the Long Short-Term Memory (LSTM) architecture was introduced, which extends the memory of the RNN. It includes an input layer, a hidden layer, a cell state, and an output layer. The key component of LSTM is the cell state, which remains unchanged as it passes through the chain, with only linear interaction. The gate mechanism of LSTM, consisting of the forget gate, input gate, and output gate, helps to delete or modify the information stored in the cell state [22].

LSTM can capture long-term dependencies due to its ability to store important features from inputs and preserve this information over a long period of time. During the training process, the weights assigned to the information help the model learn what information is worth retaining or removing [21]. The visual representation of the LSTM architecture is shown in Figure 5.

![Figure 5. Visual illustration of the structure of LSTM](image)

**Forget gate:** The forget gate uses a sigmoid function which decides what information needs to be removed from the memory. The sigmoid layer is applied on the input of the current state and short-term memory of the prior cell. Then, the output of a number between 0 and 1 is generated where 0 illustrates ‘completely get rid of this’, while 1 represents ‘completely keep this’ [20]. The output is computed as:
\[ f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \]  (1)

where, \( W_f \) is the weight of the output gate, \( h_{t-1} \) is the short-term memory of the prior cell, \( x_t \) is the input of the current state and \( b_f \) is the bias of the forget gate.

**Figure 5.1 Forget Gate [27]**

**Input gate:** The next step is to decide what new information should be stored in the LSTM memory. A sigmoid layer and a tanh layer are used here to decide which values need to be updated and to create a vector of new candidate values that will be added to the cell state respectively. The output of the two layers is multiplied to determine the amount of information to be added to the cell state [27]. To produce the current cell state, the output value of the forget gate is multiplied by the previous cell state followed by adding the new candidate value. The mathematical equations are given as follows:

\[ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \]  (2)

\[ C'_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \]  (3)

\[ C_t = C_{t-1} \cdot f_t + C'_t \cdot i_t \]  (4)

where, \( i_t \) is the output value of the input gate, \( C'_t \) is the new candidate information, \( C_{t-1} \) is the long-term memory of the prior cell and \( f_t \) is the output value of the forget gate.
**Output gate**: This gate first uses a sigmoid layer that decides which portion of the cell state will be present in the output, then a tanh layer is used to shift the output in the range of -1 and 1 [27]. The output value of the output gate is generated using the sigmoid function whereas tanh layer is applied to the new cell state. The output of tanh layer is multiplied with the output of output gate to generate new the hidden state as follows:

\[
o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad \text{(5)}
\]
\[
h_t = \tanh(C_t)^* o_t \quad \text{(6)}
\]

where, \(o_t\) is the output value of the output gate, \(C_t\) is the new cell state and \(h_t\) is the new hidden state which is a value between -1 and 1.

**4.2 Physics-Based Model**

This work also considers a physics-based model employed in [1]. It uses Vincenty’s direct geodesic formulas to predict the next node location for all the vessels under consideration and designs a heuristic for the track association using these predictions. A graphical illustration is presented in Figure 6. The formulas are based on the assumption that the shape of the earth is an
oblate spheroid. For each vessel, its next location is predicted using the last node’s location, bearing and distance traveled over time.

The formula for predicting new location coordinates is:

\[ \phi_{n^j} = \arcsin(\sin \phi_{(n^j-1)} \cos \delta_{jk} + \cos \phi_{(n^j-1)} \sin \delta_{jk} \times \cos \theta_{(n^j-1)}) \] 

\[ \lambda_{n^j} = \lambda_{(n^j-1)} + \arctan(\sin \theta_{(n^j-1)} \sin \delta_{jk} \cos \phi_{(n^j-1)} \cos \delta_{jk} - \sin \phi_{(n^j-1)} \sin \phi_{n^j}) \] 

where, \( \phi_{n^j} \) is the predicted latitude of the new node and \( \lambda_{n^j} \) is the longitude of the new node, \( \phi_{(n^j-1)} \) is the latitude of the last node and \( \lambda_{(n^j-1)} \) is the longitude of the last node, and \( \theta_{(n^j-1)} \) is the bearing of the last node. Here, \( j \) refers to the track for association among \( J \) number of considered tracks, \( k \) refers to each incoming node and \( n \) implies ‘next’.

The angular distance \( \delta_{jk} \) is measured by the following equation:

\[ \delta_{jk} = \frac{d_{jk}}{r} \] 

Figure 6. Illustration of predicting new node location using geodesic path [1]

where \( r \) is the radius of the earth and \( d_{jk} \) is the distance traveled along the shortest path on an ellipsoid which is estimated through:

\[ d_{jk} = \frac{v_k + v_{(n^j-1)}}{2} \times |t_k - t_{(n^j-1)}| \] 

where, \( v_k \) is the speed of the current node and \( v_{(n^j-1)} \) is the speed of the last node, and \( t_k \) is the corresponding time of the current position and \( t_{(n^j-1)} \) is the corresponding time of the last position.
The difference between the actual location of the current node and the predicted location of the current node is determined by calculating the Haversine distance as follows:

\[
    c_{\text{dist}}(p_k, p_{\text{n}j}) = 2r \times \arcsin \sqrt{\sin^2 \left( \frac{\varphi_k - \varphi_{\text{n}j}}{2} \right) + \cos \varphi_k \cos \varphi_{\text{n}j} \sin^2 \left( \frac{\lambda_k - \lambda_{\text{n}j}}{2} \right)}
\]  

(11)

where, \( p_k := (\varphi_k, \lambda_k) \) and \( p_{\text{n}j} := (\varphi_{\text{n}j}, \lambda_{\text{n}j}) \).

Also, the angular change of direction over time can be determined using the following formula:

\[
    c_{\text{ang}}(\theta_k, \theta_{(\text{n}j-1)}) = \frac{180^\circ - |180^\circ - |\theta_k - \theta_{(\text{n}j-1)}|| |t_k - t_{(\text{n}j-1)}|}{|t_k - t_{(\text{n}j-1)}|}
\]

(12)

where, \( \theta_k \) is the actual bearing of the current node. The formula is devised regarding the circular nature of angular measurements, i.e., the 0 and 360 degrees are the same [1]. After the locations are predicted for each vessel, the distance between the incoming node’s location and these predicted locations is measured as in equation 11. This distance along with the angular change of direction measured in equation 12 helps to assign the node to a particular track. A track with a lowest haversine distance and lowest angular change of direction is a likely candidate for the underlying node.

4.3 Integration Of Physics-Based Model And LSTM

The objective of this study is to accurately link vessels to their actual tracks using the AIS dataset, by employing a unified model. There are multiple techniques available for merging two separate models, and this research work aims to combine the outcomes of a physics-based model and a neural network to achieve the desired result. The proposed algorithm integrates the predictions from the physics-based model as an additional input feature for LSTM, following the approach outlined in [13]. By using the combined model, it is anticipated that the predictive accuracy will improve compared to using a single predictive model alone.

5. THE PROPOSED TRACK ASSOCIATION ALGORITHM

This section covers the process of applying regular LSTM to the dataset, followed by an explanation of the implementation method for physics-infused LSTM. Additionally, the performance metrics employed to compare the models' performance are also discussed.

5.1 Track Association Using LSTM

To compare how the model’s performance improves when a physics-based model is combined with LSTM, at first, the LSTM model is applied to AIS data.

The steps of implementing the LSTM method on AIS data for track association are as follows:
**Step 1:** The dataset is divided into training and testing using train_test_split function from scikit library in python. Last 20% of the data is selected for testing and the rest of them are used for training for each dataset. The data are normalized using the standard scaler equation and the output data is categorized into classes.

**Step 2:** An LSTM model is built based on the training data points. From the original dataset $X = (x_1, x_2, \ldots, x_n)$ of size $n \times k$, the sequences $\{x_1, x_2, \ldots, x_{n-1}\}$ and $\{y_1, y_2, \ldots, y_{n-1}\}$ will be created, where $x_i \in \mathbb{R}^{k \times 1}$ is the input sequence and $y_i \in \mathbb{R}$ is the output data at time $t$. Here $k$ and $n$ are the number of features and the total number of observations respectively. To incorporate the required dimension of LSTM architecture, input sequence $x_t$ will be created by taking $m$ continuous sequence $x_t: x_{t+m-1}$ which is a matrix of shape $m \times k$ for $t \in \{1, 2, \ldots, n - m - 1\}$. Here $m$ is the number of time steps. Four features are used which are longitude, latitude, speed, and direction of the vessel for generating the multivariate input sequence. Since the vessel’s ID needs to be predicted, the vessel ID is generated as output.

**Step 3:** After performing a hyperparameter selection study, it was decided that three layers should be considered to allow the network to learn more complex and abstract representations of the input data and thereby increase prediction accuracy. Thus, two more LSTM layers are added and a dropout of 25% is used after every layer to avoid overfitting. Each LSTM layer can learn different temporal features of the sequence, with the output of one layer serving as input to the next layer. The first LSTM layer can capture short-term dependencies and can learn to extract low-level features in the input sequence, while subsequent layers can capture longer-term dependencies and can learn to combine the low-level features into higher-level representations. ‘Relu’ activation function is used in every LSTM layer since it is computationally more efficient compared to the sigmoid and tanh functions. It converts a negative input to zero and does not activate that particular neuron which eventually rectifies the vanishing gradient problem [31].

**Step 4:** Since our goal is multiclass classification, ‘SoftMax’ activation function is used in the output layer to obtain the predicted probability distribution of the output classes. The number of neurons used in this layer is the number of vessels in the respective dataset. Categorical cross-entropy loss function is used to measure the difference between true probability distribution and predicted probability distribution, and the model learns to correctly classify by minimizing the loss.

**Step 5:** The model is applied to the test dataset to predict the vessel ID of each node in the test dataset.

The key components of implementing the LSTM model are summarized in Figure 7.
5.2 Track Association Using Physics Infused LSTM

The following framework is used to implement the physics infused LSTM model by merging the physics-based model with LSTM model for track association.

**Step 1:** First, the physics-based model is applied to the dataset to get the location prediction and subsequent track association.

**Step 2:** The location of the incoming node is predicted using the vincenty’s geodesic formula with the help of the features of the last node of each track.

**Step 3:** The distance between the actual location and the predicted location for each track is measured using equation (11).

**Step 4:** A dissimilarity score for each j is measured using equation (13) and the associated track based on the overall dissimilarity score is decided using equation (14).

\[ s_{jk} = c_{\text{dist}}(p_k, p_n) \]  
\[ z : \arg\min j \in J (s_{jk}) \]

The node is associated with that track for which the lowest dissimilarity score is generated.
**Step 5:** The node is assigned to a track and it is updated as the last node of that track for predicting the future nodes.

**Step 6:** Step 2 to step 5 is repeated for the rest of the points in the dataset and a vessel ID is assigned to all nodes. An additional column is created in the dataset and the predicted vessel IDs are stored in that column.

**Step 7:** The dataset is divided into training and testing and normalized following the procedure from step 1 in the LSTM approach.

**Step 8:** An LSTM model is built based on the training data points following the procedures from step 2 to step 4 described in the LSTM approach. In this approach, five features are used for generating the multivariate input sequence. The column of predicted vessel ID from the physics-based model is added as the fifth feature along with longitude, latitude, speed, and direction.

**Step 9:** The model is applied to the test dataset to predict the vessel ID of each node.

The process of implementation of the proposed algorithm is displayed in a schematic diagram and in a process flow diagram in Figure 8 and in Figure 9 respectively.

![Figure 8: A schematic diagram of physics infused LSTM architecture](image-url)
Figure 9. A process flow diagram of implementing Physics Infused LSTM for track association.
The proposed framework is summarized in Figure 10 combining all the elements.

![Figure 10: A block diagram to summarize the proposed framework](image)

### 5.3 Performance Evaluation Metrics

To evaluate the algorithm's performance, the predicted tracks need to be matched with the actual tracks. This matching is essential since the algorithm is based on predictions. A 'Confusion Matrix' is a table layout commonly used in machine learning and statistical classification problems to visualize an algorithm's performance [28]. The confusion matrix has two dimensions, namely 'actual' and 'predicted,' and each dimension has a set of identical classes. Table 2 portrays the layout of the confusion matrix [28].

#### Table 2. Layout of Confusion Matrix

<table>
<thead>
<tr>
<th>Actual Condition</th>
<th>Predicted Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive (P)</td>
<td>True Positive (TP)</td>
</tr>
<tr>
<td>Negative (N)</td>
<td>False Positive (FP)</td>
</tr>
</tbody>
</table>

The accuracy of the model can be determined using the following equation:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]

(17)
6. RESULT ANALYSIS
The analysis of the results is divided into two subsections. The first subsection examines and breaks down the results of the different algorithms implemented on various datasets. The second subsection evaluates the overall influence of the datasets' characteristics on the models' performance.

6.1 Performance Evaluation
As our datasets simulate different real-life scenarios with varying levels of complexity, the results obtained from applying the algorithms to them can lead to different interpretations. We consider the following cases to compare the individual performance of the LSTM model, physics-based model, and physics-infused LSTM model:

i. AIS data without time gaps and lower no. of observations
ii. AIS data with time gaps and lower no. observations
iii. AIS data without time gaps and higher no. of observations
iv. AIS data with data time gaps and higher no. of observations

6.1.1 AIS Data Without Time Gaps And Lower No. Of Observations
To assess this specific scenario, we use dataset-1 and apply the LSTM, physics-based model, and physics-infused LSTM algorithm individually to it. The performance of the LSTM model is illustrated in Figure 11’s confusion matrix. It reveals that the model can accurately assign all nodes of four out of six vessels to their respective tracks. However, for the remaining vessels, the model can only accurately assign 96.7% and 87.7% of the nodes, respectively.
Meanwhile, the physics-based model achieves over 99% accuracy in assigning all nodes to their corresponding tracks. The results from the confusion matrices suggest that the physics-based model works with more precision than the LSTM model for datasets with less complexity and lower no. of observations, as shown in Figure 12.
To evaluate whether incorporating the physics-based model's predictions enhances the LSTM model's performance, we apply the physics-infused LSTM to the dataset. Figures 13a and 13b display the learning curve plots for the LSTM model and physics-infused LSTM model, respectively. The pattern of the physics-infused LSTM model's curves shows that both the training loss and validation loss decrease and stabilize earlier and at a lower level compared to the regular LSTM model, indicating better performance.

Figure 12: Performance of physics-based model on dataset-1

Figure 13: Training loss and validation loss curves for dataset-1
The confusion matrix of physics infused LSTM is presented in Figure 14. The result of incorporating the predictions from the physics-based model into the training of the LSTM model exhibits better performance. This algorithm associates all nodes of all vessels accurately to their corresponding tracks.

Figure 14: Performance of physics infused LSTM model on dataset-1

### 6.1.2 AIS Data With Time Gaps And Lower No. Of Observations

Datasets 2 and 3 are employed to investigate this specific scenario. To analyze the performance of the proposed algorithm on these datasets, the performance of the LSTM and physics-based models are also evaluated.

The confusion matrix in Figure 15 represents the performance of LSTM on dataset-2. The model achieves 100% accuracy for two out of seven vessels (vessel 4 and vessel 6). It accurately assigns nodes for three vessels (vessel 0, vessel 3, and vessel 5) with over 90% accuracy and achieves 74.2% accuracy for one vessel (vessel 2). However, the model shows poor performance for one vessel (vessel 1), with an accuracy of only 13%. One possible explanation could be the high degree of overlap between vessel 1 and vessel 3, making it challenging for the model to differentiate them.
Physics-based model also associates all nodes of vessel 4 and vessel 6 perfectly with 100% accuracy. On the contrary, it achieves even lower accuracy than the LSTM model to correctly assign nodes for vessel 0, vessel 2, vessel 3 and vessel 5, which is less than 60%. The plausible reason could be due to time gaps in the data for these tracks. Nevertheless, while LSTM struggled to assign nodes of vessel 1, the physics-based model assigns 81.5% of nodes of this track perfectly. The confusion matrix is presented in Figure 16.
Finally, the physics-infused LSTM model is applied to the dataset. Figures 17a and 17b illustrate the learning curves for the LSTM model and the physics-infused model, respectively, displaying a clear difference between them. The training and validation loss of the physics-infused model decrease at a faster rate and stabilize at a lower point than the LSTM model.
Figure 17: Training loss and validation loss curves for dataset-2

Figure 18 displays the confusion matrix of the physics-infused LSTM. The combined algorithm accurately assigns all nodes of vessel 4 and vessel 6 with 100% accuracy. Additionally, integrating the physics-based model's predictions into training the LSTM model has resulted in a noticeable improvement in accuracy (an increase of 3-20%) for vessel 2, vessel 3, and vessel 5. However, there has been a minor and negligible decrease in accuracy (a decrease of 1%-3%) for vessel 0 and vessel 1 compared to the LSTM model, which might be a result of having lower no. of training data.
The performance of the LSTM model on dataset-3 is illustrated in the confusion matrix shown in Figure 19. The model accurately assigns all nodes of vessel 3 and vessel 7 to their respective tracks with 100% accuracy. It also assigns over 80% of the nodes of each of vessel 0, vessel 2, vessel 4 and vessel 5 to their corresponding tracks. However, the model performs poorly in assigning nodes of vessel 1 and vessel 6, although it correctly assigns more than 50% of the nodes of vessel 1. This could be attributed to a similar issue as observed in dataset-2, where the model struggles to differentiate between vessel 1 and vessel 4, as well as vessel 6 and vessel 4 due to their close proximity and multiple intersections.
The results obtained from the physics-based model exhibit a different perspective. While the model successfully detects all the nodes of vessel 7, it only manages to detect 51.6% of the nodes of vessel 3. Moreover, the model's performance in assigning nodes to the tracks of vessel 0, vessel 2, vessel 4, and vessel 5 is unsatisfactory. Like the LSTM model, the physics-based model also shows poor performance in assigning nodes to the tracks of vessel 1 and vessel 6, with an accuracy of less than 15% due to the gaps in the data. Figure 20 displays the confusion matrix for this performance analysis.
The plots of learning curves of the LSTM model and physics infused LSTM model illustrate a similar trend as before, shown in Figures 21a and 21b. Both the training loss and validation loss of physics infused LSTM model decrease and stabilize at a lower point compared to the LSTM model, which suggests a better training of the former.
Figure 21: Training loss and validation loss curves for dataset-3.

The indication of better training of physics infused LSTM model is reflected in its results shown in Figure 22. The accuracy of each vessel has improved by 2% to 19% compared to the LSTM model.

Figure 22: Performance of physics infused LSTM model on dataset-3.
6.1.3 AIS Data Without Time Gaps And Higher No. Of Observations

Dataset-4 contains a significantly larger number of observations for vessels compared to the previous datasets, with most vessels having around 5000-6000 observations. The LSTM model applied to this dataset demonstrates exceptional performance, as the accuracy for each of the 18 vessels is above 97%. The corresponding confusion matrix is displayed in Figure 23.

![Confusion Matrix](image)

Figure 23: Performance of LSTM model on dataset-4

Similarly, the physics-based model also performs satisfactorily on this dataset, securing 100% accuracy in detecting all nodes of all vessels. The confusion matrix is shown in Figure 24.
The plots of learning curves of LSTM model and physics infused LSTM exhibit a similar trend. Both models’ training loss and validation loss stabilize at the lowest point, although the losses of physics infused LSTM model decrease earlier than the regular LSTM model. The learning curves for both models are demonstrated in Figures 25a and 25b.
Finally, the combined model of LSTM and physics-based model also performs with 100% accuracy since the models individually perform well. The confusion matrix is shown in Figure 26.
6.1.4 AIS Data With Time Gaps And Higher No. Of Observations

Incorporating some random data gaps in dataset-4 as described in the data description section, we generated dataset-5. The introduction of these data gaps has minimal effect on the accuracy of LSTM model. All vessels’ accuracy remains unchanged except for vessel 2, which experienced a 1.1% decrease in accuracy only. The confusion matrix is shown in Figure 27.
In contrast, physics-based models experience a decrease in accuracy of 5 vessels out of 18 vessels. There is a decrease by 1.5% to 78% in the accuracy of vessel 1, vessel 5, vessel 8, vessel 10 and vessel 17 compared to the performance on dataset-4. The model underperforms due to the presence of time gaps in the dataset as shown in its confusion matrix in Figure 28.

Figure 27: Performance of LSTM model on dataset-5
The plots of learning curves of LSTM model and physics infused model demonstrate a comparable pattern in this particular case as well. The physics infused model exhibits an earlier decrease in training loss and validation loss compared to the LSTM model, although both of them eventually stabilize at the lowest point as shown in Figures 29a and 29b.
The integration of physics-based model with LSTM model increases the accuracy of vessel 2 to 100%, compared to the performance of LSTM model on dataset-5. However, it has had a negligible impact on the accuracy of vessel 1, decreasing it by only 2.4%. Overall, the combined model performs superior to the regular LSTM model in this case also, as shown in its confusion matrix in Figure 30.
6.2 Impact Of Dataset Characteristics On Algorithms’ Performance

The following analysis evaluates and discusses the impact of various factors on the performance of the algorithms based on the results obtained from the above scenarios, including data gap, dataset complexities, and number of observations.

1. Impact of dataset characteristics on LSTM model performance
2. Impact of dataset characteristics on physics-based model performance
3. Impact of dataset characteristics on physics infused LSTM model performance
6.2.1 Impact Of Dataset Characteristics On LSTM Model Performance

To summarize the performance evaluation of LSTM model on various datasets, it performs satisfactorily for most of the vessels of dataset-1, whereas the model shows a deteriorative performance for only one vessel of datasets 2 and 3. However, it performs remarkably well for all vessels of datasets 4 and 5.

The performance of dataset-1 proves that a higher frequency of data points can lead to better accuracy since the model can capture more detailed information about the vessel’s trajectory. On the other hand, LSTM loses its edge when the vessels are very close to one another, cross each other frequently or change it direction or speed abruptly. These factors explain LSTM model’s poor performance for a particular vessel in datasets 2 and 3. But the most significant finding is that the LSTM model’s performance escalates when there is a higher number of observations per vessel as observed for datasets 4 and 5. The more observations available for each vessel, the better the training of the LSTM model and eventually the better the performance. Even, the presence of a time gap in dataset-5 could not significantly affect the performance of the model.

Linear regression and ANOVA analysis are performed to quantify the effects of these characteristics on respective models. The analysis is conducted considering the accuracy of each model as a response variable and dataset characteristics as predictor variables. The presence of complicated trajectories, time gap, and lower number of observations are set to the value of 1, on the other hand, if complicated trajectories and time gap are not present in the dataset and the number of observations is higher, the values are set to 0.

The result shows that the linear model equation for the LSTM model is,

\[ y = 0.998 - 0.1545x_1 - 0.001x_2 - 0.022x_3 \]  

(13)

where \( x_1 \) is the representative of the complexity of trajectories, \( x_2 \) is the presence of a time gap and \( x_3 \) is the number of observations. The equation reveals that when there is a presence of complicated trajectories and the number of observations is lower, the accuracy decreases. The accuracy also decreases with the presence of time gap, however, the coefficient value is much smaller than the other coefficients. Thus, the performance declines the most with the presence of complicated trajectories and the least with the time gap.

Additionally, the results of the ANOVA analysis show that the complexity of the trajectories is the most significant factor for the LSTM model. We use (*) to represent the significant factor when the significance level is 0.1, (**) when the significance level is 0.05 and (***) when the significance level is 0.01. Therefore, the effect of the complexity of trajectories in LSTM model performance is not negligible. The p values of the characteristics from ANOVA analysis are listed in Table 3.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>p-value from ANOVA analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complicated trajectories</td>
<td>0.04108**</td>
</tr>
<tr>
<td>Time gap</td>
<td>0.62016</td>
</tr>
<tr>
<td>No. of observations per vessel</td>
<td>0.41882</td>
</tr>
</tbody>
</table>

Table 3: Results of ANOVA analysis for LSTM model performance
The effects of the dataset characteristics on LSTM model performance are summarized in Figure 31.

**Figure 31: Summary of the impact of dataset characteristics on LSTM model performance**

### 6.2.2 Impact Of Dataset Characteristics On Physics-Based Model Performance

In summary, physics-based model works with 100% accuracy for all of the vessels of dataset 1 and 4, but the model’s performance shows a decline for most of the vessels of dataset 2 and 3. Moreover, it fails to detect many of the nodes in certain vessels of dataset-5, resulting in a lower level of accuracy.

Specifically, in dataset-1, which has a higher level of granularity in the data and smaller time intervals between timestamps, the physics-based model performs better by utilizing the features of the node from the latest timestamp to predict the next position. Moreover, it does not require a large amount of labeled data to associate tracks with high accuracy. In opposition, the performance of most vessels in datasets 2 and 3 is notably low as a result of the existence of data gaps along with a high degree of complexity in the datasets. Thus, due to the long gap of missing information, the model’s ability to accurately predict the positions of the next nodes of a vessel is compromised, which potentially affects the prediction of other vessels’ positions. Finally, the accuracy of the vessels in datasets 4 and 5 reveals that the performance of the model gets impacted by the gaps present in the data, rather than the number of observations per vessel.

Following the procedures mentioned in the analysis of LSTM model performance, linear regression, and ANOVA analysis are performed on the performance of the physics-based model. The result shows that the linear model equation for the physics-based model is,

$$y=1-0.4164x_1-0.1x_2-0.0001x_3 \quad (14)$$

The presence of the critical characteristics affects the performance of the physics-based model negatively as well and the number of observations has the least impact (negligible). The presence of complicated trajectories and time gaps affects the accuracy significantly.

The results of the ANOVA analysis show that the p-value of complicated trajectories is on the borderline when the significance level is 0.1. So, the impact of complicated trajectories is not negligible. The p values of the characteristics from ANOVA analysis are listed in Table 4.
Table 4: Results of ANOVA analysis for physics-based model performance

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>p-value from ANOVA analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complicated trajectories</td>
<td>0.1020</td>
</tr>
<tr>
<td>Time gap</td>
<td>0.5150</td>
</tr>
<tr>
<td>No. of observations per vessel</td>
<td>0.9995</td>
</tr>
</tbody>
</table>

The effects of the dataset characteristics on physics-based model performance are summarized in Figure 32.

![Figure 32: Summary of the impact of dataset characteristics on physics-based model performance](image)

*Impact of number of observations is negligible

*Presence of time gap affects significantly

*Complexity of vessel trajectories along with data gap worsens accuracy

6.2.3 Impact Of Dataset Characteristics On Physics Infused LSTM Model Performance

The implementation of physics infused LSTM model for every dataset results in a higher accuracy of the LSTM model, indicating that incorporating the predictions from the physics-based model improves the performance of the regular LSTM model. Even if the datasets possess varying characteristics, the physics infused LSTM consistently outperforms both of the individual models, with only a minimal decrease in accuracy for a small number of vessels. The analysis clearly reveals that adding physical laws and principles in the algorithm provides a better understanding of the behavior of the vessels and aid in the interpretation of the results. In addition, the training process of LSTM model enhances the integrated model’s ability to handle sequential data and recognize intricate patterns, making it a reliable and robust algorithm. With the aid of a substantial number of observations per vessel, the algorithm can effectively overcome the situations involving time gap or complex vessel trajectories. The accuracy of each of the model for each dataset is summarized in Table 5.
Table 5: Overall accuracy of the individual models and the proposed hybrid model

<table>
<thead>
<tr>
<th>Dataset</th>
<th>LSTM</th>
<th>Physics-based model</th>
<th>Physics infused LSTM</th>
<th>Complicated trajectories</th>
<th>Time gap</th>
<th>No. of observations per vessel</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>97.6%</td>
<td>99.99%</td>
<td>100%</td>
<td>No</td>
<td>No</td>
<td>Low</td>
</tr>
<tr>
<td>02</td>
<td>81.2%</td>
<td>54.4%</td>
<td>84.5%</td>
<td>Yes</td>
<td>Yes</td>
<td>Low</td>
</tr>
<tr>
<td>03</td>
<td>82.9%</td>
<td>42.3%</td>
<td>89.7%</td>
<td>Yes</td>
<td>Yes</td>
<td>Low</td>
</tr>
<tr>
<td>04</td>
<td>99.8%</td>
<td>100%</td>
<td>100%</td>
<td>No</td>
<td>No</td>
<td>Low</td>
</tr>
<tr>
<td>05</td>
<td>99.7%</td>
<td>90%</td>
<td>99.99%</td>
<td>No</td>
<td>Yes</td>
<td>High</td>
</tr>
</tbody>
</table>

After applying linear regression and ANOVA analysis on the performance of physics infused model, the linear model equation is,

\[ y = 1 - 0.1289x_1 - 0.0001x_2 - 0x_3 \]  \hspace{1cm} (15)

The above equation shows that the accuracy gets impacted only by the presence of complicated trajectories. The time gap and the number of observations do not affect the performance significantly.

The results of the ANOVA analysis demonstrate that p-value of all the characteristics is greater than the significance level, which suggests that no characteristics affect the performance of the integrated model significantly. The p values of the characteristics from ANOVA analysis are listed in Table 6.

Table 6: Results of ANOVA analysis for physics-infused LSTM model performance

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>p value from ANOVA analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complicated trajectories</td>
<td>0.1621</td>
</tr>
<tr>
<td>Time gap</td>
<td>0.9986</td>
</tr>
<tr>
<td>No. of observations per vessel</td>
<td>1</td>
</tr>
</tbody>
</table>

To assess the effects of the models on the accuracy, another regression analysis is conducted. Here, an additional variable ‘model’ is considered along with the other predictor variables. The values for the physics-based model, LSTM model, and physics-infused LSTM model are set to 0, 1, and 2 respectively. The equation is given below,

\[ y = 0.911833 - 0.233267x_1 - 0.0337x_2 - 0.007367x_3 + 0.0875x_4 \]  \hspace{1cm} (16)

where \( x_1 \) is the representative of the complexity of trajectories, \( x_2 \) is the presence of a time gap, \( x_3 \) is the number of observations and \( x_4 \) is the selected model.

The only factor that affects the accuracy positively is the selection of the model. Since physics-infused LSTM has been assigned the largest value, this model will improve the accuracy the most compared to the other models. Moreover, the coefficient of trajectory complexity has the largest value that affects the accuracy negatively.

ANOVA analysis depicts that the model and trajectory complexity are the most significant factors with a p-value of 0.0282 and 0.00129 respectively. The analysis is extended by comparing the significance of the LSTM model and physics infused LSTM model to the performance of the
physics-based model. It shows that the p values for the LSTM model and physics-infused LSTM model are 0.0561 and 0.03 respectively, which indicates that there is a statistically significant difference in both the LSTM model and physics-infused LSTM model compared to the physics-based model. The p values from the above analysis are listed in Table 7 and Table 8.

Table 7: Results of ANOVA analysis for analyzing the significance of the selected model

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>p-value from ANOVA analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complicated trajectories</td>
<td>0.00129***</td>
</tr>
<tr>
<td>Time gap</td>
<td>0.70212</td>
</tr>
<tr>
<td>No. of observations per vessel</td>
<td>0.93495</td>
</tr>
<tr>
<td>Model</td>
<td>0.0282**</td>
</tr>
</tbody>
</table>

Table 8: Results of ANOVA analysis for the comparison of the LSTM model and physics-infused LSTM model to the physics-based model

<table>
<thead>
<tr>
<th>Model</th>
<th>p-value from ANOVA analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSTM</td>
<td>0.0561*</td>
</tr>
<tr>
<td>Physics infused LSTM</td>
<td>0.03*</td>
</tr>
</tbody>
</table>

To evaluate the effectiveness of our proposed algorithm, another recurrent neural network, bidirectional long short-term memory (BiLSTM) model is considered to be integrated with the physics-based model and be implemented. Bidirectional model extends the LSTM capabilities by training the input data twice in forward and backward directions [21]. It incorporates two recurrent neural networks trained in opposite directions, one of them processes the sequence from beginning to end, while the other one does the opposite, allowing the model to learn not only from past and present but also from future information [29]. The physics infused BiLSTM model also performs similarly satisfactorily for every dataset, just like physics infused LSTM. Rather, it exhibits higher accuracy compared to the physics infused LSTM model, with an improvement of around 1% to 2%. The comparison of the performances suggests that integrating neural network models other than the regular LSTM, specifically with capabilities to handle complexities would lead to enhanced accuracy. The comparison is shown in Table 9.

Table 9: Performance comparison of physics infused LSTM and physics infused BiLSTM models

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Physics infused LSTM</th>
<th>Physics infused BiLSTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>02</td>
<td>84.5%</td>
<td>86.9%</td>
</tr>
<tr>
<td>03</td>
<td>89.7%</td>
<td>90.9%</td>
</tr>
<tr>
<td>04</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>05</td>
<td>99.99%</td>
<td>100%</td>
</tr>
</tbody>
</table>
7. CONCLUSION

This study aims to demonstrate how adding physics-based equations to a data-driven LSTM model can improve the accuracy of track association using AIS data. A geodesic framework is used as the physics model to predict future vessel locations under surveillance. In contrast, LSTM is a neural network approach that can capture long-term patterns in sequential data to track future nodes. To test the hypothesis, we consider five AIS datasets of varying complexities and apply the competing approaches to these datasets for track association. The findings indicate that the physics-based model struggles with data irregularities along with complex trajectories, while the LSTM model suffers from a lack of training data and complicated trajectories. However, the integrated model can capitalize on the strengths of both approaches, resulting in improved tracking accuracy across all test datasets. This thesis also identifies the strengths and weaknesses of each competing method.

The proposed approach can be extended in several ways. In this work, the possibility of the inclusion of a new vessel is not considered. In future, an anomalous track could be generated to facilitate tracking nodes generated from new vessels. Also, LSTM model cannot capture the spatial information embedded in sequential data, which could aid in track association. In the future, a Convolutional Neural Network (CNN)-LSTM model could be developed to address this issue.

8. REFERENCES


