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Enhancing vessel arrival time prediction: A fusion-based deep learning approach

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Abstract

The logistic community of shippers has struggled to predict the precise arrival time of the seagoing vessels with reliable certainty. While deep-learning approaches are promising, the existing methods fail to provide desirable results due to a shallow prediction architecture. This research work proposes a method to predict vessel arrival time that could eventually be incorporated into an intelligent decision support system that we call *Vessel Arrival Time Prediction (VATP)*. VATP presents a hybrid architecture of Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Attention mechanism, Dropout, and Dense layers to take advantage of the coarse-grained local features produced by CNN, the longitudinal nature of AIS (long-time dependencies) via LSTM and paying attention to the influence feature on the arrival time. While many prior approaches have relied solely on AIS data, and some incorporated a combination of AIS and vessel information, our method also integrates diverse data sources, including Automatic Identification System (AIS), Augmented information (Ain), and Maritime Weather Data (MWD). Furthermore, only a few methods have considered weather information, often using minimal weather-related features. In contrast, our approach involves a comprehensive range of weather-related features, and besides these data sources, we extracted specially crafted features.

To verify the effectiveness of VATP, we conducted our experiment on large-scale datasets. The VATP model obtained a Root Mean Square Error (RMSE) of 10.63 and a Mean Absolute Percentage Error (MAPE) of 35.11%. Our results demonstrate that VATP achieves significant performance. Furthermore, these positive results demonstrate that *i)* the accuracy of the VATP approach can be improved using the AIS, MWD, and Ain information; *ii)* learning from a unified feature set can result in a significant performance improvement compared to learning from a subset of the features; *iii)* we also obtained a superior performance in comparison with other well-known methods in the literature and various state-of-the-art baseline methods. Finally, our results illustrate the consistent performance of the VATP across different datasets.

Previous Next

Keywords

Arrival time prediction; Deep learning; Fusion deep learning; Intelligent transportation systems

1. Introduction

Maritime transportation is a critical mode of transportation for domestic and international trade due to its large capacity and its relatively environment-friendly nature. Nowadays, global economic expansion has led to a rise in the need for bigger vessels for marine transportation. Moreover, shipping has become an important approach for transporting goods over a long distance. According to the results of studies (Lechtenberg et al., 2019, Mao et al., 2018), over 90% of world trade is being shipped by vessels. However, in this circumstance, for a port, where several vessels have to be loaded and unloaded every day, terminal operations that include i) Berth scheduling or berth allocation in harbours (Ambrosino & Tanfani, 2012); ii) Human resources (*number of working shifts to serve the incoming ship*); iii) equipment allocation or mechanical and spatial resources (Di Francesco et al., 2015, Fancello et al., 2011) and iv) Yard planning (Ku et al., 2012) have become key issues in maritime transportation, especially in the daily planning scenario. A significant issue in port supply chains arises from the uncertainty surrounding ship arrival times, causing disruptions in port planning (Gómez et al., 2016, Parolas, 2016, Veenstra et al., 2012). Additionally, the costs associated with supply chain services contribute to the overall transportation expenses (Zuidwijk and Veenstra, 2010, Zuidwijk and Veenstra, 2015). Therefore, enhancing the accuracy of predicting vessel arrival times could result in reduced supply chain costs. In addition, the competitiveness of the terminal will be improved because the efficiency of the terminal can then be maximized while minimizing the cost of operations. If a vessel's arrival time could be predicted with reasonable accuracy, then resources can be allocated more efficiently and the entire logistics process can be carried out smoothly. Precise vessel arrival time prediction improves the resource allocation process and investment decision-making (Mensah & Anim, 2016). It has been shown to provide significant advantages for a port in terms of achieving a competitive advantage, and planning terminal operations quickly and flexibly to achieve significant cost savings and increased efficiency (Fancello et al., 2011, Meijer, 2017). It is also useful for decision-making in scheduling operations and activities in various areas such as ships, docks, and shipyards while meeting different requirements (Fancello et al., 2011).

The advancements in information technology (IT), the accessibility of big transport data, and the capability to analyze huge amounts of data have drawn a lot of interest in studying transportation modelling for a variety of applications, such as *Arrival Time Prediction (ATP)*). ATP indicates the prediction of the date and time that a shipment is predicted to arrive at a specified destination.[2] Few studies have been conducted for vessel arrival time prediction.

Automatic Identification System (AIS) (Installed on ships) is a vital technology in maritime navigation that aims to enhance safety and security and AIS transponders automatically broadcast crucial information such as vessel identity, position, course, and speed. However, using Automatic Identification System (AIS) data for arrival time prediction brings its own set of challenges, where, the unreliability of equipment, human input, external conditions, dense traffic etc. (Emmens et al., 2021) make it difficult to create a predictive model. Therefore, a new method is needed to create a predictive model for AIS data that recognizes its challenges and combines it with less noisy datasets like Maritime Weather Data (MWD) and Augmented Information (Ain).

We propose a new deep learning-based method (DLBM) to predict the arrival time of a vessel at a port using multi-feature fusion that we call *Vessel Arrival Time Prediction* (VATP). In the context of arrival time prediction, VATP leverages a combination of techniques including CNNs, attention layer, dropout layer, LSTM, and fully connected layers to enhance the accuracy and achieve its objectives. We then conduct an empirical study to compare its performance with existing methods.

As we explain later in the 'Literature Review' section, most existing methods use only the AIS dataset to predict arrival time (*e.g.*, (Fancello et al., 2011, Salleh et al., 2017, Hardij, 2018, El Mekkaoui et al., 2022)). Papers by Abebe et al., 2020, Pani, 2014, Parolas, 2016, cover only a limited combination of different data. Our study differs from these by considering the intensities of precipitation, snow, temperature levels, etc., instead of simply examining the presence or absence of inclement weather conditions or only considering a minimal set of weather-related features.

The contributions of our research can be summarized as follows:

1) We propose a new deep learning-based method to predict vessel arrival time. Our proposed method involves utilizing a combined network that incorporates CNN, LSTM, Attention mechanism, Dropout layer, and fully connected layer. This method allows us to benefit from acquiring rough local features, carrying out sequential processing, emphasizing significant features, and overcoming the overfitting problem.

2) We combine various data sources, such as Automatic Identification System (AIS), Augmented Information (Ain), and Maritime Weather Data (MWD), while previous methods mainly depend on AIS data alone, and others integrate AIS with vessel information. We found only a limited number of methods that consider weather information, typically with minimal features. In contrast, our approach encompasses a broad array of weather-related features. Apart from these sources, we extract specially crafted features for our model.

3) We illustrate how and why the different layers of the deep learning architecture were selected for the set of features in our dataset. We think this will help researchers and practitioners in constructing a similar deep learning-based model for perhaps a different set of features.

4) We conduct extensive experiments on large data sets: firstly, we analyse the effect of the AIS Information Feature (AIF), Vessel Information Feature (VIF) and Weather and Sea information Features (WSF) on the VATP method. Secondly, we demonstrate the

effectiveness of the VATP method by comparing the VATP with other models such as LSTM, bidirectional LSTM, CNN, and a set of traditional machine learning-based techniques (i.e., Random Forest, Support Vector Machine). Thirdly, we compared the performance of the VATP with existing proposed methods. We find that VATP achieves superior performance on the measured metric and the significant results affirm the suitability of the proposed method.

The rest of this paper is structured as follows. The following Section 2 summarizes the current state of arrival time forecasting in general and recent related work as well as the challenges associated with existing proposed methods. The research methodology is presented in Section 3. Section 4 presents and discusses the experimental results. Finally, conclusions and ideas for future studies are provided in Section 5.

2. Literature review

Vessel arrival time has a key role in planning activities at a port. Uncertainty over vessel arrival time leads to difficulties for the planning activities of the stakeholders involved in hinterland transportation since inland transportation planning can be based on the vessel arrival time. Many goods are transported by sea and handled by ports worldwide and therefore arrival time predictions (ATP) of vessels can assist a company to improve its logistics related to transporting goods and services to vessels. Shipping companies can take advantage of the ATP information for various trading purposes and ATP can lead to cost reductions through better managing, planning, utilization of resources, and reduced waiting time at port. Moreover, it leads to improving the connection of various loading and unloading processes as well as to the cooperation among the different partners in a logistic chain. Therefore, being able to accurately predict the time of arrival of the vessels at the port would have a positive impact on the supply chain operations. We focus on arrival time of sea faring vessels using AIS data in this paper, please refer to (Abdi & Amrit, 2021) for a review of arrival time methods for road vehicles.

As mentioned briefly in the introduction, the AIS system is critically important in maritime navigation. It automatically broadcasts crucial information such as the vessel's identity, position, course, and speed. This real-time data facilitates vessel identification, aids in collision avoidance, and improves overall situational awareness. AIS includes different types of information such as static, dynamic and voyage. Static information includes the ship's identification number, length, beam, and type. Voyage-related data encompass information about the ongoing voyage, including draught, estimated time of arrival (ETA), and destination. Dynamic data tracks ships' movements, including their position (latitude and longitude), course over ground, and speed over ground (Emmens et al., 2021). AIS enables ship operators to make decisions based on the positions and trajectories of nearby vessels. AIS has a global reach, and its signals can be received over VHF radio frequencies. This global coverage contributes to the effectiveness of AIS in improving maritime safety on a large scale.

In the following subsection, we describe some of current methods for the ATP of vessels.

2.1. Current methods on arrival time prediction of vessels

In this section, we begin by offering an overview of techniques (prediction methods) that can be used for predicting arrival times. Subsequently, we explore recent research focused specifically on maritime arrival time prediction. We then move on to an examination of research employing traditional machine-learning methods and progress to those utilizing more advanced deep-learning methods.

Regression-based method — Such methods utilize a linear mathematical formula to model the relationship between the input and the output/target variables (Dhivyabharathi et al., 2016). In other words, each input (x) is associated with a value of the output/target variable (y). The accuracy of the regression-based method is determined by the identification of suitable input (x) variables as well as their correlation and linearity. Furthermore, a regression model can give a good result when the relationship between input variables and output is linear. Therefore, the difficulty of this method is how to define the non-linear relationship between arrival time and various factors.

Deep learning-based method (DLBM) — Traditional ML-based methods (TMLBM) have diverse applications that have been developed for different objectives. However, traditional methods often encounter challenges when handling large datasets (Lv et al., 2014). Therefore, Deep Learning (DL)-based approaches have attracted the interest of scholars. DL-based approaches are employed for various real-world problems such as classification and pattern recognition, data processing, control, robotics, and prediction. DL is a sub-field of machine learning method that instructs computers to accomplish things that humans do naturally and there are several DL-based methods such as DNN, CNN, RNN, etc.

Yu and Voß (2023) addresses the concept of Just-In-Time (JIT) arrival in green shipping, focusing on optimizing container ship operations through the integration of berth allocation, quay crane assignment, and vessel speed optimization. It introduces a two-stage model combining machine learning-based vessel arrival time prediction with the optimization of berth allocation and vessel speed. The study emphasizes the importance of JIT arrival to reduce fuel consumption, emissions, and service delays in maritime transportation, which plays a significant role in global trade.

The study presented by Kolley et al. (2023) explores data-driven optimization for berth allocation, addressing uncertainty in vessel arrival times. Four machine learning methods are employed for arrival time prediction, enhancing robustness in berth scheduling. The approach combines AIS data exploration, machine learning forecasts, and optimization methods, aiming to reduce uncertainty and improve robustness in berth allocations while considering potential trade-offs with efficiency. The study's contributions include insights into AIS data utilization, evaluation of machine learning methods, and the development of a robust berth allocation model, showcasing practical relevance through real data analysis.

Pani (2014) proposed a method to provide accurate information about the arrival time of ships to help planners and improve daily strategies such as berth planning, loading, or unloading operations, transport of containers, and yard stacking. The author uses different algorithms including Logistic Regression, CART and Random Forest. Furthermore, the methods exploited vessel-related information and weather-related information to predict vessel arrival time. They obtained the best performance by using Random Forest algorithms.

Salleh et al. (2017) proposed an approach to forecast ship arrival time at a specific port. They utilized a hybrid technique including a Fuzzy Rule-Based Bayesian Network (called the FRBBN method). For the analysis of punctuality of arrival, theyconsidered important factors of the port and vessel conditions. Parolas (2016) also presented an approach to estimate the vessel arrival time. The author uses Neural Networks (NN) and Support Vector Machines (SVM) for arrival time forecasting using a combination of AIS (*e.g., position and speed*) and weather information. They use historical data to train the NN and SVM approaches, and they claim that their method obtained a significant improvement in the prediction of arrival time. Interestingly, their research indicates that weather information does not affect the performance of the proposed method. Moreover, compared to the neural network, SVM obtained good results in terms of error metrics.

Hardij (2018) presented a neural network-based approach (LSTM) to estimate arrival times for tanker ships using the AIS dataset. The author also compares the performance of their proposed method with other machine learning methods. Fancello et al. (2011) also developed a method for vessel arrival time prediction. They find that their method based on a neural network (an MLP) achieves a substantial reduction in costs and can assist operators at ports or terminals. In their model, the information (input variables) is first fed into the model, then the information flows across the network layer by layer to produce an output. The method uses AIS information, such as estimated time of arrival (ETA) month, ETA Day of the week and ETA hour. However, it does not consider weather information. The results show that a neural network makes the most accurate prediction regarding the ETA of a container vessel.

Park et al. (2021) proposed a method for optimizing port operations by leveraging a combination of path-finding algorithms (Alessandrini et al., 2018) and AIS data for accurate ETA prediction. The proposed method consists of two key steps. In the first step, the method utilizes a Markov Decision Process (MDP) based Reinforcement Learning (RL) framework to identify and learn vessel patterns based on AIS data. In the second step, the method estimates both the Speed Over Ground (SOG) and Estimated Time of Arrival (ETA) based on the predicted vessel trajectory. To estimate SOG, the method applies the Metropolis-Hastings algorithm (MH algorithm). Moreover, the ETA calculation is performed by dividing the estimated SOG by the distance covered along the predicted trajectory.

Bodunov et al. (2018) developed an approach aimed at delivering predictions for both ship destinations and their corresponding arrival times within a streaming framework, specifically tailored to the maritime domain. The method leverages geospatial data, combining an ensemble of machine learning models along with a deep learning model to provide reliable predictions. El Mekkaoui et al. (2020) present an approach based on the Neural Networks (NN) models to predict the arrival time of a ship to its destination using AIS data.

Ogura et al. (2021) introduce a prediction method for estimating vessel arrival time, considerin weather conditions. The approach comprises two primary stages: route calculation and voyage speed determination. During the initial stage, the analysis focuses on past routes taken by vessels that share similar gross tonnage (GRT) as well as the vessel types. By computing the difference between future and past weather conditions for each route, the selection process identifies the route with the least discrepancy. Subsequently, in the second stage, historical operational data for vessels of comparable type and GRT are gathered, considering similar future weather conditions at each location along the chosen route. By employing Bayesian learning techniques, the voyage speed is ascertained based on factors such as bow direction and future weather conditions at each site. The time required to travel between sites is then calculated by dividing the distance by the voyage speed.

The study conducted by Bourzak et al. (2023) presents an approach based on deep learning models to predict the Estimated Time of Arrival (ETA) of vessels. The models were trained on different data sources, considering various types and characteristics of vessels. It emphasizes the potential of these methods to leverage maritime data for ETA prediction, offering solutions to enhance supply chain management in the maritime industry. The research aims to introduce innovative machine-learning approaches to improve the efficiency and reliability of maritime logistics, addressing issues such as delays, port congestion, and cost optimization. Various deep-learning models such as Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks, and Transformers are analyzed for vessel ETA prediction. By comparing the performance of various models, the BiLSTM model was selected as the most effective for vessel ETA prediction.

Noman et al. (2021) use Gradient Boosting Decision Trees (GBDT), Multi-Layer Perceptron Neural Networks (MLP), and Gated Recurrent Unit Neural Network (GRU) algorithms to predict ETAs using AIS data. The performance of the models is analyzed, and as a result, GRU provides the best prediction accuracy and outperforms the other models (Noman et al., 2021).

El Mekkaoui et al. (2022) also address the problem of vessel arrival time prediction to destination ports using machine learning-based methods and the AIS dataset. The author compared different techniques such as Neural Network (NN), Support Vector Regression (SVR), Random Forests (RF), Gradient Boosting (GB), and Multiple Ridge Regression (RR) models. The results show that the Neural Network model performs better than the other models (El Mekkaoui et al., 2022).

Abebe et al. (2020), utilize a machine learning approach to predict ship speed over the ground using the automatic identification system (AIS) and weather data. This framework includes Data Acquisition, Data Preprocessing, Feature Selection and Extraction, and Prediction Models. Various machine learning regression techniques are employed, such as linear regression (LR), polynomial regression, decision tree regressors (DTRs), gradient boosting regressors (GBRs), extreme gradient boosting regressors (XGBRs), random forest regressors (RFRs), and extra trees regressors (ETRs). The models' accuracy result displayed that the ETR model has shown better accuracy than the other models (Abebe et al., 2020).

3. Research methodology

In this study, we aim to present a DLBM to predict vessel arrival time. To achieve this, we primarily use the Design Science methodology to design and develop our method VATP (Hevner et al., 2004, Peffers et al., 2007). Design Science research methodology (Hevner et al., 2004, Peffers et al., 2007) is a research approach focused on creating practical solutions for real-world problems. It involves the creation of a viable artefact in the form of a model or a method, rigorously evaluating its effectiveness, and communicating the findings. Key principles include problem relevance, rigorous research methods, and clear contributions to design theory and practice (Hevner et al., 2004). By applying the Design Science research methodology to our research goal, we arrive at the following steps, and each step is described in detail in the corresponding section. We first present the VATP and then introduce the applied techniques. The important phases of data analytics are then connected to create a more precise forecasting method. These phases are Data pre-processing, Feature extraction, CNN, LSTM, Attention mechanism, Dropout, and Fully connected/dense layers. We also evaluated the performance, robustness, and effectiveness of the VATP method using RMSR and MAPE. Subsequently, we describe the data collection, data processing, dataset resources, and the required pre-processing steps. We use four data sources in the experiment along with feature fusion for performance optimization. We also investigate the potential of various DLBM and TMLBM methods to predict the arrival time of the vessel. We then not only present and discuss the outcomes of this study, but also compare the performance of VATP with the existing proposed systems. The entire VATP system is presented in Fig. 6.

We first present our input dataset and then we discuss how one can create an effective deep neural network for predicting arrival time.

3.1. Dataset

The objective of this section is to provide a detailed process of the overall data collection and analysis process for the current research work. The dataset is collected from different online repositories: Automatic Identification System (AIS) data, Vessel information, weather, and sea information. By incorporating this information, we aim to enhance the transparency and applicability of our findings. The linked ships in this dataset (*e.g.*, Container Ships and Tankers) represent a typical selection commonly observed during maritime operations at a particular port (*e.g.*, Rotterdam and Amsterdam). We employed common identifiers to link and collect corresponding information from multiple datasets. For example, we used the Global Positioning System (GPS) coordinates and timestamps as shared identifiers to collect data on sea conditions and weather at specific points or positions. Furthermore, we used vessel identification numbers (ship ID) to link AIS data with vessel information. Through linking these datasets using common identifiers, we successfully integrated the relevant information.

The Automatic Identification System (AIS) — is a safety system of navigation and maritime traffic enforced by the International Maritime Organization (IMO). All vessels with a gross tonnage greater than 300 are obliged to have an AIS system. The AIS information can be used for various vital applications, such as vessel monitoring, maritime surveillance, security, rescue, traffic management, and collision avoidance (Sampath, 2012). Fig. 1 presents the factors influencing the arrival time of a ship. It also shows various subfigures (*including sea information, weather information, ship details, and AIS data*) that provide an overview of these interconnected elements and their impact on ship arrival. The sea information (*e.g., details on sea currents*) aids in understanding the challenges ships may face during their journey. The weather information shows meteorological data (*e.g.,* wind speed) for assessing the impact of weather on ship performance and arrival time. The ship information offers insights into vessel information (*e.g., size, type*). Finally, the AIS data provide real-time ship information (*e.g., positions, speed*) that enables the assessment of navigational efficiency and potential delays. Fig. 1 provides an overview of the various factors contributing to ship arrival time, facilitating analysis and decision-making processes for optimal planning and management.

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Fig. 1. Factors and information influencing the arrival time of a ship.

As shown in Fig. 2, during a voyage, each ship emits thousands of signals at periodic intervals, which are then received by satellites, ground stations, and other ships. The AIS dataset includes various information that can be categorized into dynamic information (*e.g., speed, course, and position*) and static information (*e.g., ship name, MMSI, ship type*). Table 1 presents the fields of the AIS dataset as well as the corresponding explanation of each field.

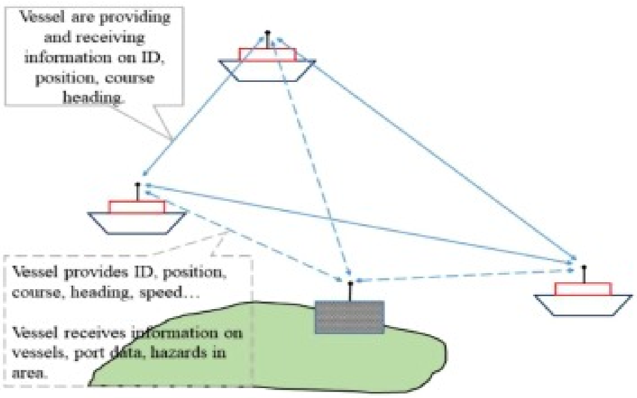

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Fig. 2. AIS system overview (Lee et al., 2019).

Table 1. Typical AIS message.

Field	Description
Ship name:	Name of the ship.

Field	Description
Destination:	Port of destination.
Heading:	The heading of the vessel in degrees.
MMSI:	Maritime Mobile Service Identity – a unique nine-digit identification number of the ship.
IMO number:	International Maritime Organization – a unique identifier related to a specific ship.
longitude:	The longitudinal position of a ship, $-180 \leq \mathbf{longitude} \leq 180$.
latitude:	The latitudinal position of a ship, $-90 \leq \mathbf{latitude} \leq 90$.
ETA:	Mariners try to arrive at the provided estimated time of arrival.
Draught:	Draught is the vertical distance between the ship's keel and the waterline.
COG:	Course over ground – is the actual direction of a vessel in decimal degrees.
SOG:	Speed Over the Ground – is the speed of the vessel relative to the surface of the earth.
ship type:	Type of the ship such as Tanker, Cargo, Passenger, Military ops, Fishing, and others.
Timestamp:	UTC second when the report was generated by the electronic position system (EPFS).
ZONE:	Name of the World zone where the ship is located.
Navigation status:	the navigational status of a ship that can be '*at anchor*','*not under command*', '*moored*', '*aground*', '*underway sailing*', etc.).

Vessel information — We also derived *vessel information* from the aforementioned websites (Fig. 3) using IMO or MMSI. This information can be considered complementaryto the AIS dataset. As presented in Table 2, the information includes the IMO, MMSI, Vessel Type, Status, Gross Tonnage, Deadweight tonnage, ship's length, and Breadth. Status is used to check whether the vessel still is active or not.

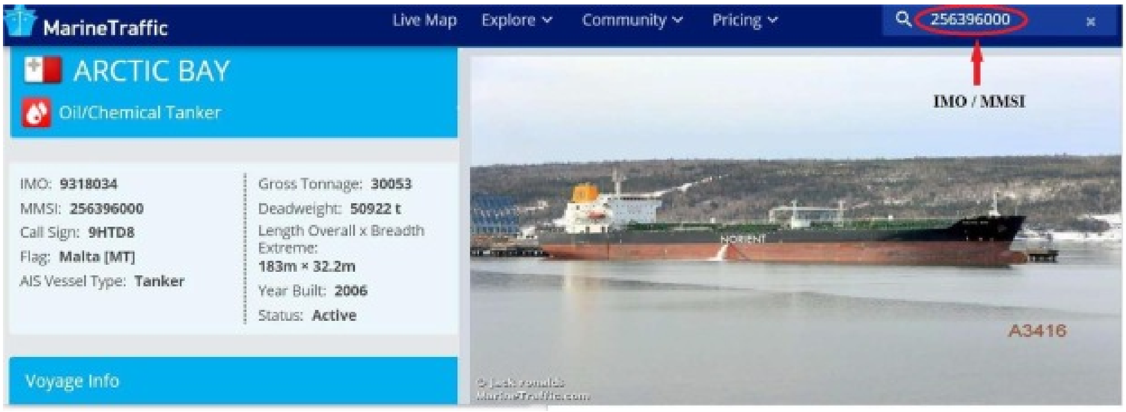

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Fig. 3. Vessel information extraction using the corresponding website.

Table 2. General characteristics of a ship.

Field	**Description**
Length:	A ship's length (m).
Breadth:	A ship's width (m).
Gross Tonnage:	Tonnage is a measure of the cargo-carrying capacity of a ship.
DWT:	Deadweight tonnage is a measure of how much weight a ship can carry.
IMO:	International Maritime Organization – a unique identifier related to a specific ship.
Vessel Type:	Type of the ship such as Tanker, Cargo, Passenger, Military ops, Fishing, and others.
MMSI:	Maritime Mobile Service Identity – a unique nine-digit identification number of the ship.
Status:	the navigational status of a ship.

Weather and Sea information — We also use marine *weather information* to enhance the vessel arrival time forecasting performance. As AIS data does not provide marine weather information, it is required to get marine weather information. ERDDAP (Fig. 4) provides meteorological data, which enables users to access data based on the date, latitude, longitude, and other factors. A sample of weather information that is shown in Table 3 includes temperature, precipitation (*e.g., rainfall and snowfall*), sky conditions (*e.g., visibility, wind speed*), significant wave height, wave direction, wind direction, wave period in seconds (*the time between two peaks of a wave at the same point in space*), etc.

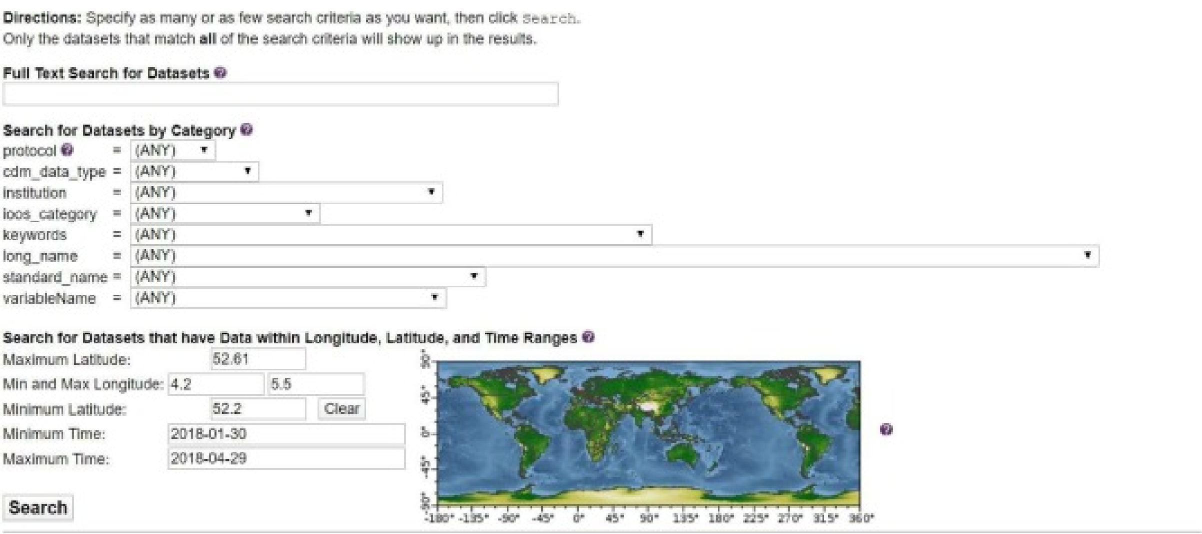

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Fig. 4. Vessel information extraction using the corresponding website (ERDDAP).

Table 3. A sample dataset of ERDDAP.

Date	Latitude	Longitude	Wind_speed	Vapor_content	Cloud_water_con	Rainfall_rate
2019-12-31	1.125	154.625	2.80	60.90	0.12	0.0
2019-12-31	1.125	154.875	4.80	62.40	0.24	0.3
2019-12-31	1.125	155.125	5.20	63.60	0.31	0.6
2019-12-31	1.125	155.375	5.20	63.00	0.32	0.5
2019-12-31	1.125	155.625	5.40	62.40	0.22	0.1
2019-12-31	1.125	155.875	4.80	62.10	0.14	0.0
2019-12-31	1.125	156.125	5.20	62.40	0.24	0.3
2019-12-31	1.125	156.375	3.00	63.60	0.29	0.3
2019-12-31	1.125	156.625	4.60	63.60	0.16	0.0

Augmented information — indicates invariant features (such as length, width, and vessel type) and new features (NF) created using one or more existing variables (we utilized the AIS dataset).

As can be seen from the above datasets, apart from *Vessel Information* all other datasets are essentially time series. There is not much guidance on how one can create a deep learning model with such different input datasets with features varying in both space and time. In the following section, we will describe our approach to creating VATP.

3.2. VATP – Proposed method

VATP employs a sequential model since various factors in different situations or steps can have a different effect on vessel arrival time prediction. In other words, the problem is that the vessel speed, weather conditions, etc. may not remain constant for the entire journey due to the wind, rolling of the ship, waves, and surface sea currents along the route of the vessel. Thus, to establish a sequential model and get more accurate predictions of the arrival time, we divide the route between source and destination (Fig. 5) into several segments using position or location information (*e.g., latitude and longitude*). This means, the journey is divided into segments based on specific latitude and longitude coordinates. This division results in an equal number of these segments along the route from source A to destination B.

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Fig. 5. Segmentation of route between source and destination.

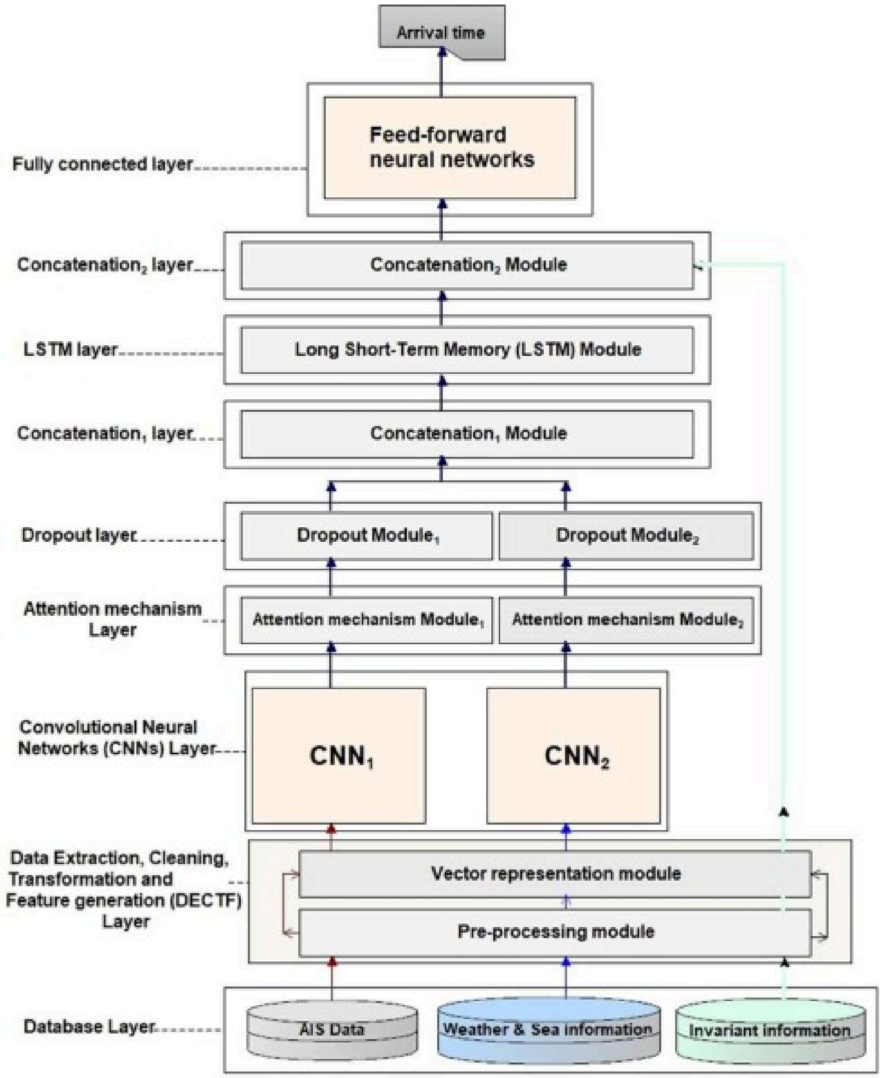

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Fig. 6. The architecture of the proposed method VATP.

Fig. 5 shows the visualization of the full trajectory of a sample vessel from source (A) to destination (B). We, therefore, consider a chronological collection of positions $\{P_1, P_2, \ldots, P_i, P_j, \ldots, P_n\}(1 \leq i \leq n,$

$j=i+1$), where each point or step $\mathrm{P_i}$ indicates feature information such as longitude, latitude coordinate, etc. Earlier research has not considered the sequential aspects of arrival time forecasting. Therefore, by using a recursive approach, RNN-LSTM (refer to Appendix), our proposed method uses a different approach compared to the previous research by considering the dependence between entries. On the other hand, compared to previous research, VATP integrates different resource information, features, or factors.

The architecture of the VATP system based on the fusion model is presented in Fig. 6. The system architecture is composed of several layers, namely: '*Database layer*', '*Data Extraction, Cleaning, Transformation and Feature generation (DECTF) layer*', '*Convolutional Neural Network (CNN) layer*', '*Attention mechanism layer*', '*Dropout layer*', '*Concatenation$_1$ layer*', '*LSTM layer*', '*Concatenation$_2$ layer*' and '*Fully connected layer/ Dense layer*'. In the following sub-sections and section "*4. Experimental Results and Discussion*", we present the structure of the VATP system layer by layer.

3.2.1. Dataset and DECTF layers

Dataset organizes data and information required in the system. It consists of the input data, including the AIS dataset, weather & sea information, and invariant/vessel information.

The DECTF layer consists of two main parts: a pre-processing module and a vector representation module. The entire process of the DECTF layer involves two main steps:

Step I: Pre-processing module

It is used to perform data pre-processing. Briefly, the pre-processing task includes the following steps:

i) Data cleaning: indicates the correction of data problems. The data is checked to eliminate missing values (*e.g., there is no entry for a variable*), and erroneous values.

ii) Domain values determination: the definition of the values to be used at each feature.

iii) Feature extraction: extracting a set of features from the corresponding dataset.

iv) Creating a new variable or feature: using one or more existing features to create a new one.

It is worth noting that the additional information about the pre-processing step can be found in section '*3.4 Pre-processing*'.

Step II: Vector representation module

A feature refers to a data attribute that can be utilized for the purpose of analyzing and capturing patterns within the data. The module comprises multiple steps aimed at transforming input data into a collection of features for the purpose of predicting arrival time. The vector is defined as $\mathrm{X_t} = \{\mathrm{x_1}, \mathrm{x_2}, \mathrm{x_3}, \mathrm{x_4}, \ldots \mathrm{x_n}\}$ where $\mathrm{x_i}$ is established based on the corresponding feature. Feature extraction procedure is described in the section "*3.5 Input features*".

3.2.2. Convolutional Neural Networks (CNNs) layer

The current layer consists of two CNN architectures (CNN_1 and CNN_2), and each CNN processes one of the two input data (*e.g., AIS dataset and weather & sea information*). CNN is a form of NN that has been successfully used for image processing and other computer vision tasks. A CNN architecture (Fig. 7) includes different layers that contain an Input layer, Convolution layer, Pooling layer, and Flatten layer.

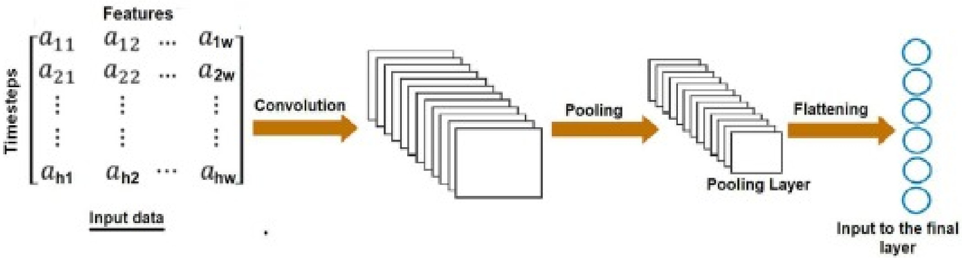

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Fig. 7. The Convolutional Neural Network architecture.

Input layer: includes input data that can be an array in the form of $[\mathbf{h} \times \mathbf{w} \times \mathbf{d}]$ where each row (h=Height) represents a specific timestamp associated with each GPS coordinate and each column (w=Width) corresponds to a feature. The dimension (d) refers to the number of channels or RGB values. We considered the input matrix as a single channel (channels=1).

Convolution layer: It is the first step in the process of extracting significant features from input data. A convolution layer has several filters or kernels that perform the convolution operation to create afeature map. Mathematically, convolution is the summation of the element-wise product of 2 matrices. As shown in Fig. 8 (1), the input data is on the left, the filter or kernel is in the middle and the output (feature map) is on the right. The input data is a 5x5 array, and the filter matrix is 3x3 which is smaller than the input data. The figure also shows how the feature map matrix is obtained: the values in the filter are multiplied by the original values of the input data using the dot product. Then, these multiplications are all summed up and the result is a single number (*e.g.*, 5). This number is the result of a filter when it is at the top left of the input data. The same process is repeated for every location on input data. To do this, the filter can move to the right by n (n is the stride value) unit.

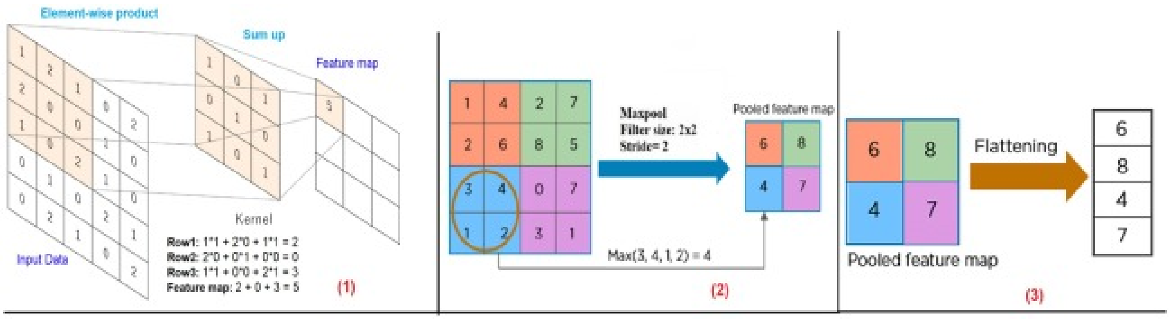

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Fig. 8. The convolutional layer process.

Pooling layer: Following the convolutional layers, CNNs often include pooling layers. It reduces the output of the convolutional layer to the most salient elements. In other words, it reduces the dimensionality of the feature map. Max pooling is a commonly used technique in which the maximum value within each pooling region is selected as the representative value. As shown in Fig. 8 (2), suppose the output of convolutional layers is 4x4. If we apply the filter (2x2) and the max pooling method to the matrix, the biggest value among all the values in the receptive field is passed to the output (*e.g.*, rose color=7, light green color=8, orange color=6, blue color=4) and the 4x4 dimension input is reduced to 2x2 dimension as the output matrix.

Flattened layer: The convolutional and pooling layers are followed by a flattened layer, Fig. 8 (3). Flattening is used to convert all the resultant 2-dimensional arrays from pooled feature maps into a single one-dimensional vector. The flattened matrix is fed as input to the next layer, the attention layer. The processing of input data through the different layers of CNN is explained in the Appendix.

3.2.3. Attention mechanism layer

This is a crucial component that allows a model to identify the most relevant and informative information from an input sentence during the training process. This layer plays an important role in directing the model's focus towards the most effective features of the input, allowing it to optimize its performance. As detailed in Bahdanau et al. (2014), the attention layer is precisely defined and designed to support this critical function. However, the attention layer is defined as follows:

$$\mathrm{e_i} = \tanh\left(\mathrm{W.h_i} + \mathrm{b}\right) \tag{1}$$

$$\alpha_\mathrm{i} = \mathrm{Softmax}\ \left(\mathrm{W'.e_i} + \mathrm{b'}\right) \tag{2}$$

$$\mathrm{v_i} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\alpha_\mathrm{i}.\mathrm{h_i}\right) \tag{3}$$

Where W, $\mathrm{W'}$, b and $\mathrm{b'}$ are utilized and updated during the training process. To compute the output value of every node within the network, the activation functions SoftMax (.) and tanh (.) are utilized. A one-layer feedforward neural network is represented by Eq. (1), where the tanh activation function is utilized to derive a new hidden representation of $\mathrm{h_i}$, denoted as $\mathrm{e_i}$, from each state of LSTM. Additionally, attention weights α_i are computed using the SoftMax function, as illustrated in Eq. (2). Ultimately, Eq. (3) is used to compute a new vector $\mathrm{v_i}$.

3.2.4. Dropout and the concatenation layers

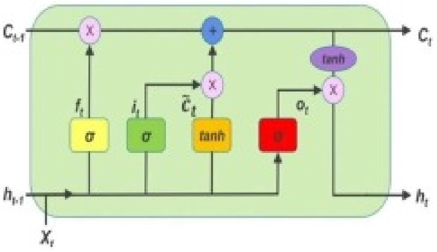
Dropout layer is used to avoid overfitting. During training, some nodes are randomly dropped out. It includes two dropout modules that accept the outputs of two attention mechanism layers.

The Concatenation_1 layer concatenates the outputs of both dropout modules to form a single long feature vector.

Unlike the concatenation_1 layer, the concatenation_2 layer is employed to combine the vector representation extracted from the LSTM layer with invariant features, leading to the creation of a completed vector. Following this, the resultant vector is then passed on to the fully connected layer (FCL) to reveal the arrival time.

3.2.5. LSTM layer

LSTM is used to learn from temporal sequential data. LSTM can handle and learn from long-term dependencies which alleviates vanishing and exploding gradient problems. LSTM processes temporal data using the forget gate, input gate, and output gate to append or delete information to the cell state throughout the processing of the sequence data (Fig. 9). The cell state is the main part of LSTMs that carry and transfer relevant information from earlier timesteps to later timesteps. The LSTM section in the Appendix indicates how the LSTM memory cell is updated. However, the output of the concatenation$_1$ layer is given to the LSTM layer.



$$(1) \quad i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

$$(2) \quad f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

$$(3) \quad o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

$$(4) \quad \tilde{c}_t = Tanh(W_c x_t + U_c h_{t-1} + b_c)$$

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Fig. 9. The LSTM architecture.

An overview of the utilized methods: In the Appendix, we have provided a concise explanation of the fundamental principles behind several applied techniques.

3.2.6. Methodological distinctions in VATP approach

The VATP method shares a common goal with the previously mentioned studies, but it distinguishes itself through differences in methodology and the way the process is represented.

1) In comparison with the existing methods, VATP is a novel method that integrates CNNs, LSTM, Attention mechanism, Dropout, and dense layers i) to extract robust features, ii) to take advantage of sequential processing to deal with long-time dependencies, a consideration that is often lacking in existing methods, and iii) to assign different weights to the outputs of LSTM in order to emphasize effective features.

2) VATP utilizes multiple data sources (AIS, maritime weather, augmented information) for arrival time prediction, unlike previous methods that rely solely on AIS or limited data combinations.

3) Existing Traditional Machine Learning (TML) models for arrival time prediction are shallow, limiting forecasting accuracy due to the nonlinear nature of prediction variables.

We now provide a detailed description of the measures employed to evaluate the performance of VATP. Additionally, we will present an in-depth explanation of each experiment conducted and the sequence in which they were carried out.

3.3. Performance measurement

We use two Key Performance Indicators (KPI) to evaluate and compare the performance of different predictive models. These metrics are as follows.

i) Root Mean Square Error (RMSE): the square root of the average squared error. Where the error is the difference between the predicted and actual arrival time.

ii) Mean Absolute Percentage Error (MAPE): the average difference between the predicted and actual arrival time. MAPE and RMSE are defined as shown in Eqs. (4), (5).

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_1 - y_0}{y_0}\right| \times 100\% \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_1 - y_0\right)^2} \tag{5}$$

where, y_1 is the predicted arrival time, y_0 is the actual arrival time and *n* is the number of a data point in the dataset.

3.4. Pre-processing (Data Quality Issues)

We pre-processed the dataset before applying the VATP method *s*ince one of the main challenges involved in handling raw datasets is cleaning them to ensure the removal of noise and invalid or corrupted data. The q*uality control and* process that we followed include: i) adding new variables that can be computed using the existing information, ii) standardizing and normalizing the data, iii) verifying and editing the dataset to eliminate errors, missing values, and creating input variables that would be used for vessels arrival time prediction.

AIS data is not reliable. As stated subsequently there are diverse reasons for faulty and missing pieces of information.

i) Failures to update information,

ii) Inaccurate information and failing to follow required procedures,

iii) Installation failures (*e.g., installing the equipment*) and the quality of equipment,

iv) The data being affected by external conditions such as weather conditions,

v) Human failures/mistakes (*when a mistake is made by a human this can lead to errors in data*).

The possible errors in the AIS dataset can be (Meijer, 2017): a data item that has to be manually input when an AIS system is installed on a vessel. For instance, the MMSI has been input incorrectly. The MMSI might be assigned to a different vessel with different details/specifications. MMSI is a unique identification number that's used to identify AIS. The *ship type* is also selected from a predetermined list during AIS installation. However, this field is sometimes left empty or referred to as “ship/vessel”. The other data fields also suffer from the same problem. For example, the field *ship name*, which is left blank, includes an incorrect name or uses an abbreviation instead of the ship’s name. there are errors in the *length and width* fields of a vessel in an AIS dataset. Both are static data that should be entered into the device when the AIS system is installed. On the other hand, *the ship position* (latitude, longitude) is dynamic information that must be updated. We eliminated data that was out of range, such as latitudes less than 90° and more than 90°, and longitudes less than 180° and greater than 180°. Draught is also a data field of AIS information. However, in some cases, a ship did not report it or reported a draught of 0m. There were also errors in the fields of destination and the estimated time of arrival (ETA). The errors in the ETA field were that it was often out of date or that the ETA was in the very distant future. The fields of destination may also have a NULL value, different names, abbreviations, a number rather than a destination, or a country rather than a port. To assess our prediction model, the dataset is randomly divided into two parts: testing (30%) and training (70%). The training dataset included samples that were used to create the model. A set of examples were used to train the model and fit the parameters (*e.g.* weights and biases in the case of Neural Network). The VATP model is trained on the samples using a supervised learning method. This meant that the samples included pairs of an input vector and the corresponding output vector, where the answer/output indicated the target or label. The test dataset was used to qualify performance and assess the final model fit on the training dataset. A test dataset included a set of examples that were independent of the training dataset and had never been used in training.

3.5. Input features

The following sub-sections present a list of input features that are used for predicting the arrival time of vessels. A feature is a measurable property or attribute of data that could be utilized for data analysis and pattern detection in data. The feature extraction method converts the input data into several features that can be used to predict the arrival time. In this study, we select the AIS information (AI), weather-sea parameters *(*WSP*),* and vessel specification (VS) as the elements of vector representation. The definition of the vector is as follows: $\mathrm{AI_t} = \{\mathrm{AI_1}, \mathrm{AI_2}, \ldots, \mathrm{AI_m}\}$, $\mathrm{WSP_t} = \{\mathrm{WSP_1}, \mathrm{WSP_2}, \ldots, \mathrm{WSP_n}\}$, $\mathrm{VS_t} = \{\mathrm{VS_1}, \mathrm{VS_2}, \cdots, \mathrm{VS_k}\}$, where m, n, and k are the number of features. In addition to these vectors, we also include the new variables as new features (*NF, as explained in the following sub-section*). However, the features that are considered for addressing *arrival time prediction* can be summarized as follows:

3.5.1. AIS information and new features (NF)

We create new features using one or more existing variables. To do this, we used the AIS dataset as follows:

The distance between two adjacent points (DAP): Latitude and longitude are time-varying location data. However, given latitude and longitude, the following equation is used to determine the distance (L) between two neighboring locations/points (Zhu et al., 2011).

$$\mathrm{L} = \arccos\left(\sin(\varphi_1)\sin(\varphi_2)\cos(\lambda_1)\cos(\lambda_2)\cos(\lambda_1 - \lambda_2)\right) \times \mathrm{R_e} \tag{6}$$

where λ and φ are the longitude and latitude of two points $\mathrm{P_1}$ and $\mathrm{P_2}$ respectively. $\mathrm{R_e}$ is the earth radius.

The average speed (s) between two adjacent points: (SOG, COG)

As shown in Fig. 10, the entire section $(P_1 P_2)$ is divided into smaller sections $(q_1, \cdots, q_n)$ and the average speed between two points is calculated using the following equation:

$$\bar{V} = \frac{(V_1 + V_2 + \cdots + V_n)}{n} \tag{7}$$

where n is the number of subsections.

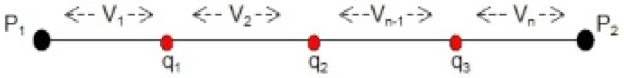

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Fig. 10. Segmentation of a section.

Time intervals per day (TID):

The timestamp of each position/ location (P_t) is broken into four new variables: night (00–06), morning (06–12), afternoon (12–18), and evening (18–24). We use a constant binary vector (four-dimensional vector: "*morning*", "*afternoon*", "*evening*", "*night*") to concatenate with the other feature vectors.

Time intervals per year (TIY):

the timestamp of each position/ location (P_t) is also broken into four new variables: spring, summer, autumn, and winter. We also use a constant binary vector (four-dimensional vector: "*spring*", "*summer*", "*autumn*" and "*winter*") to concatenate with the other feature vector.

We used the following features from the AIS dataset:

• Heading	• Longitude
• Draught of the ship	• Latitude
• DAP	• Navigational status of the vessel
• $\bar{V}_{SOG}, \bar{V}_{COG}$	• TIY
• TID	

3.5.2. General parameters of a vessel

We also consider the following characteristics of a vessel as input features.

• Deadweight (tons)	• Length
• Gross Tonnage (tons)	• Beam
• Type of vessel	

3.5.3. Specified weather parameters

Variables concerning weather and sea information are presented in Table 4.

Table 4. Weather and sea information.

• Snowfall [*kg m-2*s^{-1}]	• Temperature [*degree (C)*]
• Rain rate [*mm/hr*]	• Surface specific humidity
• Monthly mean rainfall amount [*mm/day*]	• Total cloud cover
• Wind stress* [*pa*]	• Ice thickness at the surface [*m*]
• Wind speed root mean square [$m\ s^{-1}$]	• Ice velocity in the x-direction [*m/s*]
• Surface eastward wind [$m\ s^{-1}$]	• Ice velocity in the y-direction [*m/s*]
• Surface northward wind [$m\ s^{-1}$]	• Surface primary wave direction [*deg*]
• Wind speed [$m\ s^{-1}$]	• Surface eastward gravity wave stress [*n m-2*]

- Maximum surface wind speed [$m\ s^{-1}$]
- Wind in y-direction [m/s]
- Wind in x-direction [m/s]
- Surface sig height of wind waves and swell [m]
- Surface northward gravity wave stress [$n\ m$-2]
- Surface primary wave mean period [s]
- Surface albedo*
- Surface albedo for visible diffuse

* Wind stress: wind stress signifies the shear stress exerted by the wind on the surface of the oceans, seas, estuaries and lakes (Bryant & Akbar, 2016).

*Surface albedo: the surface albedo quantifies the fraction of the sunlight reflected by the surface of the Earth (Coakley, 2003).

3.5.4. Features overview

Fig. 11 shows the overview of feature extraction and categorization procedures.

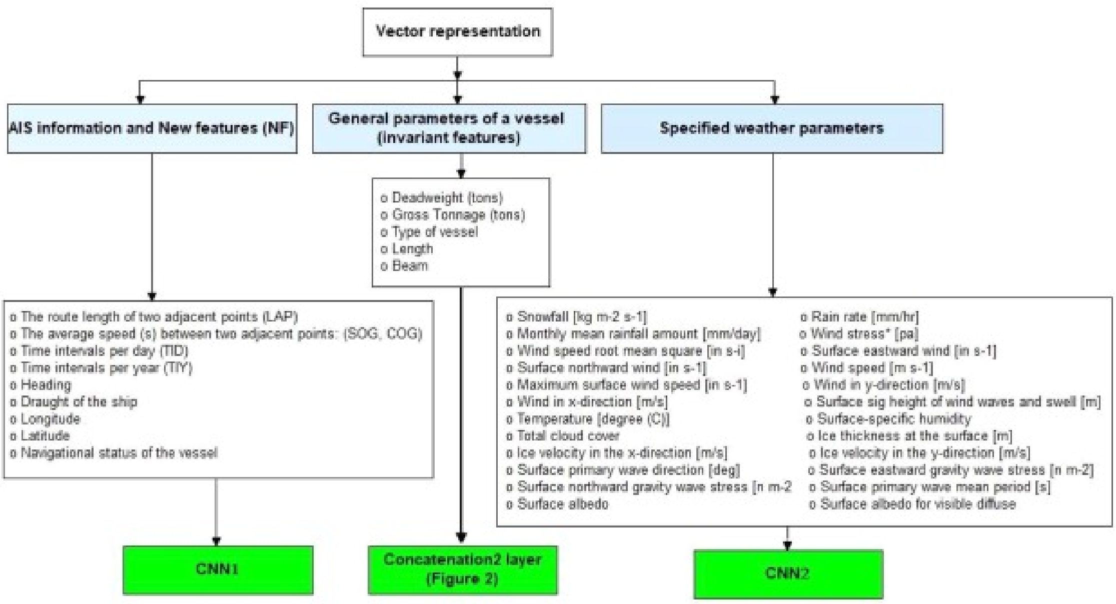

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Fig. 11. Vector representation.

3.6. Hyper-parameter optimization

In the context of machine learning models, hyperparameter optimization is crucial for effective model training. This is because specifying a significant number of parameters is necessary to achieve the best performance. Therefore, ensuring the accuracy and reliability of a model requires appropriate tuning of these hyperparameters. Tuning hyperparameters is based on finding a balance between overfitting and underfitting. Overfitting occurs when the gap between the training error and the validation error is too large, while underfitting happens when the model cannot achieve sufficiently low error on the training set. A good model would have a small training error and a minimal gap between the training and test or validation errors. In this study, we utilize a combination of Random search functionality and a tenfold cross-validation testing strategy that uses 70% of the data for training, and 30% of the data for testing to identify the optimal hyperparameters for our prediction models.

In K-fold cross-validation, the training dataset is initially divided into K subsets, each called a 'fold.' One subset acts as the validation set while the remaining $(K-1)$ subsets serve as the training data. This procedure repeats K times, guaranteeing each subset acts as the validation set at least once. The ultimate validation outcome is determined by averaging the performance across all folds used as validation sets.

The VATP model encompasses several hyperparameters. To obtain the optimal prediction results in this study, we tune the following main hyperparameters: Activation functions, Layer-specific parameters, and additional parameters. The selected hyperparameters are provided in Fig. 12. To run the search, random search works by randomly selecting combinations of hyperparameters to try, rather than searching through all possible combinations. This approach is particularly useful when the hyperparameter space is large and complex, as it can help to accelerate the optimization process and improve model performance. For each set of hyperparameters chosen, the model is trained and evaluated using a validation dataset. This process is repeated for a specified number of iterations or until a certain performance threshold is reached. After evaluating the performance of each combination, the hyperparameters that resulted in the best performance are selected for the final model. The primary focus is on exploring multiple parameters to achieve optimal outcomes. The learning process of VATP can be influenced by several factors, which are outlined in Fig. 12.

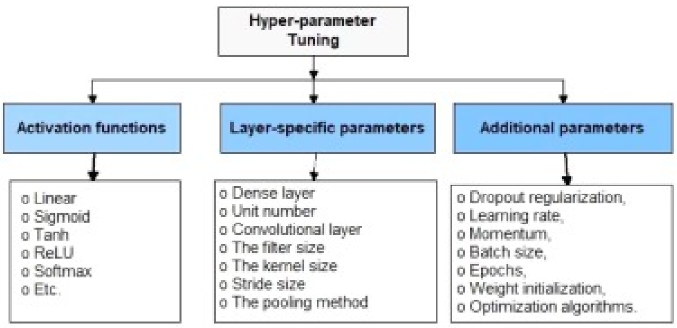

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Fig. 12. Hyper-parameter Tuning.

3.6.1. Overfitting analysis

As mentioned earlier, overfitting occurs when an artificial intelligence-based model performs very well during training but experiences a significant drop in performance on new data. We can use overfitting analysis to explore under what conditions a particular model overfits on a specific dataset. By examining a learning curve plot, we can identify whether a machine learning model has overfitted. A learning curve plot displays the model's performance on both the training and test sets. It consists of one curve representing the model's performance on the training set and another for the test set.

We trained our model to analyze its performance on the training and test dataset. Fig. 13 (a) illustrates a case of overfitting. The model's performance on the training dataset steadily decreases in loss, indicating effective learning. However, on the test set, its performance initially improves up to a certain point and then begins to get worse. Therefore, we can presume the model is overfitting and may not generalize well on unseen data. However, given the significant overfitting observed, it is essential to address it before applying the model to new data.

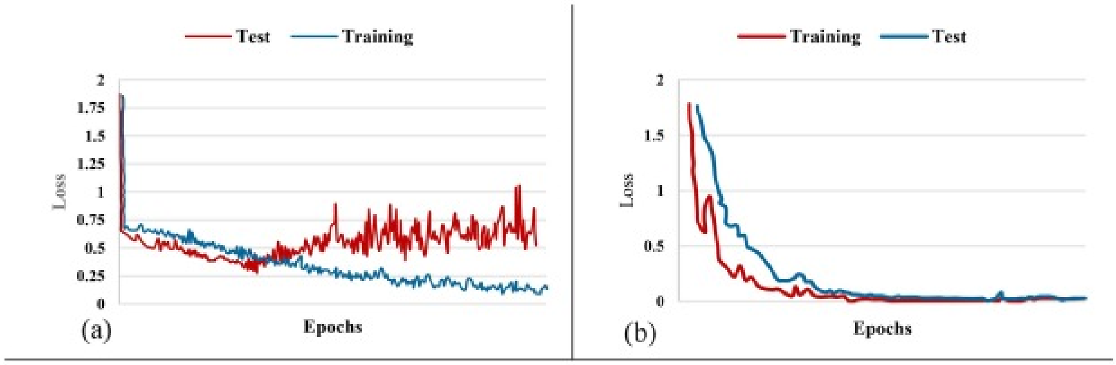

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Fig. 13. Learning curve plot. (a) Loss curves for train and test sets without optimal hyperparameter values. (b) Loss curves for train and test sets with optimal hyperparameter values.

We utilize a combination of random search and K-fold cross-validation (CV) methods to identify the optimal hyperparameters for our prediction models to overcome overfitting. Hyperparameters refer to predefined configuration variables that influence both the learning process and the performance of the models such as dropout regularization, L2 Regularization, Activation function, Weight constraint, etc.

In the random search approach, we specify the hyperparameters that we want to tune and their respective ranges (search space). Then, we randomly sample some hyperparameter combinations from that space, train models with those settings, and select the one that performs the best. This approach allows us to efficiently explore a wide range of possibilities and optimize various hyperparameters. This includes training parameters such as the number of 'Epochs' (10–100) and the 'Batch size' (10–100) used during the training process. Additionally, we compare various optimization algorithms such as ‘SGD’, ‘RMSprop’, and ‘Adagrad’ to determine the most effective algorithm for our model. Random search evaluates different ‘Learning rates’ and ‘Momentum’ values to identify the optimal settings that control the speed and direction of weight updates during training. ‘Weight initialization’ techniques, which influence how the initial weights in the network are set, are also being explored through random search using methods like ‘uniform’, 'normal', and 'glorot_normal'. To introduce non-linearity into the network and improve its ability to learn complex patterns, random search compares different 'Activation functions' available in Keras, such as 'relu' and 'tanh'. We also used regularization techniques like 'Dropout' rate (0.0–0.9) and 'Weight constraint' (1–5) through random search to prevent overfitting and improve the model's generalizability. Dropout (Kim, 2014) is a popular technique to regularize the model by randomly omitting some hidden units within each layer during the training. The objective of dropout is to train the network so that the output is not dominated by some hidden units, hence mitigating overfitting. Additionally, we considered 'L2 regularization' (; Hinton et al., 2012), which penalizes the model for having large weights and reduces overfitting. We also considered hyperparameters that influence the model's architecture and learning process. This includes exploring different 'Kernel' sizes and 'Pooling' methods for Convolutional Neural Networks (CNNs). Furthermore, the architecture of the network itself was optimized by exploring different numbers of 'neurons' within a 'hidden layer'.

Fig. 14 displays a sample of the results obtained using the random search method. The primary focus is on examining the influence of various parameters on the quality of the outcome. By conducting a random search on these hyperparameters, the aim is to discover the configuration that effectively reduces overfitting and enhances the generalization performance of our model. Identifying the optimal values for various parameters results in minimizing the loss. A lower loss signifies improved performance, indicating that the model is making more accurate predictions.

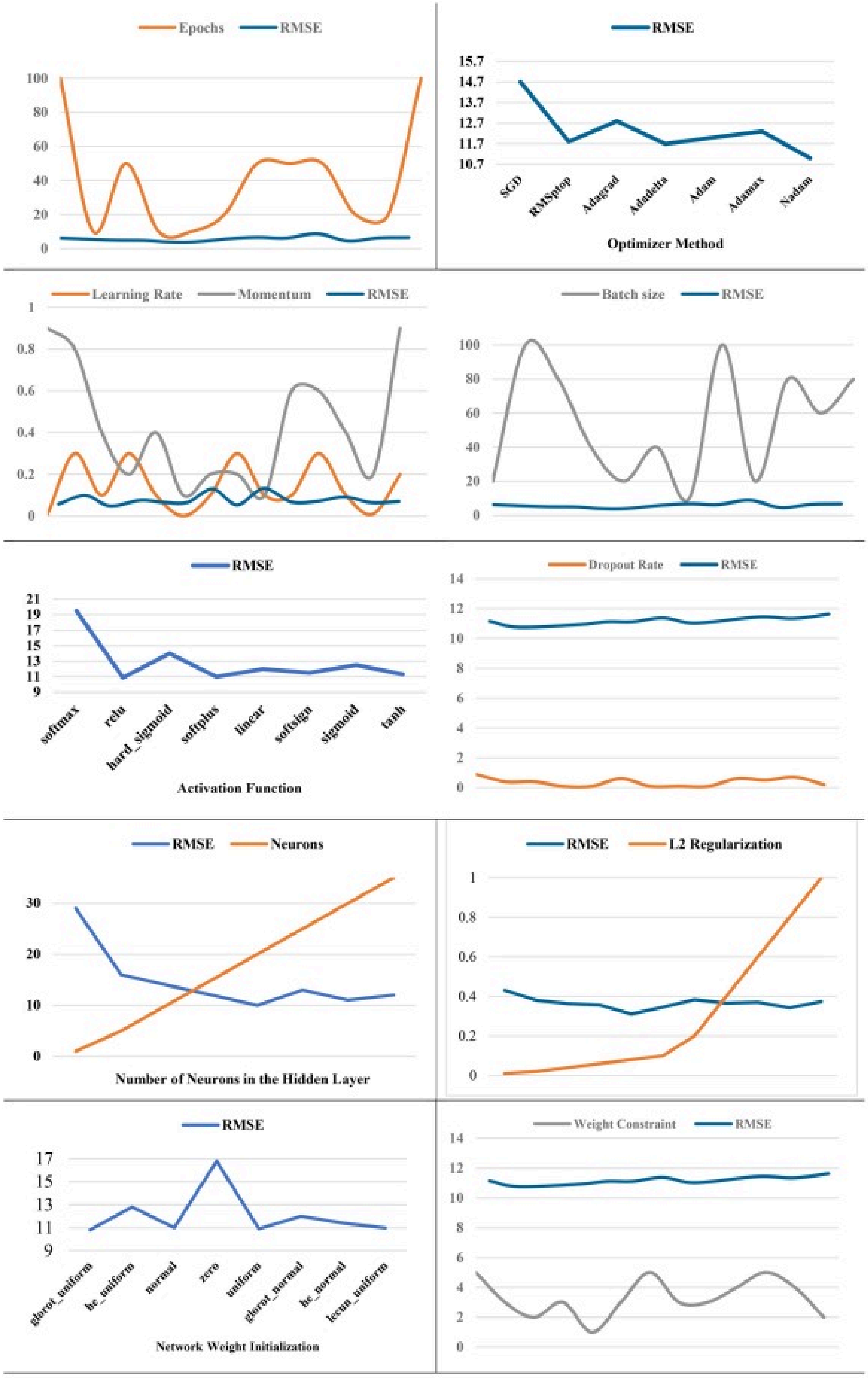

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Fig. 14. Left to right, top to bottom: Batch size and No. of epochs, Optimization algorithm, Learning rate and momentum, Weight initialization, Activation function, Dropout regularization, No. of neurons in the hidden Layer and L2 regularization.

We also present loss curves for the training and test sets using optimal values in Fig. 13(b). As we can see, these curves confirm the model's effective learning and validate its performance. As depicted, the plot of the loss on the training set decreases reaching a point of stability. Similarly, the plot of the test set also decreases, with a small gap observed between the training and test losses. The model's performance on the test dataset becomes more stable compared to the performance observed in Fig. 13(a).

4. Experimental results and discussion

The subsequent sections involve conducting various experiments to evaluate the effectiveness of *VATP*, and provide answers to the following research inquiries: 1) Can VATP solve the problem of arrival time prediction? 2) How to incorporate different types of resource information into the VATP model? 3) How does performance vary with various input features? 4) How does performance vary among the different Naive techniques? 5) In comparison with the existing methods, can VATP enhance the tweet classification performance? To achieve these objectives, a series of experiments were conducted as described below:

i) Considering that our proposed method incorporates various resources, including AIS information and New Features (AINF), Vessel Information Feature (VIF), and Weather and Sea information Features (WSF), we investigated the impact of distinct feature sets. As such, we evaluated the efficacy of VATP by combining various feature sets.

ii) The comparative analysis of the VATP performance is carried out against diverse TMLBMs and DLBMs (*including different variations of a CNN model and a baseline LSTM model*). Additionally, we carried out an evaluation of the performance of the VATP approach under two conditions: employing both attention and dropout layers, and non-attention and dropout layers.

iii) The effectiveness of VATP is assessed by comparing its performance to other recently published research.

However, we provide a general description of the dataset employed in this research before proceeding further. Subsequently, we will provide a detailed description of the measures employed to evaluate the performance of VATP. Additionally, we will present an in-depth explanation of each experiment conducted and the sequence in which they were carried out. Finally, a comprehensive analysis and discussion of the obtained results are provided, along with their implications.

4.1. Model varieties: Effect of AIS, vessel, weather, and sea levels features

We apply the VATP with the combination of different feature sets on our dataset to predict the arrival time. The prediction performance is also measured using RSME and MAPE. To be specific, we aim to analyze the effect of the AIS information and New Features (AINF), Vessel Information Feature (VIF), and Weather and Sea information Features (WSF). Consequently, the combination of features that exhibit the best result is selected.

We use different combinations of features to train a different type of VATP approach as follows:

- $\mathrm{VATP_{Full}}$: This technique combines all the accessible features: AINF, VIF, and WSF.
- $\mathrm{VATP_{AINF+WSF}}$: This method represents the VATP in the absence of the VIF feature set. It is taught and assessed using AINF and WSF features.
- $\mathrm{VATP_{AINF+VIF}}$: A VATP approach that includes AINF and VIF features.
- $\mathrm{VATP_{AINF}}$: A VATP approach that is taught and assessed with the AINF feature.
- $\mathrm{VATP_{WSF}}$: A VATP approach that is taught and assessed with weather and sea information feature.
- $\mathrm{VATP_{VIF}}$: A VATP approach that is taught and assessed with vessel information feature.

Table 5 and Fig. 15 present the results of varying VATP methods with different input combinations. We observe that among all the various VATP models, the $\mathrm{VATP_{Full}}$ (*RMSE=10.6301, MAPE=35.11%*) achieves the best results compared to other methods and outperforms the other approaches. It outperforms $\mathrm{VATP_{AINF}}$ by (*RMSE=6.7043, MAPE=18.17%*) points, $\mathrm{VATP_{WSF}}$ by (*RMSE=15.9328, MAPE=38.82%*) points, $\mathrm{VATP_{VIF}}$ by (*RMSE=12.5852, MAPE=30.11%*) points, $\mathrm{VATP_{AINF+WSF}}$ by (*RMSE=5.0514, MAPE=13.61%*) points and reports approximately (*RMSE=3.6196, MAPE=7.87%*) points better accuracy compared to $\mathrm{VATP_{AINF+VIF}}$.

Table 5. Experimental results using varying VATP.

Methods	AINF	WSF	VIF	RMSE	MAPE (%)
$VATP_{WSF}$		+		26.5629	73.93
$VATP_{VIF}$			+	23.2153	65.22
$VATP_{AINF}$	+			17.3344	53.28
$VATP_{AINF+WSF}$	+	+		15.6815	48.72
$VATP_{AINF+VIF}$	+		+	14.2497	42.98
$VATP_{Full}$	+	+	+	10.6301	35.11

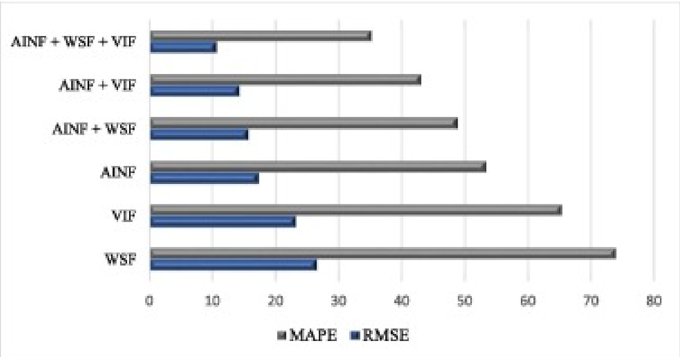

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Fig. 15. The results were achieved using varying feature sets.

From the computational results, it is found that the most accurate result is achieved when the VATP integrates all the feature sets. The AINF, by itself, did not yield optimal prediction outcomes. Therefore, it should be employed in conjunction with other feature sets. For this purpose, $\mathrm{VATP}_{\mathrm{Full}}$ exploits AIS, vessel, weather, and sea information. The results also show that vessel-level information has performed significantly better than weather and sea-level information. Furthermore, the results suggest that all three sets of information (AINF+VIF+WSF) have contributed to arrival time prediction. Consequently, this unified feature set learning model can perform better than the feature subset learning model.

4.2. Performance comparison with TMLBM and DLBM models

To validate the efficiency of the proposed method, the performance is compared with several representative approaches, including TMLBMs, and baseline DLBM. To achieve this objective, diverse approaches are implemented in the following manner:

LSTM+FCL: Initially, an LSTM network receives a unified feature vector extracted from the dataset, which is followed by the implementation of a fully connected layer (FCL) for the vessel arrival time prediction. It is worth noting that a unified feature is created by combining different features extracted from AIS, Vessel, weather, and sea information using common variables such as Vessel Identification Number (*e.g.*, IMO number, MMSI), Time and Date (timestamp of data collection) and Latitude and Longitude (position coordinates).

Bi-LSTM+FCL: In contrast to LSTM, BiLSTM can capture information from both forward and backward directions. The initialization of BiLSTM begins with a unified feature vector, followed by FCL to predict vessel arrival time.

CNN+FCL: The initial step in this method involves initializing the CNN with a unified feature vector that is gained from the dataset. Subsequently, the vessel arrival time prediction is carried out using a fully connected network.

CNN+LSTM+FCL: The current approach involves utilizing CNN and LSTM for the arrival time prediction. The initial step is to set up CNN using a unified feature vector extracted from the data set. After that, The LSTM layer is situated above the CNN, and ultimately ATP is accomplished via a fully connected network.

CNN+BiLSTM+FCL: In the current model, the BiLSTM layer is placed over the CNN layer. Subsequently, was ATP executed using a FCL network.

CNN+Attention+LSTM+FCL: This model is an extension of the CNN+LSTM approach, which integrates an attention mechanism to weigh the importance of features extracted by the CNN. The aim is to enhance the model's performance by giving more weight to important features. In this model, the ATP is carried out based on the combination of the CNN, attention mechanism, and LSTM. The process begins with the initialization of the CNN using the vector representation. The attention mechanism and LSTM are located over the CNN layer, respectively.

CNN+Dropout+LSTM+FCL: Unlike the previous model (CNN+LSTM), this model adds a dropout layer to avoid overfitting problems. However, arrival time prediction is computed using CNN, the dropout layer, and LSTM. In the beginning, a CNN is initialized using vector representation derived from the dataset. Subsequently, the LSTM layer is positioned above the Dropout layer to complete the architecture. Finally, arrival time is predicted through the fully connected network.

Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machine (SVM) (traditional machine learning-based method): The arrival time of a vessel is computed based on the SVM, RF, and ANN.

Table 6 shows the results of the $\mathbf{VATP_{Full}}$ model vs other techniques, which are assessed by MAPE and RMSE. Each row in Table 6 illustrates a technique, and each column describes an assessment metric. As shown, RF performs the worst when compared with the other algorithms. In comparison with SVM and RF, ANN presents a good result in terms of MAPE and RMSE. This implies that the ANN algorithm can reduce the number of larger prediction errors. Furthermore, according to the results shown In Table 6, we see that the method $\mathbf{VATP_{Full}}$ achieves the best performance. In other words, $\mathbf{VATP_{Full}}$ demonstrates remarkable superiority over the other methods, exhibiting remarkable effectiveness, and robustness with less error as compared to the other models. The VATP obtained the best result (*RMSE*=10.6301, *MAPE*=35.11%) in comparison with $\mathbf{VATP_{CNN + Dropout+LSTM + FCL}}$, which is the best method and has *RMSE and MAPE* measures of (19.7480) and (67.55%) respectively. Generally, the DLBMs obtained better results in comparison with the TMLBMs or machine learning-based models. On the other hand, among the deep learning-based models, $\mathrm{CNN_{CNN + FCL}}$ performed the worst.

Table 6. The performance comparisons between VATP and other methods.

Group	Method	RMSE	MAPE (%)	VATP improvement (%)	
				RMSE	MAPE
Other	RF	41.4968	216.05%	74.38	83.75
	ANN	39.3426	203.91%	72.98	82.78
	SVM	40.4446	210.60%	73.72	83.33
Recurrent	Bi-LSTM+FCL	29.8831	124.23%	64.43	71.74
	LSTM+FCL	26.3662	105.83%	59.68	66.82
CNN	CNN+FCL	31.8296	137.17%	66.60	74.40
	CNN+LSTM+FCL	21.1559	77.66%	49.75	54.79
	CNN+BiLSTM+FCL	25.3583	99.45%	58.08	64.69
VATP	CNN+Attention+LSTM+FCL	17.5545	61.13%	39.45	42.56

Group	Method	RMSE	MAPE (%)	VATP improvement (%)	
				RMSE	MAPE
	CNN+Dropout+LSTM+FCL	19.7480	67.55%	46.17	48.03
	CNN+Attention+Dropout+LSTM+FCL	10.6301	35.11%	----	----

As shown in Table 6, The "VATP improvement" column demonstrates the relative enhancement achieved by comparing the VATP technique with other approaches. The subsequent equation is used to compute this relative improvement: $\left(\frac{\text{Our Method}-\text{Other method}}{\text{Other method}}\right) \times 100$. The symbol (+) indicates that VATP enhances the corresponding method performance by reducing the error rate. As an illustration, the VATP technique significantly boosts the performance of the SVM, leading to a considerable enhancement of+73.72 RMSE and 83.33 MAPE. Furthermore, the VATP reduced the error as follows: $(39.45\% \leq \text{RMSE} \leq 74.38\%)$ and $(42.56\% \leq \text{MAPE} \leq 83.75\%)$. Additionally, large reductions in error occurred for the RF algorithm. Fig. 16, Fig. 17 present a comparison of VATP with several models in terms of RMSE. As shown in the figure, the actual time is denoted as a blue line and the VATP prediction of arrival time is represented in orange. We see that VATP provides a promising performance in predicting the arrival time. There is a slight discrepancy between the predictions of the VATP model and the actual time. Moreover, the findings presented in the table are also summarized and visualized through bar graphs (Fig. 18) to provide a broader overview of the results for better comprehension. The bar represents the RMSE of each method. Based on the visualization, the performance of the models in terms of RMSE varies across the different methods. In Fig. 18 the smaller bars demonstrate lower error and thus represent a superior model.

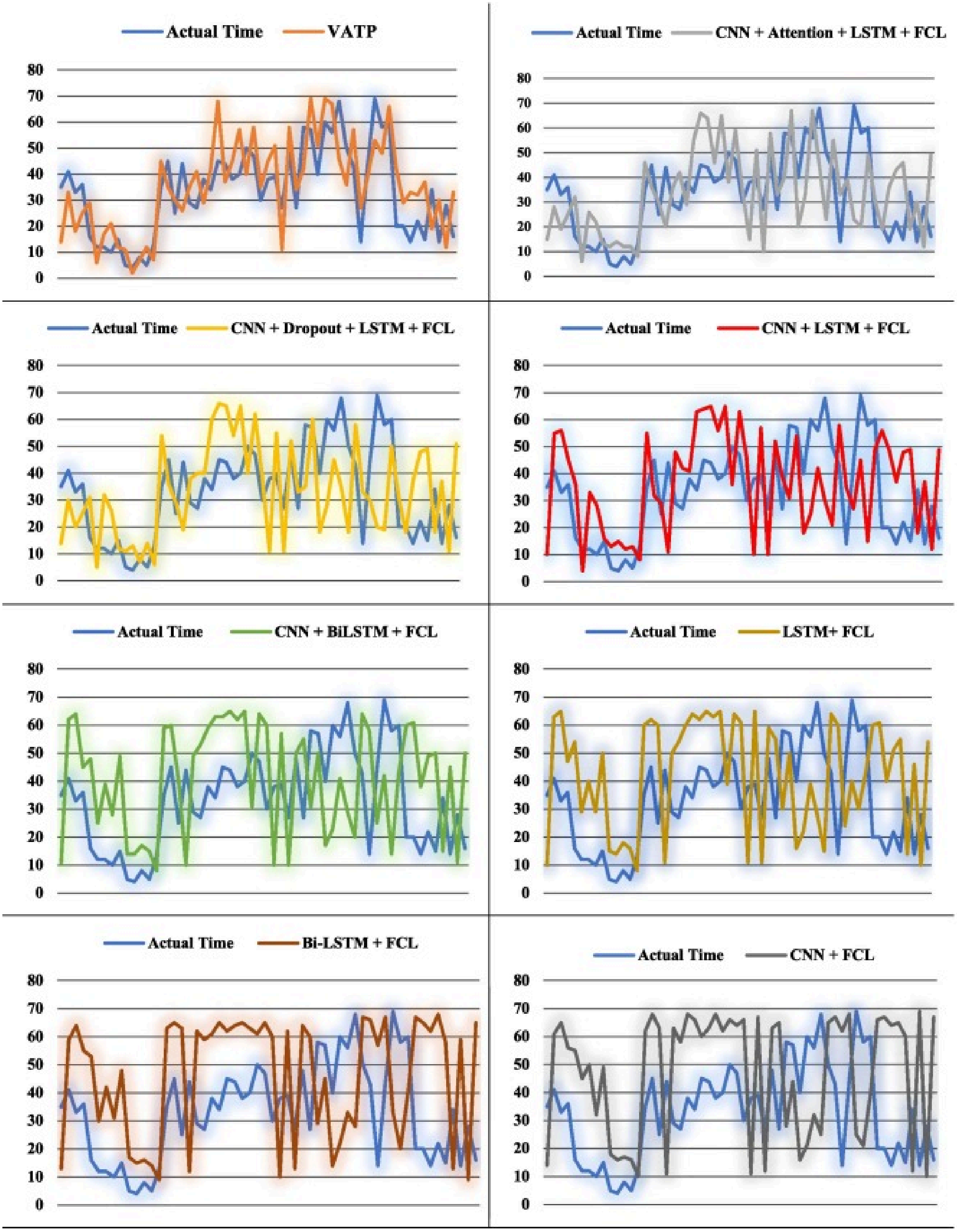

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Fig. 16. A sample of prediction values vs actual values using various methods.

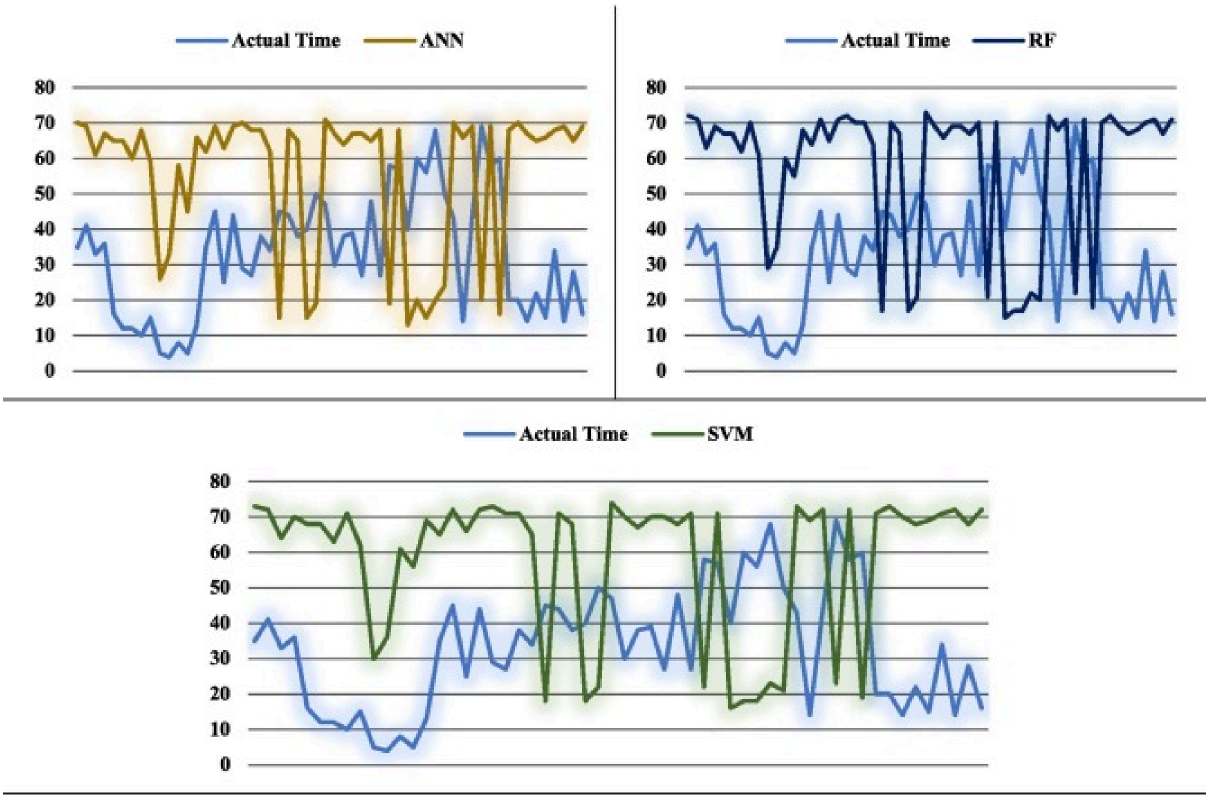

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Fig. 17. A sample of prediction values vs actual values using various methods.

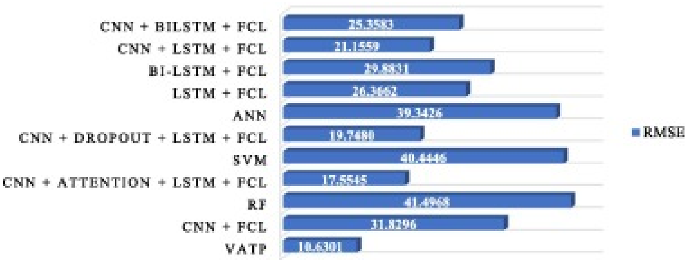

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Fig. 18. The performance comparisons between different models.

Statistical significance test –Using the Wilcoxon signed rank test (Diebold & Mariano, 2002), we conducted a statistical comparison between the VATP method and both TMLBMs and baseline DLBM methods concerning RMSE. To do this, we create eleven groups: RF, 2) ANN, 3) SVM, 4) BiLSTM+FCL, 5) LSTM+FCL, 6) CNN+FCL, 7) CNN+LSTM+FCL, 8) CNN+BiLSTM+FCL, 9) CNN+Attention+LSTM+FCL, 10) CNN+Dropout+LSTM+FCL, 11) VATP. At each comparison, two groups are assessed simultaneously, such as the VATP and SVM groups. The RMSE score is incorporated within each respective group. The P-values generated by Wilcoxon's signed rank test for the comparison of two groups individually are presented in Table 7. We formulated two hypotheses for our analysis: H0 (Null hypothesis): There is no significant difference between the RMSE values of the two groups. HA (Alternative hypothesis): There is a significant difference. As indicated in Table 7, all the P-values are below the significance level of 0.05. For instance, the examination conducted between VATP and the SVM yielded a P-value of 0.031 for the RMSE metric. The same outcome is observed across all other methods as well. Nevertheless, this provides strong evidence to support the alternative hypothesis and reject the null hypothesis.

Table 7. Wilcoxon signed-rank test with respect to the RMSE: Comparing VATP with TMLBM and DLBM models.

RF	ANN	SVM	BiLSTM+FCL	LSTM+FCL	CNN+FCL	CNN+LSTM+FCL	CNN+BiLSTM+FCL	CNN+Attentio
RMSE metric								
0.041	0.030	0.031	0.022	0.021	0.023	0.012	0.011	0.004

However, since the proposed VATP method yielded the smallest RMSE values, as well as the best scores on the two-tailed Wilcoxon signed-rank test for RMSE measure, we can conclude that the prediction performance of the proposed VATP model is significantly better than that of the other models.

4.3. Comparison with related methods

We evaluate the effectiveness of VATP in comparison to other previously published articles employed for ship arrival time prediction. The outcomes of the VATP model in comparison to other methods are presented in Table 8, primarily evaluated based on the metrics of RMSE and MAPE. Each row in Table 8 illustrates a technique, and each column describes an assessment metric for the various approaches. When considering the other methods, Pani (2014) exhibits the least favourable performance. In comparison with Pani, 2014, Parolas, 2016, Fancello et al., 2011, Bourzak et al., 2023, Noman et al., 2021 and El Mekkaoui et al., 2022, Hardij, 2018 has the lowest RMSE value. This indicates that the algorithm provided by Hardij (2018) can predict the arrival time significantly better than others. However, the VATP model achieves the best performance, as seen by the results provided in Table 8. The VATP yielded the best result (RMSE=10.6301, *MAPE=35.11%*) compared to Hardij (2018), which was previously the top-performing method in our comparison, with RMSE and MAPE measures of (38.8583) and (203.68%) respectively.

Table 8. Comparative evaluation of VATP performance against other relevant works.

Method	**Method**	**Dataset**	**RMSE**	**MAPE (%)**	**VATP improvement (%)**	
					RMSE	**MAPE**
Pani (Pani, 2014)	RF	AIS data, Weather*	44.0475	237.50%	75.87	85.22
Parolas (Parolas, 2016)	SVM	AIS data, Weather*	42.2885	218.52%	74.86	83.93
El Mekkaoui, et al. (El Mekkaoui, Benabbou, & Berrado, 2022)	MLP	AIS data	41.4171	217.53%	74.33	83.86
Hardij (Hardij, 2018)	LSTM	AIS data	37.6051	203.68%	71.73	82.76

Method	Method	Dataset	RMSE	MAPE (%)	VATP improvement (%)	
					RMSE	MAPE
Bourzak, et al. (Bourzak et al., 2023)	BiLSTM	AIS data,Vessel Features	39.6140	210.15%	73.17	83.29
Fancello, et al. (Fancello et al., 2011)	MLP	AIS data	40.2978	214.42%	73.62	83.63
Noman, et al. (Noman et al., 2021)	GRU	AIS data	38.4250	200.21%	72.34	82.46
VATP $_{\text{CNN + Attention + Dropout + LSTM}}$	---	AIS, Weather & Sea, Vessel information	10.6301	35.11%	---	---

* The method used a binary vector (1/0), the presence or absence of inclement weather conditions.

The column ("*VATP improvement*") shows that VATP improves the performance of the Hardij (2018) with −71.73% RMSE and 82.76% MAPE. Furthermore, VATP improves the performance as follows: ($\mathbf{71.73\%} \leq \mathbf{RMSE} \leq \mathbf{75.87\%}$) and ($\mathbf{82.46\%} \leq \mathbf{MAPE} \leq \mathbf{85.22\%}$). Additionally, as shown in Fig. 19, each bar indicates the RMSE of each method or work, which are VATP, Pani, 2014, Parolas, 2016, Hardij, 2018, Fancello et al., 2011, Bourzak et al., 2023, Noman et al., 2021 and El Mekkaoui et al. (2022). In Fig. 19, we observe the variation in model performance in terms of RMSE across different methods. Smaller bars indicate lower error, suggesting a superior model. Overall, VATP outperforms the others, as shown in the figure.

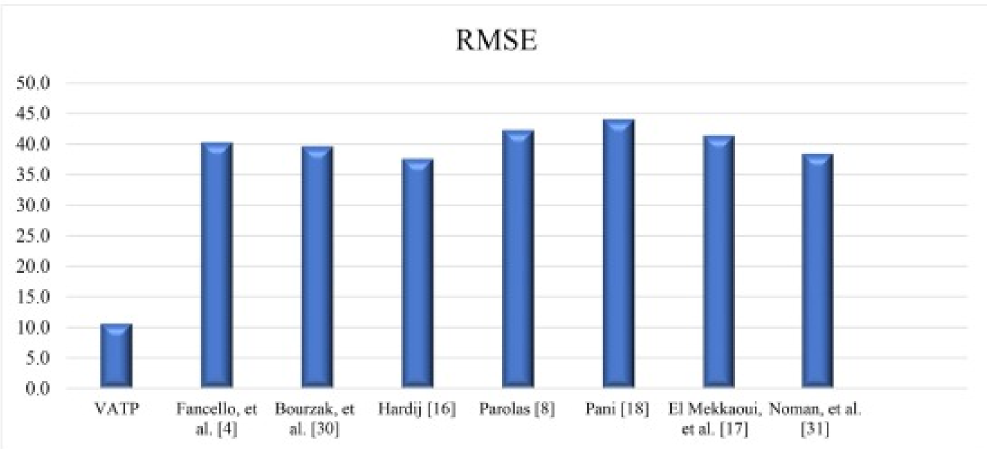

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Fig. 19. Comparison of the VATP with different relevant works.

4.4. Discussion

The findings showed the VATP outperformed other methods and was the best model. We think this is due to the following reasons:

1) The VATP method combines different resource information. The vector representation in terms of AIS, vessel, weather, and sea information enhances the accuracy of a ship's arrival time forecast. From the data presented in Table 5, it is evident that the performance of the VATM model exhibits a superior improvement when trained on the unified set of features as compared to when it is trained on a subset of features. The findings illustrate that VATP can offer valuable insights regarding the connections among different resource information. Furthermore, our experimental results are in line with other research whose results indicate that the weather condition affects the vessel arrival time prediction (*e.g.*, Du et al. (2015) and Filtz et al. (2015)). Moreover, unlike the findings of Parolas (2016), this study indicates that weather information affects the performance of the proposed method.

2) Traditional Machine Learning based methods (TMLBMs) performed poorly in comparison to the other methods. Several reasons could explain the poor performance of TMLBMs, such as the need for feature engineering, which requires the expertise of a specialist to identify and extract relevant features from the dataset. The performance of the traditional ML-based methods is highly dependent on the accuracy of the feature selection and extraction process. In contrast, deep learning-based methods (DLBMs) are capable of automatically extracting features and learning from the data, unlike TMLBMs. Furthermore, a fundamental distinction between TMLBMs and DLBMs pertains to their reliance on data. Specifically, TMLBM is more suited to working with a limited amount of data, whereas a DLBM is capable of learning and achieving superior performance when trained on a larger dataset.

3) TMLBM also have their limitations in capturing relationships between observations, as they assume by default that each observation/variable is independent of the other. In other words, they don't consider their prior condition or the results of earlier observations. Since the data are sequential, recurrent neural networks capture the time dependence better. In our case, some of the variables (*e.g., weather conditions, speed, etc.*) do not remain constant during the entire journey. Therefore, the basic component of our approach is a recurrent neural network (RNN). Technically, an RNN can process sequential data, consider long-range dependencies, and ensure superior performance compared to other methods. Moreover, our experimental results are in agreement with other studies that find sequence relation promising in series data prediction (*e.g.*, Duan et al., 2016, Carbonneau et al., 2008).

4) Based on our results, among the different VATP models, $VATP_{CNN + Attention + Dropout + LSTM}$ obtains the best result. It is a model that is structured with CNN, an Attention mechanism, a Dropout layer, and an LSTM layer where the accuracy of feature extraction is increased.

4.5. Practical implications

Intelligent decision support systems (IDSS) have significant implications for logistics and transport systems such as it causes enhancing efficiency and optimization. Using advanced algorithms and real-time data analysis, IDSS can provide insights and decision support to logistics managers as well as improve operational efficiency and reduce costs. Furthermore, IDSS enhances decision-making and risk management by analyzing complex data from multiple sources. Additionally, IDSS improves customer service through accurate demand forecasting and real-time monitoring. Moreover, IDSS can contribute to significant improvements in the industry using enhancing efficiency, optimizing processes, and improving decision-making. Moreover, improving operations planning can have a significant environmental impact (Cammin et al., 2020). The environmental benefit is reducing vessels' emissions both during their voyages and in areas nearby ports. Our model helps a planner predict the arrival time of ship at a distribution center. The next step after predicting delayed trucks is identifying the causes of the delay, some of which are discussed in Awaysheh et al. (2021). The idea of proposing and developing a VATP model has a high potential for maritime transportation, terminal operations, yard planning, and the port supply chain. In this research, we proposed the following hypotheses: i) By constructing a comprehensive feature set using feature vectors derived from AIS information, vessel information, weather, and sea information, the performance of vessel arrival time prediction can be enhanced. ii) A significant outcome can be achieved by utilizing a composite network comprising CNN, Attention mechanism, Dropout layer, LSTM, and fully connected layer. However, to verify our hypotheses, it is necessary to establish a suitable testing environment that enables us to investigate the possibilities and advantages of implementing deep learning-based approaches. For this purpose, we introduce the VATP approach, which incorporates the CNN, LSTM, attention mechanism, and dropout layer. Subsequently, we evaluate the effectiveness of the VATP method on the corresponding dataset. We observe a promising influence on arrival time prediction when multiple variables are integrated together. Our findings demonstrate that VATP can be a practical method to predict arrival time. It can help platform managers make better decisions. Furthermore, by employing the findings and results of this research in the design and development of a vessel arrival time prediction model, researchers can propose a new model or improve the existing models.

5. Conclusion and future work

This paper presents VATP, a deep learning model that is based on CNN, LSTM, Attention mechanism, and dropout layers, for predicting the arrival time of a vessel. VATP takes advantage of coarse-grained local features produced by CNN and LSTM and can therefore learn the long-term dependencies present in the data. The attention mechanism highlights discriminative and effective features, and the dropout layer is used to avoid overfitting problems. VATP includes the following main layers: Database layer, DECTF layer, CNN layer, Attention mechanism layer, Dropout Layer, Concatenation layer, LSTM layer, and fully connected layer. Firstly, the dataset after pre-processing is converted into an input vector. Secondly, The AIS and weather & sea features are fed into CNN_1 and CNN_2, respectively Thirdly, the output of the CNN layer is given to the attention mechanism. The output of the attention layer is then fed into the dropout layer. Subsequently, the output from the dropout layer is fused using the concatenation layer. The concatenated features are then fed to the LSTM layer. The final concatenation layer combines the vector representation extracted from the last LSTM cell with invariant features to create a conclusive vector representation. Subsequently, the resulting vector is passed through a fully connected layer to predict arrival time. We show that this is the appropriate architecture to deal with the complexity of the input variables.

To validate our method, we have performed experiments on the datasets. Initially, we assess various VATP approaches through the following comparative analysis: $VATP_{AINF+WSF}$, $VATP_{AINF}$, $VATP_{AINF+VIF}$, $VATP_{Full}$, where the subscripts stand for AIS information feature and New Features (AINF), Vessel Information Feature (VIF), Weather and Sea information Features (WSF). The results show that among all the various VATP methods, the $VATP_{Full}$ obtains the best performance in comparison with the other methods. Furthermore, the result indicates that these different sets of features can complement each other. Moreover, we assessed and compared the effectiveness of the VATP method against several supervised machine-learning techniques. The results obtained from the conducted experiments confirm the validity of our method, and we observed that the VATP method outperforms other baseline methods in terms of performance. Additionally, we found that the VATP method, which integrates the attention layer and dropout layer, demonstrated significantly enhanced performance. We also performed a comparison between VATP and previously proposed methods in the literature. The results indicate that the VATP method achieved the highest performance among all the methods compared.

For future research, we would like to consider a set of new features as an independent variable to enhance the prediction method. It could include features such as engine power, demand, waiting times at the port, mechanical problems, strikes, fuel prices, trade lane congestion, vessel dwell times, natural disasters, sailing schedules, and many others. The main question is how to incorporate different independent variables into deep learning-based models. Another potential direction for future research involves exploring and developing a methodology that integrates a wide range of deep learning techniques.

CRediT authorship contribution statement

Asad Abdi: Conceptualization, Methodology, Investigation, Software, Writing – original draft, Data curation, Formal analysis, Writing – review & editing, Validation. **Chintan Amrit:** Funding acquisition, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

The following are the Supplementary data to this article:

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Supplementary Data 1.

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