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Development of an Interpretable Maritime Accident Prediction System Using Machine Learning Techniques

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ABSTRACT Every year, maritime accidents cause severe damages not only to humans but also to maritime instruments like vessels. The authors of this work therefore propose a machine learning-based maritime accident prediction system that can be used to prevent maritime accidents from happening by predicting and interpreting the accidents. This work overcomes the limitations of the existing works that lack practicability in the sense that the ex-post analyses are conducted to suggest accident prevention strategies but maritime accidents are not analyzed holistically. Using extensive literature reviews and expert interviews, a large number of risk factors associated with maritime accidents are identified, and related data are collected and utilized in the work. Throughout variable selection, data retrieval, hot-spot identification, and the maritime accident prediction model construction process, various machine learning algorithms are exploited in order to construct an organized system. In addition, interpretations for the resulting accident predictions are given using interpretable machine learning algorithms so as to provide explainable results to users. Finally, the proposed system is evaluated using a SERVQUAL model and proves its effectiveness in real-world applications.

INDEX TERMS Maritime accident, ocean engineering, accident prediction, interpretable machine learning.

I. INTRODUCTION

A maritime accident is defined as an accident that occurs in oceanic areas. These accidents are not only confined to vessels (i.e., ships) used for the transportation of people and logistics but also include fishing vessels that catch, store, and transport fish [1]. Even though the rate of maritime accidents is relatively low compared to other kinds of accidents, each maritime accident incurs significant loss in diverse ways, such as marine pollution due to oil leaks, casualties due to crashes, costly vessel repair, etc. In addition, even though more advanced sensors are employed in vessels and related technologies are improving, the number of maritime accidents is increasing. For instance, maritime accidents in the Republic of Korea have been steadily increasing since 2015 (Fig. 1).

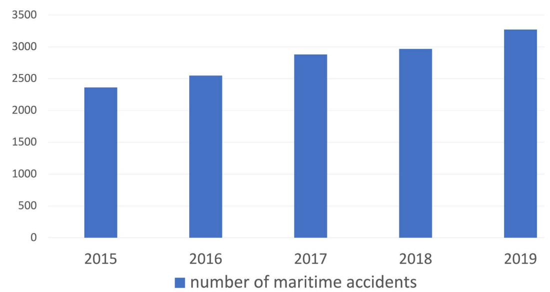

FIGURE 1. The number of maritime accidents in the Republic of Korea.

There are a variety of causes of maritime accidents including crash, collision, grounding, tangling with suspended

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particles (solids), instrument/machinery malfunction, fire, explosion, etc. [2]–[4]. In fact, some causes of maritime accidents are man-made and are thus preventable if enough precautions are followed [5]. For instance, regular checkups of vessel instruments could prevent instrumental malfunctions. Some accident types are affected by unpreventable natural phenomena. For instance, a typhoon accompanied by drastic wind or waves might capsize a vessel. In this regard, maritime accidents associated with unpreventable causes are excluded from the analysis as well as the construction of the prediction model in order to eliminate uncertain noise. Most maritime accidents, however, are caused by latent factors that could be quantitatively measured and used. In other words, these types of maritime accidents are predictable and thus preventable to some degree. In fact, a number of existing works on maritime accident risk assessment use quantitative logs for developing accident prediction models [6]–[8]. This work proposes a maritime accident prediction system that uses accident logs, most of which are deemed to be predictable to some extent, and various risk factors associated with these accidents.

Although there are a large number of latent risk factors that influence the occurrence of maritime accidents, only factors that can be accurately identified and qualified are used to establish an accident prediction system in this work. Like existing works on maritime accident prediction, this work also assumes that there are certain complex regularities, which could be partially identified and modeled with sophisticated data mining or machine learning techniques, behind the occurrence of accidents [9]. Provided that sufficient wave and wind data are collected, more accurate prediction models for influencing variables could be constructed so as to give a more realistic estimation of maritime accident risks. In this work, latent risk factors assumed to affect maritime accidents are gathered from an extensive literature review as well as multiple surveys with maritime domain experts. To the best of our knowledge, there has not been a machine learning-based framework for a system that provides maritime accident prediction and corresponding interpretations. In addition, there is a lack of studies on maritime accident predictions, especially compared to extensive research development on risk analysis, safety assessment, and accident analysis in the field of ocean engineering [10]. Developing a maritime accident prediction system using machine learning techniques not only provides a novel research direction and contributes to data-driven maritime approaches [83] but also sets up practical applications in many fields, such as autonomous vessel navigation, smart vessel maintenance, and big data-driven maritime safety analysis.

This work proposes a maritime accident prediction system based on machine learning techniques. Furthermore, this system not only gives predictions and risk scores for maritime accidents are also provides interpretations to system users. An overview of the proposed maritime accident prediction system is shown in Fig. 2. This work's contributions to the literature are as follows:

1) Maritime accident log data and associated risk factor data are utilized to improve prediction performance for accident prediction tasks in a novel framework.
2) Compared to existing data-driven accident prediction approaches, diverse and new accident risk factors including fishery information are used and validated.
3) A holistic approach based on machine learning methods, including variable selection, data retrieval, and maritime accident prediction, is conducted.
4) The proposed system not only predicts future maritime accidents but also provides reasons for the predictions using interpretable machine learning IML) techniques.

The remainder of this work is organized as follows. Section II discusses existing literature related to this work. Section III illustrates a design of the proposed system, including identification of risk factors, description of data used for the system, data preprocessing, and variable selection in detail. The detailed methods, as well as the components of the proposed framework, are explained, and an overall mechanism of the system is provided in Section IV. The service quality evaluation of the proposed system is conducted in Section V. Finally, a conclusion is drawn, and future research topics are discussed in Section VI.

II. LITERATURE REVIEW

This section illustrates previous works related to 1) maritime risk assessment and accident prevention and 2) maritime accident prediction.

A. MARITIME RISK ASSESSMENT AND ACCIDENT PREVENTION

There are a number of works that have addressed the risk assessment/estimation of maritime accidents. These works naturally lead to practical suggestions, such as strategies or policies for the prevention of maritime accidents. For maritime risk assessment, identification of risk factors is essentially conducted in advance of the risk assessment step. In particular, there is a large body of literature on the analysis of the latent risk factors that affect maritime accidents. While the identified risk factors associated with maritime accidents vary across studies, existing studies address multiple common risk factors. Zhang *et al.* categorize risk factors into four groups according to their inherent characteristics: human, vessel, environment, and management [11]. Wan *et al.* identify major risk factors associated with maritime risk and safety from five perspectives: society, environment, management, technology, and operation [12]. Similarly, risk factors associated with vessel characteristics as well as meteorology have been identified and used to develop a maritime risk assessment framework [13]. This framework is further developed with additional variables including factors related to vessel speed and location with respect to shipping lanes [14]. Li *et al.* have proposed a Bayesian network-based maritime risk analysis using quantitative accident data resources instead of expert estimation information [15]. The proposed work also utilizes fully quantitative maritime accident log

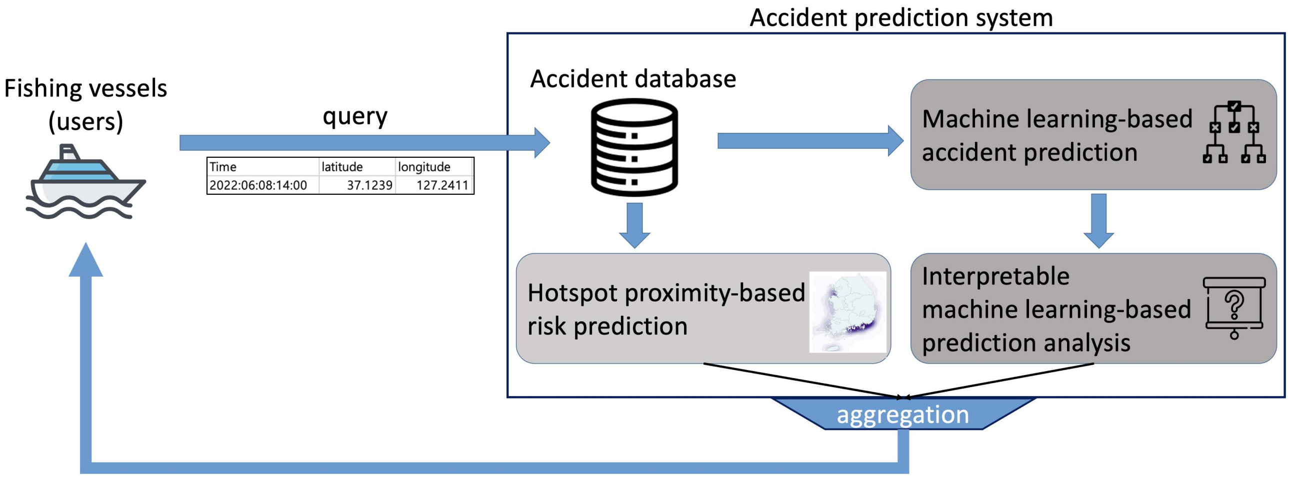

FIGURE 2. **An overview of the proposed maritime accident prediction framework.**

data for developing a prediction model. Jiang *et al.* use a Bayesian network for accident risk analysis and identify risk factors that influence the occurrence of maritime accidents [16]. Accidents associated with fishing vessels are analyzed using a Bayesian network and Chi-squared test [1]. Multiple fishing vessel characteristics are used to determine causal factors for various types of maritime accidents.

Human factors, such as working conditions and individual factors, have also been considered as risk factors for maritime accidents [5], [6], [17]–[19]. Zhang *et al.* explore various combinations of human factors that have been shown to affect outbreaks of maritime accidents [20]. Fan *et al.* exploit a Bayesian network to incorporate human factors for maritime accident analysis [21]. Human decisions and actions that directly affect the occurrence of maritime accidents are investigated for accident analysis [22]. In addition, human factors that affect psychological conditions, such as welfare, stress, and communication between ship personnel, including crews and captains, have shown to influence maritime safety [86], [87]. In particular, Sutherland and Flin discuss the effect of crew working conditions and stress levels in the maritime industry [85]. Despite the considerable effects of human factors on maritime accidents, this work's proposed framework does not incorporate them due to several reasons. First, the effects of human factors are relatively difficult to measure and are more costly to accurately collect. Second, the inherent variability in human factors has a high possibility of compromising the performance of the prediction model. Associated matters are discussed in detail as future works in Section VI.

For the purpose of accident prevention, multi-criteria decision-making (MCDM) methods have been widely used to develop safety strategies. In particular, the Bayesian network has been utilized in numerous works because it provides probabilistic interpretation and modeling of the decision-making process [11], [23]. Guo *et al.* exploit the analytic hierarchy process (AHP) and neural network to analyze historical maritime accident data and propose preventive measures [24]. Fan *et al.* exploit Bayesian networks and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to develop maritime accident prevention strategies using qualitative risk factors [17]. Hänninen also exploits Bayesian networks for maritime safety modeling [25].

Compared to existing works, this system uses more diverse and detailed exogenous variables, such as marine weather or fishery information, associated with maritime accidents in marine environments. These variables will be discussed later in Section III. In addition, many existing works that use Bayesian networks and MCDM methods explain maritime accidents that have already happened rather than provide concrete risk estimations. Thus, Bayesian network-based approaches are limited in providing high-level explanations and prevention strategies. However, this work proposes local/low-level predictions for each voyage. Furthermore, the proposed system uses quantitative data to offer accurate and detailed accident prediction results.

B. MARITIME ACCIDENT PREDICTION

There are many studies on maritime accident prediction, some of which are coupled with risk assessment and accident prevention analysis. Otay and Özkan develop a simulation model for accident prediction by modeling vessel positions using associated variables that include geographical characteristics [26]. Although simulation-based methods are effective in situations when not enough data exist, data-driven accident predictions that use real accident logs like the proposed system of this work are more accurate. Weng *et al.* utilize a binary logistic regression model to construct a maritime accident prediction model that uses historical accident logs [27]. However, this approach is not easy to use in practice because the variables used include ex-post parameters like accident type. Considering these prediction methods' limitations, ex-ante risk variables should be used only for accident prediction. Since predictions should aim to

TABLE 1. Risk factors used for maritime accident prediction in existing works of literature.

Reference	Vessel age	Vessel size	Gross tonnage	Time of day	Seasonality	Sea state (geographical)	Visibility (fog)	Weather	Wind	Wave (current)	Traffic	Fishery distribution	Keywords
Uğurlu et al. [1]	✓	✓				✓	✓	✓					fishing vessel Bayesian network
Zhang et al. [11]	✓		✓	✓	✓		✓		✓	✓			risk matrix Bayesian network
Balmat et al. [13] Balmat et al. [14]	✓		✓	✓		✓	✓		✓				fuzzy risk factor MARISA
Jiang et al. [16]	✓			✓			✓	✓	✓		✓		risk analysis Bayesian network
Otay & Özkan [26]		✓				✓			✓				risk map vessel casualty
Weng & Yang [27]				✓				✓					mortality logistic regression
Zhang et al. [28]				✓									grey system negative binomial
Zhang et al. [29]	✓	✓	✓				✓	✓	✓				risk entropy projection pursuit
Ours (proposed)	✓		✓	✓	✓	✓		✓	✓	✓	✓	✓	–

forecast future maritime accidents, variables that can be collected and measured before potential accident outbreaks should be used.

Poisson regression and the negative binomial regression model are employed for accident prediction [28]. Zhang *et al.* propose a real-time maritime accident risk prediction model using multiple independent variables, such as human factors, environmental factors, and navigation operational factors, and information diffusion specialized for the Arctic route [29]. Li *et al.* propose a machine learning-based maritime accident prediction model for developing an effective emergency response strategy [30]. However, there are few inherent limitations in existing accident prediction studies. First, maritime accidents are low-probability events [31] that very seldom take place. Thus, there are not enough data to accurately measure the effectiveness of a prediction model. Second, since the variables used in prediction models vary across studies, the developed methods are not universally applicable. The proposed accident prediction system is developed using relatively large-scale data consisting of around 13,000 accident logs. In addition, the proposed framework can be easily adapted to different data that have various features.

The risk factors associated with maritime accidents, which are used for prediction in existing works and the proposed system, are illustrated and compared in Table 1. Compared to existing works, the proposed system utilizes more diverse variables for accident prediction and analysis. In addition, the utilized risk factors are identified not only through domain expert interviews but also through quantitative methods. However, there are two risk factors that could not be used in this work due to practical reasons: vessel size and visibility (fog). These two factors were excluded due to a lack of data and an inability to match existing accident logs. First, existing maritime accident logs used in the proposed system lack vessel size data and could not be collected via other sources. Second, visibility (fog) data could not be matched with existing accident logs, as there was not a key (e.g., location, time, ID) that both data share. Fortunately, it is postulated that vessel size could be substituted with gross tonnage to some extent, as in other works [88], [89]. The details for risk factors used in this work are elaborated upon in the next to section.

III. SYSTEM DESIGN

This work aims to propose an effective and practically useful maritime accident prediction system. To this end, specific system dimensions should be clearly identified and defined prior to actual implementation and provision. In particular, who will be utilizing the system in practice, what potential users want from the system, and which factors of the system would fulfill needs should be specified in advance. In order to concretize the system, expert interviews are conducted first.

A. EXPERT INTERVIEWS

Interviews are conducted with eight maritime experts from diverse domains, such as government ministries, port/harbor managements, fisheries cooperatives, shipbuilding companies, and autonomous vessel navigation developing companies. The semi-structured interviews contain multiple shared questions and related conversations. The questions belong to three topics regarding the proposed system: potential users and the needs of a maritime accident prediction system, including the one this work is proposing; the characteristics or functions that would be helpful in a maritime accident prediction system; and the risk factors considered significant for maritime accidents and the variables that would be helpful for accident prediction.

All experts involved in the interviews agree that maritime accident prediction is an important task, since it is directly related to vessel safety. In addition, seven experts agree that accident predictions for fishing vessels would be more effective in real-world applications. As such, stakeholders in the fishery industry and maritime safety management would need the prediction system. The efficacy or accuracy of the prediction system is considered most important by the experts. Some interview responses imply several indicative implications, too. Few responses indicate that the prediction results should be delivered in real-time despite technical constraints. For instance, weak mobile connections on the ocean or the computational capacity of local devices must be taken into account. Most importantly, some experts mention that interpretations (i.e., explanations) of the prediction results would increase user satisfaction and assurance. In accordance with these responses, the proposed system incorporates and reinforces interpretability as a distinctive feature. Intuitively, considering the fact that accident predictions are provided by machine learning techniques, interpretable predictions would make the proposed framework more trustworthy by users. Some expert responses identify some maritime risk factors that should be taken into consideration: oceanic characteristics, including sea weather; fishery catches; and vessel characteristics. Even though many risk factors identified by the experts coincide with those that have been frequently used in existing works in maritime risk assessment and accident prediction/prevention, a few variables are selected to be taken into consideration. In fact, data selection and collection are conducted according to responses from expert interviewees.

B. DATA COLLECTION

Datasets collected from various sources are gathered and used in this work, and all variables are explained in detail in Table 2. Detailed explanations of the datasets/variables, as well as the reason for use, are illustrated. Among the factors determined to be associated with the occurrence of maritime accidents based on expert interviews, some are selected and collected, whereas those that are difficult to collect, like vessel characteristics (e.g., block coefficient), are abandoned. The maritime accident log data used in this work are collected from January 2010 to December 2020 in Korean waters, mainly in offshore or coastal waters. There are 12,584 accident logs (i.e., instances) in total. However, based on variable gross tonnage, several outliers are removed. As Fig. 3 shows, the gross tonnage (GT) values of vessels engaged in accidents are highly skewed. Thus, data that have a GT value smaller than the 90th quantile, which is 228 *tons*, are only selected and used in later analyses. Since there are various types of dominant causes of maritime accidents given in the data, accident categories are used to separate the data into groups for more precise analysis and prediction suited for each cause. The number of occurrences of maritime accidents for each cause is shown in Table 3.

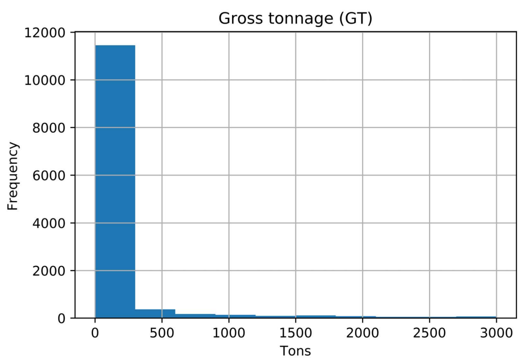

FIGURE 3. Histogram of gross tonnage values.

In addition to the maritime accident log data, the associated data containing maritime risk factors identified in various pieces of literature, as well as the results of interviews with experts discussed in the previous section, are utilized. In particular, risk factors related to maritime/oceanic characteristics, including subsurface topology, maritime weather, and wave, are used. Depth of water, which indicates geographical features associated with the bottom of the sea, is used as representative of subsurface topology. Variables associated with maritime weather include wind speed, wind degree, atmospheric pressure, humidity, and temperature. Wave, one of the most intuitive risk factors, is represented by various types of wave heights and wave periods.

In addition, 69.5% of total maritime accidents have been shown to be those of fishing vessels. The remaining accidents are those of bulk cargo vessels, passenger vessels, container vessels, etc. Because fishing vessel accidents are deemed to be more affected by the identified risk factors, only these accidents are selected and analyzed in this work. As a result, 7,871 accidents logs are eventually used. Thus, as previously mentioned, the fishing vessels whose GT value is below or equal to 228 *tons* are analyzed in this work, since a large portion of maritime accidents that happen in coastal waters are that of fishing vessels [77].

Compared to existing works on maritime risk assessment and accident prediction/prevention, the proposed framework utilizes novel risk factors, such as fish catch and fish distribution. According to interviews with maritime experts, fishery information might help construct better maritime accident prediction models. The potential effects on fisheries can be twofold. First, in the case of the Republic of Korea, certain kinds of fish are caught in different and distinct seasons. For instance, shads are caught in fall, squid or octopus in summer, and mackerel from spring to summer. Furthermore, fish type catch varies by locations. These catching trends indicate that the density of fishing vessels may be affected. Second, the distribution of fishing vessels has a close relationship with the occurrence of maritime accidents, especially collisions or contact/crush. For instance, fishing vessels that use fish-luring lights for catching squid might interfere with the visibility of other vessels, thus increasing the risk of crash or collision. As such, the total fish catch is used as a proxy for the number of vessels nearby or the density of fish.

C. DATA PREPROCESSING

In advance of the analysis and prediction model construction, all data are normalized and scaled so that each variable falls into 0 and 1. The data are normalized along with each variable according to (1).

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}. \tag{1}$$

where:

x: original independent variable
x_{min}: minimum value
x_{max}: maximum value
x_{scaled}: scaled independent variable

In order to merge multiple data logs, a certain ID, which is shared across different data sources, is required. The geographical information for each accident log, such as longitude and latitude, is used as a key for data merge. In particular, the Haversine distance measure is used to calculate an accurate distance between two coordinates. This measure provides a distance approximation considering the nearly spherical surface of the Earth [80]. Given two coordinates p_1 and p_2, the distance between the pair of locations is calculated using the Haversine distance measure (2).

$$\begin{aligned} d_{Haversine}&(p_1, p_2) \\ &= 2r \cdot \arcsin\,[\sin^2(\frac{\psi_2 - \psi_1}{2}) \\ &\quad + \cos(\psi_1)\cos(\psi_2)\sin^2(\frac{\lambda_2 - \lambda_1}{2})]^{\frac{1}{2}}. \end{aligned} \tag{2}$$

where:

p_i: each location point $= (\psi_i, \lambda_i)$
ψ: latitude
λ: longitude
r: radius $= 6{,}371$ (km)

Because accident severity is not explicitly given in the data, it is calculated using collected variables that exist in the accident logs, such as the number of deaths, missing, and injured. Accident severity is assumed to be linearly proportional to

TABLE 2. Description of variables.

Category	Variable	Type	Description
Maritime accident log	Cause (category)	Nominal	The corresponding main cause of an accident
	Vessel ID	String	The identifiable ID of a fishing vessel
	Vessel age	Integer	The age of a fishing vessel
	Gross Tonnage	Integer	The gross tonnage of a vessel measured in ton
	Number of death	Integer	The Number of people deceased due to an accident
	Number of missing	Integer	The Number of people missing due to an accident
	Number of injuries	Integer	The Number of people injured due to an accident
	Time	Date-time (numerical)	The time for an accident including year, month, day, and hour
	Location	Numerical	The latitude and longitude of the location where an accident took place
Subsurface topology	Depth of water	Numerical	The depth of water measured in m
	Location	Numerical	The latitude and longitude of the location of the measurement
Maritime weather	Wind speed	Numerical	The average speed of wind measured in m/s
	Wind degree	Numerical	The degree of wind measured in $^\circ$
	Atmospheric pressure	Numerical	The average atmospheric pressure measured in hPa
	Humidity	Numerical	The average humidity measured in $\%$
	Air temperature	Numerical	The average temperature of air measured in $^\circ C$
	Water temperature	Numerical	The average temperature of water measured in $^\circ C$
	Location	Numerical	The latitude and longitude of the location of the measurement
Wave	Maximum wave height	Numerical	The maximum height of wave measured in m
	Significant wave height	Numerical	The height of significant wave measured in m
	Average wave height	Numerical	The average height of wave measured in m
	Wave period	Numerical	The average period of wave measured in sec
	Location	Numerical	The latitude and longitude of the location of the measurement
Fishery catch	Species	Nominal	The type of fish species (e.g., red crab, mackerel, squid, yellowtail, etc.)
	Amount of catch	Integer	The total amount of fish catch measured in kg
	Time	Date-time (numerical)	The time for fish catch including month
	Location	Numerical	The latitude and longitude of the location of the fish catch
Fishery distribution	Species	Nominal	The type of fish species (e.g., red crab, mackerel, squid, yellowtail, etc.)
	Amount	Integer	The total number of fish
	Time	Date-time (numerical)	The time for fish distribution including month
	Location	Numerical	The latitude and longitude of the location of the fishery distribution

TABLE 3. Number of maritime accidents by cause.

Category	Occurrences	Percentage (%)
Collision	6321	50.23
Contact & crush	1958	15.56
Grounding	1523	12.10
Flooding	1509	11.99
Capsize	710	5.64
Sinking	442	3.51
Others	121	0.96

the number of deaths and missing [77] as does the number of injuries but to a half degree [78]. Thus, in this work, severity is calculated according to (3).

$$severity = \#death + \#missing + \frac{1}{2}\#injury. \tag{3}$$

D. VARIABLE SELECTION

After delicate data preprocessing and data aggregation, 53 variables (columns) in total remain. In order to reduce the dimensionality of the data and complexity of the model for better generalization performance, a variable selection process is conducted using regression analysis. In particular, an ordinary least squares (OLS) regression model is used (4), where y_i is the severity of the i-th accident and x_{ip} the p-th independent variable associated with maritime accidents.

$$y_i = \beta_0 + \sum_{p=1}^{53} \beta_p x_{ip}. \tag{4}$$

where:

β_0: intercept term
β_p: regression coefficient ($p = 1 \cdots 53$)

The estimates of the fitted OLS model are shown in Table 4. Only variables that have been shown to be significant at a significance level $\alpha = 0.1$ among the total 53 original variables are shown in Table 4. Interestingly enough, the variables found to be significant align well with the risk factors that existing works on maritime accident prediction have used, which are shown in Table 1. Furthermore, only variables in the table are later used as input (i.e., independent) variables for maritime accident prediction models. According to the regression analysis, the GT and catch of squid have been shown to be most significant. In addition, risk factors related to fishery information, such as catch of mackerel, catch of crab, and catch of shad, and those related to sea states, such as a depth of water and average wave height, have shown to be significant.

TABLE 4. Estimates of the ordinary least squares (OLS) model.

Variable	Estimate	Standard error	t-value	p-value
Gross tonnage	-0.173	0.056	-3.12	<0.005
Depth of water	0.485	0.207	2.34	<0.05
Atmospheric pressure	0.087	0.052	1.69	<0.1
Significant wave height	1.955	1.072	1.82	<0.1
Average wave height	-1.844	0.763	-2.41	<0.05
Catch of red crab	-0.198	0.109	-1.81	<0.1
Catch of crab	-0.549	0.285	-1.92	<0.05
Catch of mackerel	0.169	0.068	2.50	<0.01
Catch of Spanish mackerel	0.095	0.051	1.88	<0.1
Catch of shad	0.421	0.162	2.60	<0.01
Catch of squid	-0.484	0.160	-3.02	<0.005
Catch of lumpfish	0.118	0.076	1.57	<0.1
Distribution of anchovy	0.265	0.126	2.10	<0.05
Distribution of big head croaker	-0.128	0.077	-1.67	<0.1
Distribution of croaker	0.265	0.137	1.94	<0.05

IV. METHOD

An overview of the framework of the proposed maritime accident prediction system is shown in Fig. 2. Various methods have been used appropriately in parts of the proposed framework: 1) data retrieval from a maritime accident database, 2) maritime accident prediction and analysis, and 3) interpretation of maritime accident predictions.

A. DATA RETRIEVAL

Given the historical maritime accident log data, the construction and validation of the prediction models are discussed in a later section. During actual system use, however, the inputs, which should be provided for the prediction model, are difficult to be obtained before a voyage. In other words, the associated values for the independent variables used in the proposed system should be generated or retrieved in advance of accident prediction. Thus, the proposed framework exploits a proximity-based data search (i.e., data/information retrieval) algorithm for generating pseudo-inputs for the execution of accident prediction. In particular, k-nearest neighbors (kNN) is used to find similar historical data points whose input variables could be used for future prediction of the new instance. kNN has been widely employed in domains dealing with similar tasks as the one this framework has faced, including data/information retrieval, data imputation, and search system [32], [33]. kNN is used to predict each value for risk factors using queries, including voyage time and destination location. First, based on geographical information, kNN finds the closest neighbors (i.e., accident logs) and later uses the voyage time to further narrow down the k-nearest neighbors that could be used for input value imputation. The Haversine distance (2) is again used as a distance measure between the locations of the data points. The kNN process for data retrieval in the proposed system is illustrated below. The input is a query point consisting of time ($month$; day; $hour$) and the voyage destination ($latitude$; $longitude$), where the output is a set of input values that are imputed using the selected k-nearest neighbor accident logs.

Algorithm 1 Modified kNN for Data Retrieval

Input: $\mathcal{Q}$, a set of queries and $\mathcal{R}$, historical accident logs
$\mathcal{R} = \{x_1, x_2, \ldots, x_n\}$
for all *query point* $q \in \mathcal{Q}$ **do**
compute distances between q and $r \in \mathcal{R}$ using geographical information;
sort the computed distances based on temporal information;
select $2k$ nearest accident logs $\mathcal{R}_{2k}$;
end for
for all *query point* $q \in \mathcal{Q}$ **do**
compute proximities between q and $r \in \mathcal{R}_{2k}$ using temporal information;
sort the computed proximities based on temporal information;
select k nearest accident logs;
return average input values of k nearest accident logs
end for
Output: The imputed input values x_{new}

For validation of the usage of kNN-based data retrieval system components, the proposed approach is compared with existing alternatives, such as k-dimensional tree (K-d tree) [34] and Ball tree [35]. Since the proposed system has not yet been made publicly available, thus lacking real-world queries from users, randomly generated queries (1,000 in total) containing the time and location of the voyage are used for validation. The comparison results, shown in Table 5, indicate that the proposed kNN-based data retrieval approach outperforms other alternatives with respect to three measures: precision, recall, and F_1 score (i.e., a harmonic mean of precision and recall). As the number of actual queries and accident/non-accident data will increase when the system

TABLE 5. Performance comparison of data retrieval methods.

Data retrieval algorithm	Precision	Recall	F_1 score
k-d tree	0.2031	0.2093	0.2045
Ball tree	0.2060	0.2162	0.2090
kNN-based approach **(proposed)**	**0.3197**	**0.3294**	**0.3224**

is made public, the retrieval performance of the proposed system would also increase spontaneously.

$$precision = \frac{true\,positives}{true\,positives + false\,positives}. \quad (5)$$

$$recall = \frac{true\,positives}{true\,positives + false\,negatives}. \quad (6)$$

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}. \quad (7)$$

B. HOT-SPOT IDENTIFICATION

In advance of the development of the maritime accident prediction system, regions where accidents have frequently taken place, called hot-spots, are identified. Given the assumption that future accidents can be forecasted using historical accident log data, spatial hot-spots with historically high occurrences of accidents could be helpful for primary accident prediction. For spatial clustering, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is used [36]. DBSCAN is an effective clustering algorithm that computes data point clusters and assignments using the data's density information. DBSCAN is robust to noise because it uses the minimum density threshold as well as the distance threshold while conducting clustering [37]. As accident hot-spots are defined as regions with a high rate of accident occurrence, the clusters derived by DBSCAN could be used as hot-spots. For clustering evaluation, the Davies-Bouldin score [38] and Silhouette coefficient [39] are used to compare the proposed DBSCAN clustering algorithm with alternatives, such as K-means, agglomerative clustering, and spectral clustering. Each clustering algorithm is performed for each maritime accident category, and the number of clusters found in the DBSCAN algorithm has been used for the predefined number of clusters for other clustering algorithms. The scores for clustering measures are averaged over the accident categories. The comparison results are shown in Table 6, where the lower Davies-Bouldin score ($min = 0$) and higher Silhouette coefficient ($min = -1$, $max = 1$) indicate better clustering results.

Accident hot-spots are identified using DBSCAN. For each accident category, spatial clusters (i.e., hot-spots) are identified and plotted in Fig. 4. In addition, for each category, the density of maritime accidents is visualized using a spatial kernel density estimation. For each group of clusters, the centroid is used as an accident hot-spot. The centroids of the clusters indicate that there are certain water locations where vessels may have a higher accident risk. During accident prediction,

TABLE 6. Performance comparison of clustering methods.

Algorithm	Davies-Bouldin score	Silhouette coefficient
K-means	0.6434	0.5304
Agglomerative clustering	0.7112	0.4941
Spectral clustering	0.3575	0.5323
DBSCAN	**0.3102**	**0.7976**

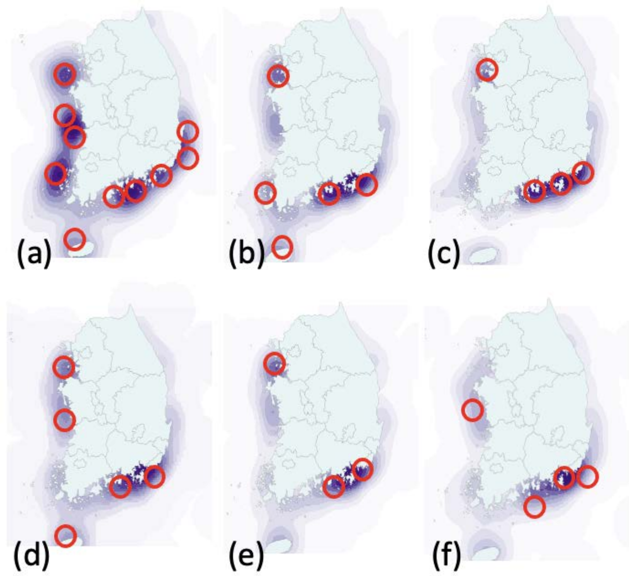

FIGURE 4. Accident hot-spots using DBSCAN results by accident category. (a): collision, (b): contact/crush, (c): grounding, (d): flooding, (e): capsize, and (f): sinking.

if the planned voyage destination is within a certain boundary (e.g., 3 *km*) from accident hot-spots, the risk score is elevated. Thus, the distance from the hot-spots is used to calculate potential risk.

C. MARITIME ACCIDENT PREDICTION

Decision tree-based models are deemed appropriate for accident prediction. First, due to the algorithm's structure, the data instances that have similar characteristics in terms of features are set into the same leaf node, thus locally behaving as the nearest neighbors algorithm [82]. In addition, since the nodes are selected after calculating information gain, compared to naïve nearest neighbors that consider every feature equally, the decision tree spontaneously takes the feature importance into consideration. In this work, a gradient boosting-based algorithm called XGBoost (i.e., extreme gradient boosting) [40] is used as a backbone prediction model for the prediction system. Currently one of the most widely used machine learning algorithms, XGBoost not only is computationally efficient but also provides high prediction performance in various tasks. For a comparison and validation of the selection of the backbone prediction algorithm, XGBoost is compared with other existing machine learning algorithms used for prediction, such as linear regression (LR), support vector machine (SVM), multi-layer perceptron (MLP), and random forest (RF). Accident prediction is a regression task on a dependent variable called severity, which is computed for every accident in the previous section. R^2 is used as a metric for evaluation, and the comparison results are provided in Table 7. Predictions are conducted for each maritime accident category separately. All experiments are conducted independently using a 10-fold cross-validation scheme [41]. The hyper-parameters for the prediction models are selected based on a random search algorithm [42].

TABLE 7. Performance (in R^2) comparisons of accident prediction methods including XGBoost and other existing machine learning algorithms.

Algorithm	LR	SVM	MLP	RF	**XGBoost**
Collision	0.1303 (±0.0337)	0.0560 (±0.0166)	0.5871 (±0.1886)	0.6039 (±0.1505)	**0.7007 (±0.1993)**
Contact/crush	0.1693 (±0.0712)	0.1601 (±0.1031)	0.2926 (±0.2772)	0.4185 (±0.2736)	**0.4969 (±0.2878)**
Grounding	0.1726 (±0.1436)	0.0707 (±0.0389)	0.6430 (±0.2610)	0.4890 (±0.3564)	**0.7374 (±0.2505)**
Flooding	0.1426 (±0.0223)	0.0490 (±0.0038)	0.1302 (±0.7210)	0.1441 (±0.0135)	**0.1829 (±0.3816)**
Capsize	0.3259 (±0.1054)	0.3093 (±0.2039)	0.7606 (±0.1670)	0.6975 (±0.0892)	**0.8064 (±0.1483)**
Sinking	0.2432 (±0.2044)	0.1687 (±0.1183)	0.5252 (±0.2509)	0.5743 (±0.2940)	**0.7075 (±0.2604)**
Others	0.1419 (±0.1932)	0.2532 (±0.4295)	0.1954 (±0.3939)	0.1657 (±0.2946)	0.0974 (±0.2217)

According to Table 7, XGBoost outperforms other machine learning prediction algorithms in most maritime accident categories. Thus, XGBoost is selected as a valid backbone prediction model that can be exploited in the proposed maritime accident prediction system. To further validate the effectiveness of the XGBoost model, it is again validated for each accident category. Prediction performance is evaluated in a 10-fold cross-validation scheme, and the results are shown in Table 8. For most accidents categories, the average values of the R^2 on training folds are relatively higher than those of the validation fold used in cross-validation. This is due to the characteristics of the XGBoost model since the decision tree-based models tend to fit the training data. In addition, the variability of the R^2 values tends to be high in certain categories, such as *flooding* or *capsize*, because the accident data are small (see Table 3). Since the prediction performance as well as the training for some categories of maritime accidents, such as *flooding* and *others*, are inappropriate to be loaded into the proposed prediction system, the two categories are not further used.

D. INTERPRETATION

XGBoost as well as other gradient boosting-based models can provide interpretable results due to the inherent properties of a decision tree. The important variables identified by the feature importance values computed by each prediction model

TABLE 8. Prediction performance of the maritime accident prediction models.

Category	Cross validated R^2 (training)	Cross validated R^2 (validation)
Collision	0.8661±0.0028	**0.7007**±0.1993
Contact/crush	0.8956±0.0010	**0.4969**±0.2878
Grounding	0.9189±0.0042	**0.7374**±0.2505
Flooding	0.3929±3.7005	0.1829±0.3816
Capsize	0.8899±5.3812	**0.8064**±0.1483
Sinking	0.7798±3.1027	**0.7075**±0.2604
Others	0.1997±1.3227	0.0974±0.2217

for accident categories are detailed in Table 9. Since the constructed prediction models for categories like *flooding* and *others* seem to have insufficient prediction abilities, the two are excluded in later analysis as well as in the proposed framework. Five variables that show higher relative importance values most commonly throughout the accident categories are shown in bold. It is important to note that fishery-related risk factors, such as catch of Spanish mackerel and distribution of anchovy, are relatively important factors across multiple accident categories. This aligns with the survey results from maritime experts discussed in Section III. GT and depth of water are significant in several accident categories.

TABLE 9. Top-5 accident risk factors found by prediction models.

Category	Top-5 important risk factors
Collision	catch of squid, **catch of Spanish mackerel**, distribution of croaker, **gross tonnage**, **average wave height**
Contact/crush	**distribution of anchovy**, catch of mackerel, distribution of croaker, **gross tonnage**, **average wave height**
Grounding	catch of mackerel, catch of crab, **gross tonnage**, **distribution of anchovy**, **depth of water**
Capsize	catch of lumpfish, catch of shad, **catch of Spanish mackerel**, **gross tonnage**, **depth of water**
Sinking	**depth of water**, catch of shad, catch of crab, **catch of Spanish mackerel**, catch of lumpfish

A partial dependence plot (PDP) is a method that can be used to show the marginal effects of a variable on the prediction outcome of a certain model [43], [44]. The x-axis of the PDP shows the value of the selected accident risk factor, where the y-axis is the associated target value, which is the accident severity or risk. PDPs are applied to the five variables showing the highest importance from the trained model, as shown in Fig. 5. The plots of the variables indicate that they have a peculiar relationship with respect to the predicted severity of maritime accidents. For instance, the PDP of GT indicates that as the value of GT increases, the accident risk is likely to decrease.

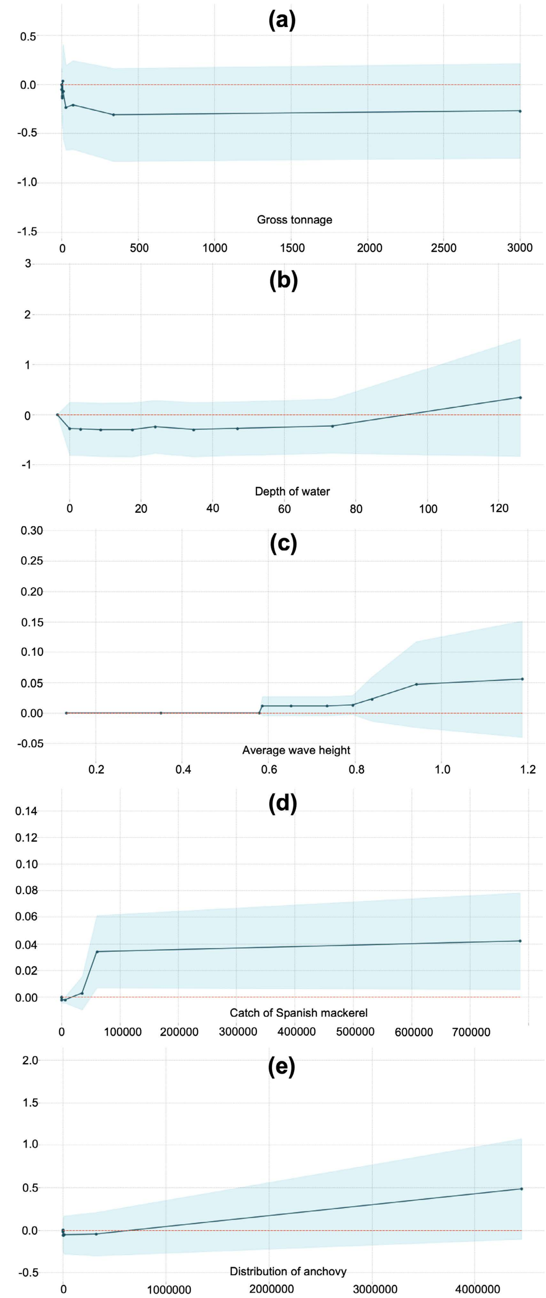

FIGURE 5. **Partial dependence plots of five important variables. (a): gross tonnage, (b): depth of water, (c): average wave height, (d): catch of Spanish mackerel, and (e): distribution of anchovy.**

In addition, interpretable machine learning (IML) algorithms are utilized in order to provide a more detailed interpretation of maritime accident predictions in the proposed framework. IML algorithms have been widely used in a variety of fields where trust and transparency of AI-based systems are emphasized, such as healthcare, finance, legal, and public services [44]–[46]. In this work, the two most widely used interpretable machine learning algorithms, also known as explainable artificial intelligence (XAI) models, are employed. They are local interpretable model-agnostic explanations (LIME) [47] and Shapley additive explanations (SHAP) [48]. Both algorithms are used for providing local interpretations or explanations, which are given for each prediction result from the constructed maritime accident prediction model.

First, LIME is a proxy model-based approach, in which the explanation model (linear model) approximates the original prediction model. The original prediction model is treated as a black-box, of which the weights, as well as the inner mechanism, are ignored, and only the behaviors are approximated. Because the method can thus be applied to any machine learning prediction model, these method types are called model-agnostic approaches. LIME interprets individual predictions based on locally approximating the model around a given prediction [47]. The inputs are minutely distorted via local perturbations, and the model outputs are used to compute the relative feature importance scores. In other words, randomly generated neighborhood samples are used for the explanation of the prediction model in LIME [68].

Second, SHAP value is based on a Shapley value from cooperative game theory [49], which is used as a feature importance for linear models [50]. SHAP is a unified approach of additive feature attribution methods for retaining three desirable properties: local accuracy, missingness, and consistency. Similar to LIME, SHAP works model-agnostically and assigns each feature a feature additive importance score for a particular prediction, thus providing local interpretations [51]. SHAP is able to compute not only the positive but also the negative effects of variables on prediction.

Because LIME and SHAP are model-agnostic IML methods, both methods aim to find surrogate model g for the explanation of the original prediction model f, where low model complexity for interpretability of g is desired [52]. Thus, the approaches optimize the loss function (8).

$$\mathcal{L}(f, g, \pi_x) = \sum_{x' \in X'} [f(x') - g(x')]^2 \pi_x(x') + \Omega(g) \tag{8}$$

where:

x: original input
x': locally perturbed version of input
π_x: proximity between x and x'
Ω: model complexity

Both LIME and SHAP are used in the proposed maritime accident prediction system, especially for ex-post interpretation of the prediction results. For each prediction, LIME and SHAP are used to generate interpretations including the relative feature importance scores. Based on the scores, whether consensus of the two methods has been made is checked as shown in Fig. 6. In particular, risk factors determined to be significant by both methods are only selected and provided to users. In this way, predictions and interpretations can be delivered in a more robust and deliberate way.

For further validation of the interpretability of the proposed accident prediction system, 500 accident predictions are randomly selected. With 100 prediction test cases for each

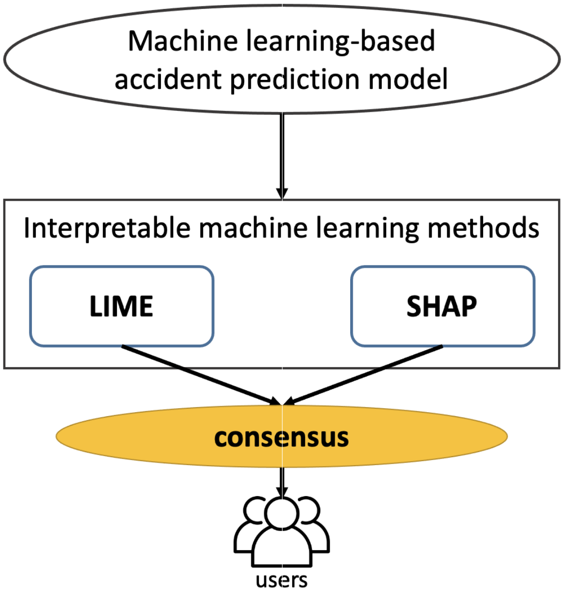

FIGURE 6. Provision of interpretation results of the proposed prediction system.

TABLE 10. Top-5 significant risk factors identified by LIME and SHAP.

Category	Method	Top-5 significant risk factors
Collision	LIME	catch of Spanish mackerel, catch of shad, gross tonnage, catch of tiny shrimp
	SHAP	gross tonnage, depth of water, distribution of big head croaker, catch of Spanish mackerel, catch of mackerel
Contact/crush	LIME	significant wave height, catch of lumpfish, gross tonnage, catch of shad, distribution of big head croaker
	SHAP	catch of mackerel, distribution of croaker, catch of red crab, gross tonnage, average wave height
Grounding	LIME	depth of water, average wave height, distribution of big head croaker, catch of shad, gross tonnage
	SHAP	gross tonnage, catch of crab, distribution of anchovy, depth of water, distribution of croaker
Capsize	LIME	gross tonnage, significant wave height, distribution of big head croaker, average wave height, catch of Spanish mackerel
	SHAP	depth of water, catch of red crab, gross tonnage, catch of Spanish mackerel, significant wave height
Sinking	LIME	distribution of anchovy, catch of crab, significant wave height, distribution of big head croaker, gross tonnage
	SHAP	gross tonnage, atmospheric pressure, depth of water, distribution of croaker, average wave height

accident category (i.e., *collision*, *contact/crush*, *grounding*, *capsize*, and *sinking*), the five most significant risk factors determined by each method (i.e., LIME and SHAP) on average are selected. The results are shown in Table 10. Even though some results are different from that of Table 9, since the results show significant risk factors identified by the IML methods in test prediction cases, there are still some common factors in each accident category. Table 11 shows the percentage of consensus that has been made for each accident category. For the same test case predictions and corresponding interpretation results, the percentage of consensus (i.e., when two IML methods output the same results) has been checked. The results indicate that two IML methods agree on local interpretation results throughout most accident categories.

TABLE 11. Ratio of consensus of interpretations from IML methods.

Category	Number of risk factors with consensus	Percentage (%)
Collision	0	15
	1	38
	2	31
	3	12
	4	3
	5	1
Contact/crush	0	16
	1	36
	2	29
	3	14
	4	5
	5	0
Grounding	0	5
	1	28
	2	30
	3	19
	4	14
	5	4
Capsize	0	7
	1	25
	2	34
	3	24
	4	7
	5	3
Sinking	0	9
	1	16
	2	29
	3	27
	4	13
	5	6

E. CONTINUOUS IMPROVEMENT OF THE PROPOSED SYSTEM

The proposed system has room for improvement in two ways. First, one limitation of the current version of the proposed

TABLE 12. Criteria and sub-criteria for evaluating the quality of the proposed system framework.

Dimension (criteria)	Sub-criteria	Criteria ID
Reliability	The system is carrying out necessary and helpful functions for the users.	R1
	The prediction models are using reasonable input variables (risk factors).	R2
	The prediction results are plausible and trustworthy.	R3
	The interpretation results on predictions are reliable and definitive.	R4
Assurance	Prediction system is trustworthy in terms of overall quality.	A1
	The users are satisfied with the provided accident prediction system.	A2
	The system seems to have a level of understanding of maritime safety/risk/accidents.	A3
Tangibility	Visual representations of the system are available.	T1
	The system is easy to use and user-friendly.	T2
	The system operates 24 hours.	T3
Empathy	The service provided is understanding the needs of the users.	E1
	Individual accident prediction interpretation is given in a spot-on manner.	E2
Responsiveness	Prediction services, as well as modifications, are provided/reflected promptly.	R5
	The prediction results are provided in a short time (i.e., promptly).	R6
	The system is open to accommodate and receive feedback from the users.	R7

system is the insufficiency of normal data, which consist of sailing logs without accidents. As the system is used further by users (i.e., installed base), sailing logs, in which accidents have not happened, will be continually collected. These normal voyage logs would help improve the performance of the maritime accident prediction model [81]. In addition, the level of interpretation of the prediction system is expected to be enhanced. Second, in a similar manner, the identified accident-associated variables will be collected from actual voyages, thus improving the quality of data used in the data retrieval phase of the framework. As the amount and variability of data increase, the proposed framework will become more robust to changes in maritime factors.

V. SERVICE QUALITY EVALUATION

After designing and implementing the maritime accident prediction system, a qualitative evaluation is conducted. Because the proposed system is basically a service, a proper means of service quality evaluation is used. A SERVQUAL analysis method [53] is employed in a bid to specify the dimensions of the proposed maritime accident prediction system and evaluate the quality level. SERVQUAL analysis is one of the most widely used methods for measuring and evaluating service quality considering five dimensions: reliability, assurance, tangibility, empathy, and responsiveness [53]–[55]. This method evaluates the difference between service expectations and perceptions in order to determine system quality. It has been used in various fields, such as healthcare, retail, banking, information systems, transportation systems, etc., for a long time [55]–[60]. Demir *et al.* exploit SERVQUAL when evaluating the quality of occupational health and safety systems [61]. The quality of service provided at commercial ports associated with customer satisfaction is analyzed using

TABLE 13. Demographic data of survey respondents. (N = 31).

Category		N	Percentage
Gender	Male	22	71.0%
	Female	9	29.0%
Age	20s or below	16	51.6%
	30s	6	19.4%
	40s	5	16.1%
	50s	3	9.7%
	60s or above	1	3.2%
Years of experiences	less than 5 years	19	61.3%
	6 to 10 years	5	16.1%
	11 to 20 years	5	16.1%
	more than 20 years	2	6.5%
Occupation	Government ministry	8	25.8%
	Fishery	3	9.7%
	Naval industry	3	9.7%
	Maritime transportation	6	19.4%
	Others	11	35.5%

SERVQUAL [62]. Lopez also uses SERVQUAL in order to identify attributes affecting customer satisfaction at maritime ports [63]. Pantouvakis *et al.* use SERVQUAL-based surveys to determine the perceived level of quality of passenger shipping services [64].

According to [54], SERVQUAL is adequately adjusted (i.e., simplified) to the topic of this work, the maritime accident prediction system. Equivalent to other SERVQUAL-based evaluation methods, the five dimensions are set: reliability, assurance, tangibility, empathy, and

TABLE 14. System quality scores using SERVQUAL items.

Dimension (criteria)	Code	Expectations (E)				Perceptions (P)				Gap (P-E)
		Mean	Standard deviation	Min	Max	Mean	Standard deviation	Min	Max	Mean gap score
Reliability	R1	4.7483	0.1670	4	5	4.6451	0.5506	3	5	-0.1032
	R2	4.5559	0.6904	4	5	4.5161	0.6768	3	5	-0.0398
	R3	4.1972	0.6258	3	5	4.1935	0.7924	2	5	-0.0037
	R4	4.1222	0.7352	3	5	4.2903	0.9016	2	5	0.1681
Assurance	A1	4.4208	0.9120	3	5	4.0322	0.7951	2	5	-0.3886
	A2	4.0131	0.2376	3	5	4.2258	0.7620	2	5	0.2127
	A3	4.9487	0.2570	4	5	4.1290	0.8058	2	5	-0.8197
Tangibility	T1	4.0575	0.4034	3	5	4.1935	0.7924	2	5	0.1360
	T2	4.5215	0.7596	3	5	4.0645	0.8538	2	5	-0.4570
	T3	4.6317	0.9748	2	5	4.2258	0.6196	3	5	-0.4059
Empathy	E1	4.1536	0.1331	3	5	4.1290	0.8058	2	5	-0.0246
	E2	4.6350	0.3598	3	5	4.1612	0.6878	3	5	-0.4738
Responsiveness	R5	4.3134	0.2572	3	5	4.0645	0.9638	1	5	-0.2489
	R6	4.8296	0.4283	4	5	4.3225	0.7017	3	5	-0.1058
	R7	4.5666	0.1934	4	5	4.2903	0.7828	2	5	-0.2763

responsiveness. Each dimension has been given sub-criteria in order to specify the subject of measurement. In order to simplify the questionnaire, the number of sub-criteria is smaller than the original SERVQUAL. The proposed system attributes associated with each dimension are described in Table 12. The survey questionnaire is also constructed based on SERVQUAL. Each question requires a Likert-type five-point scale response. The survey is distributed to maritime experts including potential users of the proposed system, such as fishing vessel captains and crews, government ministry workers, the naval industry, etc.

The demographic information of the survey respondents is shown in Table 13, and the detailed results of the survey are provided in Table 14. The average Cronbach's alpha value of the survey responses is 0.8109, which is considered acceptable [75]. Table 14 shows the mean, standard deviation, minimum, and maximum of quality expectations and perceptions. In addition, the difference between the two (i.e., P-E), called the quality gap score, is provided. Although respondents show quite high levels of expectations on most service dimensions, the results on perceptions indicate that the proposed system fulfills user expectations in general. The total mean expectation score is 4.4476, and the perception score is 4.2322, thus showing an average mean gap score of -0.2154. The mean expectation score of the dimensions ranges from 4.0131 (A2) to 4.9487 (A3), while the perception scores span from 4.0322 (A1) to 4.6451 (R1). On average, the responsiveness dimension expectations show the highest score (i.e., 4.5698) among the five dimensions, meaning that the prediction system also fulfills potential users' service-related needs. In addition, the reliability dimension perceptions show the highest score (i.e., 4.4112), revealing the strength of the proposed system in providing trustworthiness to users. Furthermore, in terms of the mean gap score, the proposed system has shown the best score (0.0053) among the five on average, thus fulfilling criteria associated with the reliability dimension. Considering the fact that the proposed system requires credibility to be widely used in the real-world, the results indicate the validity of the system.

VI. CONCLUSION AND FUTURE WORKS

The authors propose a machine learning-based maritime accident prediction system. Compared to existing works on maritime accidents, including risk assessment, accident prevention, and accident prediction, the proposed system utilizes diverse risk factors associated with the occurrence of maritime accidents. Using various data sources, multiple risk factors pertaining to maritime accidents, such as maritime weather and fishery information, are identified, validated, and used as independent variables for accident prediction. In particular, a new maritime accident risk factor, fishery information that includes fishery catch and distribution, is used for accident prediction. In addition, various machine learning techniques are employed to serve indispensable roles in the accident prediction system. From variable selection, data retrieval, hot-spot detection, and accident prediction, a variety of assorted machine learning techniques comprise the proposed maritime accident prediction system. Furthermore, the proposed accident prediction system provides explainable results to users through IML algorithms (i.e., LIME and SHAP).

The proposed research is comprised as follows. First, expert interviews are conducted with eight maritime experts in order to clearly identify and define specific dimensions of the proposed system, including risk factors. Then, various datasets related to maritime accident logs, subsurface topology, maritime weather, waves, fish catches, fish distributions, etc., are collected, and data preprocessing, including data normalization, is conducted. An OLS regression model and kNN are used for variable selection and for generating pseudo-inputs for the execution of accident prediction, respectively. Then, machine learning-based models, which are based on DBSCAN and XGBoost, are proposed for identifying hot-spots (i.e., the regions where accidents have frequently taken place) and maritime accident prediction, respectively. IML techniques, which are LIME and SHAP, are used for the ex-post interpretation of the prediction results, including the relative feature importance scores. Finally, the proposed system is evaluated using a SERVQUAL model and proves effective in real-world applications.

The proposed maritime accident prediction system has the potential to be applied to various real-world applications, including not only predicting the risk of maritime accidents and preventing potential accidents from happening [71], [72] but also managing and preparing for emergency situations [30], [70]. In addition, predicting maritime accidents would help develop and establish safe and optimal maritime routes for vessels [65], [83], [84]. Furthermore, the system can be effectively used in autonomous vessels and navigation systems [74]. For instance, there is a possibility of the system being loaded onto autonomous vessel navigation systems [76].

Remaining future works are associated with the improvement and diversification of the proposed system. First is to extend the scope of the prediction system so as to predict and take other types of maritime accidents into account. For instance, including unpreventable natural phenomena, such as typhoons or tsunamis, would improve the completeness of the system. To improve the proposed system's prediction performance, supplementing risk factors, such as vessel size, visibility (fog), and human factors that affect the psychological conditions (e.g., welfare, stress, communications) of ship personnel including crews and captains, plan to be included. In addition, incorporating human factors for maritime accident prediction would also improve the proposed system. In particular, combining existing methods on managing human factors in maritime voyages, such as mental fatigue of personnel (e.g., crews, captains) [69] and tiredness of personnel [73], would make the system more practically useful. Furthermore, combining with other popular accident prediction systems based on deep learning and fuzzy systems in diverse domains, such as railway, transportation, and industrial safety, would be helpful for improving completeness of the prediction system. Last, a mobile connection problem in maritime situations is needed in order for users to use the system during a voyage. In particular, maritime networking ability is required for the system to effectively conduct predictions and interpretations during a voyage [66], [67].

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