STUDY OF DETERMINING RISK LEVEL REGARDING SWIMMING CONDITION ON BATHING BEACH USING AI

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In Japan, 2,000 to 3,000 drowning accidents occur every summer season at major bathing beaches. In order to prevent drowning accidents, beachgoers themselves need to be aware of the dangers and avoid them. As a way to do this, bathing beaches provide daily risk levels regarding swimming conditions to beachgoers using three levels of beach safety flags. However, the risk levels are determined subjectively and empirically by lifesavers and beach administrators based on weather and sea conditions. The characteristics of past drowning accidents are not taken into account. In this study, we suggest an objective method of determining the risk levels based on the probability of drowning accidents. We have created an AI model that can predict the probability of drowning accidents with high accuracy using a total of 53 features such as usage, weather and sea conditions of a study beach in Japan. This method enables appropriate judgment of swimming conditions to prevent many drowning accidents. The reliability of the model was examined using XAI, and it was found that time series of rescue factors were important in predictions. On the other hand, the accuracy decreased when the created AI model was applied to other beaches. It was thought to be caused by differences in the natural environment such as waves and wind.

Keywords: coastal hazards; beach safety; information flags; accident prediction; AI; XAI

INTRODUCTION

In Japan, 2,000 to 3,000 drowning accidents occur every summer season at major bathing beaches (Ishikawa et al. 2014). Before the drowning accidents, lifesavers or beach administrators provide risk levels for beachgoers. After the drowning accidents, lifesavers rescue and provide first aid to the drowning person, and hand over this person to emergency services. If lifesavers provide first aid, survival rates for a person with cardiac arrest are more than three times higher than if paramedics do so on arrival (Komine et al. 2015). So, lifesavers play an important role in saving drowning people. However, the most effective way to prevent drowning accidents is for beachgoers themselves to recognize the danger and avoid it. As a way to do this, bathing beaches provide daily risk levels regarding swimming conditions to beachgoers using three levels of beach safety flags as shown in Fig. 1. Blue, yellow, and red flags which indicate whether there is a good condition, warning condition, or prohibited condition, respectively. In particular, since beachgoers are not allowed to enter the water, red has a direct effect on preventing drowning accidents. These risk levels are determined subjectively and empirically by lifesavers and beach administrators based on weather and sea conditions, but the characteristics of past drowning accidents are not taken into account. In this study, we suggest an objective method of determining the risk levels based on the probability of drowning accidents.

Examples of warning flags

Blue	Good swimming condition.
Yellow	Warning swimming condition.
Red	Prohibited swimming.

Figure 1. Risk level regarding swimming condition on bathing beaches.

STUDY BEACH

The study beach is Onjuku Chuo beach in Chiba, Japan as shown in Fig. 2. At this beach, lifesavers determine swimming conditions. According to the patrol logs, in which lifesavers record daily sea conditions, the total number of beachgoers per season is about 80,000. As an example of the busiest days, 7 to 11 lifesavers were active for 9,200 beachgoers. Many drowning accidents occurred at this beach

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when the swimming condition was yellow as shown in Table 1. The reason for this seems to be rip currents, which are the main cause of drowning accidents at this beach as shown in Fig. 3. Rip currents are likely to occur during this condition due to relatively high wave heights (Ishikawa et al. 2014) as shown in Fig. 4. Furthermore, we assumed that there were a large number of rescues when there were many beachgoers, but there was no correlation between the two of them as shown in Fig. 5. On the other hand, when the swimming condition was red, the drowning accidents did not occur as shown in Table 1. This suggests that drowning accidents can be prevented by appropriately judging when the swimming condition is red. In this study, we determined the risk levels were based on the probability of drowning accidents as shown in Fig. 6. Also, Figure 7 shows the details of the creation of the AI model.

Figure 2. Study beach.

Table 1. Actual drowning accidents at the study beach.		
Study beach (2014-2019)		Number of drowning accidents
Swimming condition	Red	0
	Yellow	135
	Blue	39

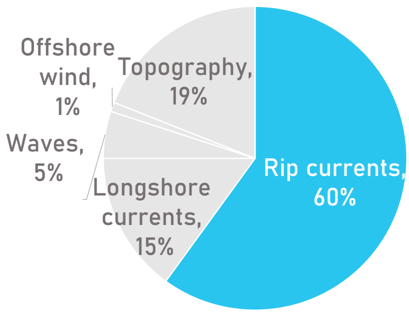


Figure 3. Outbreak factors of drowning accidents at the study beach (2014-2019).

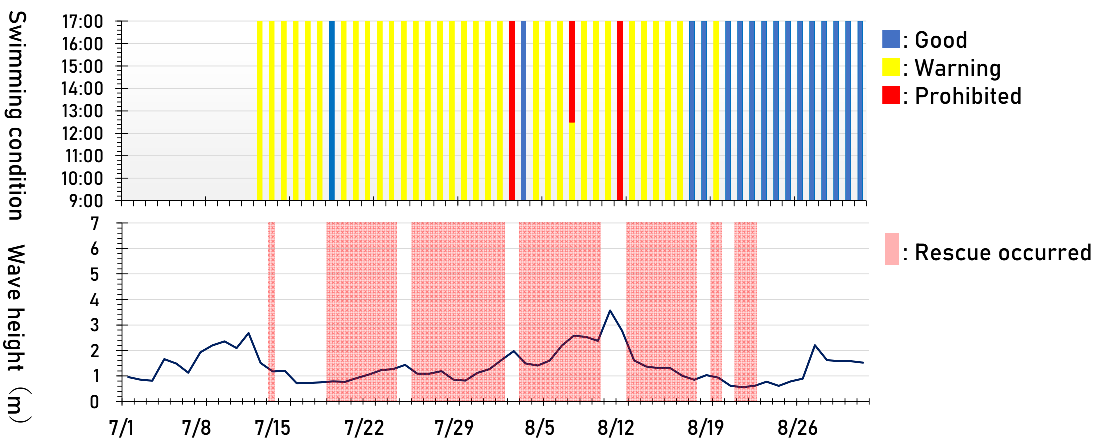


Figure 4. Swimming conditions corresponding to rescue and wave height.

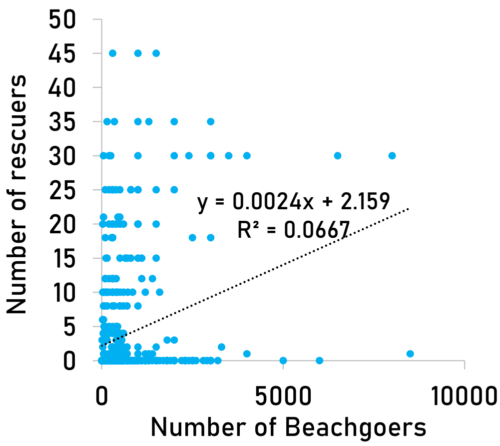


Figure 5. Correlation between number of rescuers and number of beachgoers.

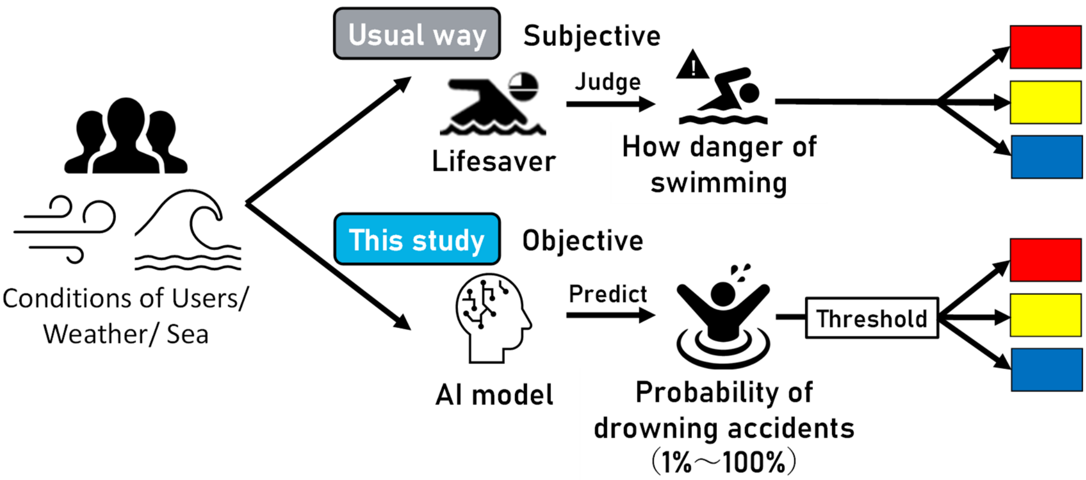


Figure 6. How to determine the beach safety flags in this study.

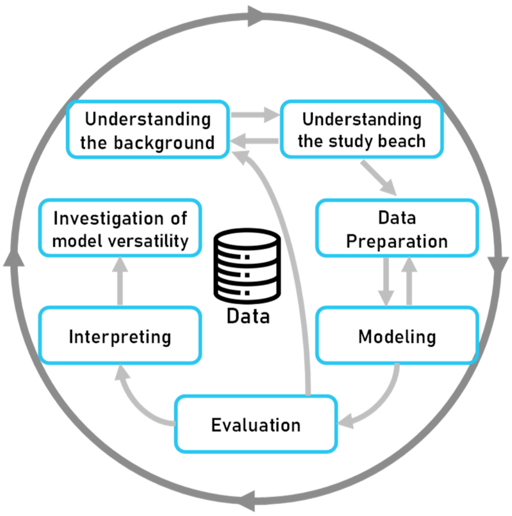


Figure 7. Creation of AI model.

CREATION OF AI MODEL

Data preparation

Data preparation consists of two components: data collection and data preprocessing.

Data collection

In order to accurately predict the probability of drowning accidents, it is necessary for AI to learn past conditions of users, weather, and sea data. By inputting the day's conditions of users, weather and sea data into trained AI, the probability of drowning accidents on the day can be predicted with a high accuracy as shown in Fig. 8.

The objective feature of the AI model was the occurrence or non-occurrence of drowning accidents at 9:00, 12:00, and 15:00 during the swimming period which was in July and August from 2014 to 2019. The occurrence of drowning accidents was extracted from the rescue records of patrol logs in which lifesavers recorded their daily activities. Rescues are divided into emergency care and preventive action for conscious drowning. We set the rescue when there were one or more rescues during a day from the logs.

The explanatory feature of the AI model were 53 features from five points as shown in Fig. 9, including 36 features related to usage conditions, weather conditions, wave and tide conditions, and actual rescue operations, and 17 features created by feature engineering as shown in Table 2. Drowning accidents at beaches are caused by the interaction of various features, including natural factors such as rip currents and longshore currents, and human factors such as beach management systems and usage conditions. Therefore, we thought that a model that could learn such relationships would be able to predict drowning accidents with high accuracy, so we collected various data from relevant institutions in the following five exploratory manners. First, related to drowning accidents references to previous studies. Second, trusted institutions such as the Japan Meteorological Agency and other government agencies. Third, objective data such as obtained and numerical analyses data. Fourth, on or near the study beach. Fifth, the data is historical and will be updated in the future. This is because it was necessary to assume that the model we created would be used.

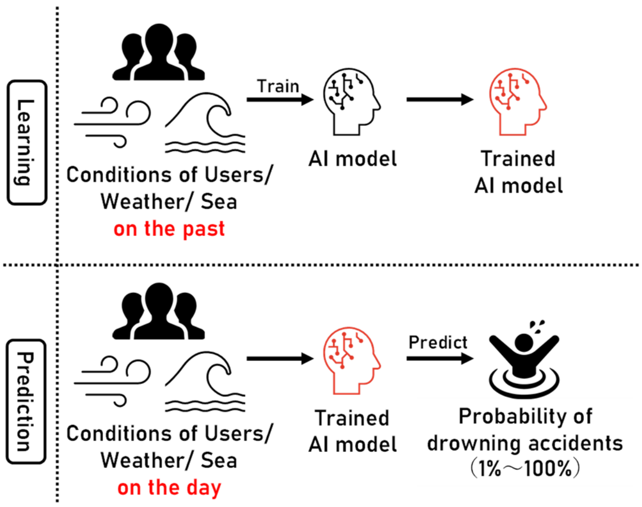


Figure 8. AI Model Training and Prediction

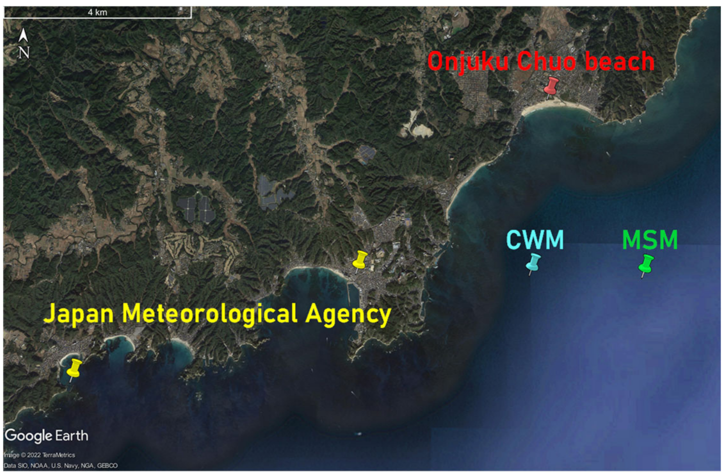


Figure 9. Locations where data was collected

Table 2. Features used to create the AI model

Conditions	Feature	Source
USAGE CONDITIONS	Weather, Temperature, Water temperature, Number of beachgoers, Number of lifesavers, Number of rescuers the previous day*, Cumulative number of rescuers *, Rescues the previous day*, Number of beachgoers per lifesaver*	Patrol Log
WAVE/TIDE CONDITIONS	Wave height, Wave period, Wave direction, East-West wind speed at sea, North-South wind speed at sea	Coastal Wave Numerical Prediction Model GPV
	Tide level, High tide level, Low tide level, Tide name*, Tidal range*	Japan Meteorological Agency
WEATHER CONDITIONS	Temperature, Wind Speed, Wind direction, Sunshine hours, Weather, Local pressure, Sea Level Pressure, Precipitation, Visibility, Total precipitation of the previous day*	
	Sea pressure correction, Ground pressure, Temperature, Relative humidity, Cloudiness (lower, middle, upper, and full clouds), Precipitation (9-10, 10-11, 11-12, 12-13, 13-14, 14-15, 9-12*, 12-15*, 9-15*), Total precipitation of the previous day*	Meso Numerical Prediction Model GPV
–	Month*, Day*, Hour*, Day of the Week*, Weekends and holidays*, holidays*	Set value

* Features added so that the AI model can take into account features of drowning accident occurrence.

Data Preprocessing

When using the data of prohibited swimming conditions, it is not possible to create a proper model, such as predicting that drowning accidents are less likely to occur even in high waves. For that reason, we excluded the collected data when the swimming conditions were red. The collected and created data were split after preprocessing these into training data with data from 2014 to 2018 and test data with data of 2019, as shown in Figure 10. In addition, the training data was split into train data from 2014 to 2016 and validation data from 2017 to 2018. Also, the test data had added 31 drowning accidents in data generated by an oversampling technique (Chawla et al. 2002).

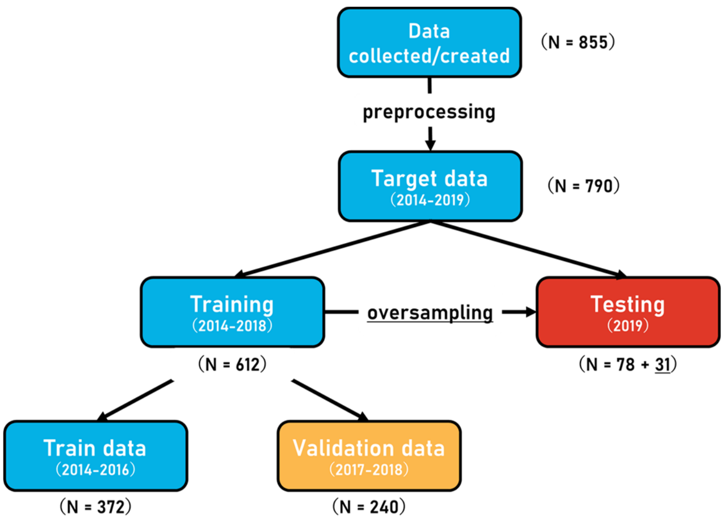


Figure 10. Data splitting

Modeling

Model training

We created various AI models using train data and calculated the AUC using validation data. The AUC takes values between 0 and 1, with values closer to 1 indicating higher accuracy (Akobeng. 2007). AI models are required to be able to predict the probability of drowning accidents on test data with high AUC, but overfitting must be prevented. Overfitting is when a model overfits the training data, resulting in a loss of AUC for the test data. We addressed this problem by using models trained on various hyperparameters to predict the probability of drowning accidents for validation data, finding hyperparameters that can predict with high AUC and using these to predict test data. Bayesian optimization (Snoek et al. 2012) was used for hyperparameter optimization. As a result, LightGBM (Ke, Guolin et al. 2017) was the most accurate among the many models and was adopted as the model used in this study as shown in Fig. 11.

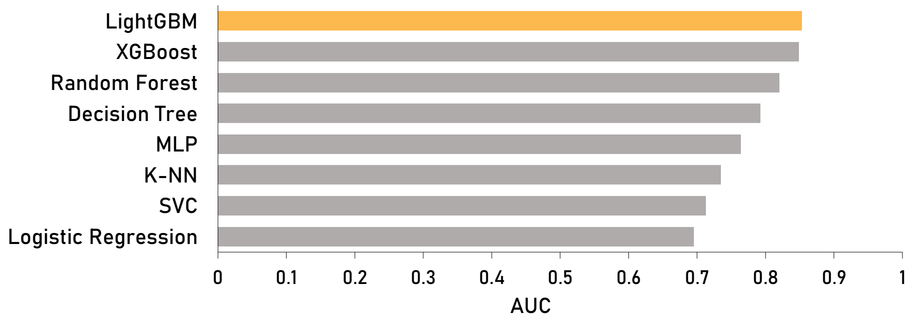


Figure 11. AUC of each model when predicting validation data.

Calculation of thresholds

A threshold for classifying LightGBM's predictions into three beach safety flags was calculated using *Youden's index* (Youden, William J. 1950). Specifically, the probability of drowning accident was predicted for the validation data using the model created from the training data and hyperparameters, and the threshold value was calculated using *Youden's index*. It is a method to calculate a threshold that emphasizes both the fact that the model can correctly judge that swimming is prohibited for data with drowning accidents and that the model can correctly judge that swimming is good or cautionary for data without drowning accidents. The threshold is the probability of the point where the value obtained by adding sensitivity (recall) and specificity-1 is the largest.

$$Youden's\ index = recall + specificity - 1 \tag{1}$$

Recall is the value obtained by dividing TP by TP+FN and is the percentage of data with drowning accidents that the model correctly judged as no-swimming as shown in Table 3.

$$recall = \frac{TP}{TP + FN} \tag{2}$$

Specificity is TN divided by FP+TN and is the percentage of data without drowning accidents that the model correctly determines are not prohibited from swimming as shown in Table 3.

$$specificity = \frac{TN}{FP + TN} \tag{3}$$

The ROC curve is represented by a line connecting all the points plotted on the x and y coordinates as shown in Fig. 12. Area under the ROC curve is an index (AUC) used to measure the accuracy of the model in this study, and its value ranges from 0.5 to 1, with a value closer to 1 indicating a higher accuracy of the model. Figure 13 shows the calculation results of the threshold values. The probability of drowning was 0.5 at the point where *Youden's index* was the largest, and the data above 0.5 could be classified as red and below 0.5 as yellow or blue. The threshold for classifying the data as yellow or blue was calculated in the same way for data less than 0.5, and the result was 0.12. Based on these results, we classified the probability of drowning accidents in the test data as follows: $0 \leq p < 0.12$ as blue, $0.12 \leq p < 0.5$ as yellow, and $0.5 \leq p \leq 0.1$ as red.

Table 3. Accuracy indicators in ROC curves.

		Actual drowning accidents	
		Occurred	Not Occurred
AI prediction	Red	TP	FP
	The others	FN	TN

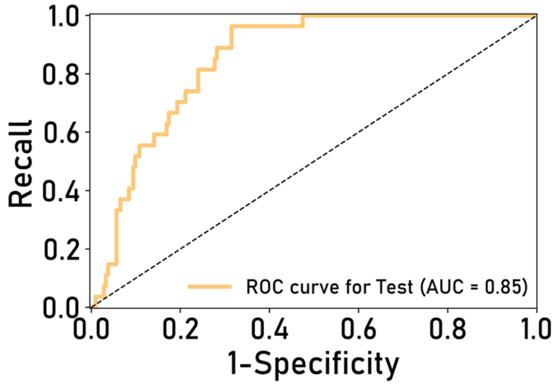


Figure 12. AUC of AI model for validation data.

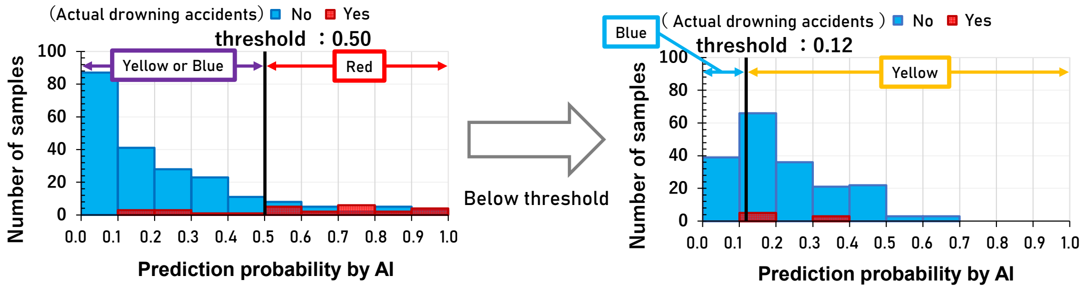


Figure 13. Calculation of threshold values for classifying swimming conditions.

Model testing

The accuracy of the model was evaluated by the AUC of the test data. The usefulness of this method was evaluated by classifying the predicted values of the test data into three beach safety flags.

The accuracy of the model

Figure 14 shows the AUC of AI model for test data, the probability of drowning was predicted with high AUC.

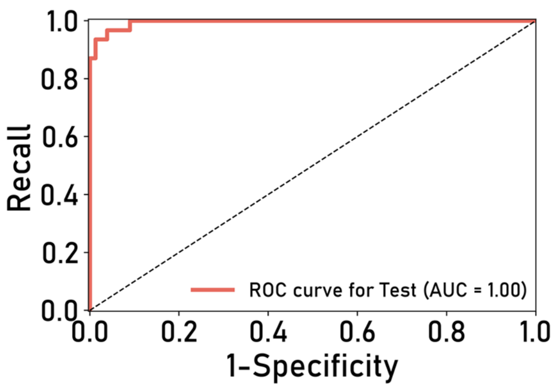


Figure 14. AUC of AI model for each dataset.

The usefulness of this method

Table 4 and Fig. 15 shows a comparison of prediction results by using this study method and actual drowning accidents in test data. The AI determined 36 of the 109 cases of test data to be red, 3 to be yellow, and 70 to be blue by the set threshold from the prediction results of the model. All 31 cases of actual drowning accident data were classified as red. This result means that many drowning accidents were prevented by the AI model because beachgoers are not allowed to enter the water in red. However, the AI determined 5 of the 78 cases of not drowning accident data to be red. This result means that there were more days when swimmers were not allowed to enter the water.

Table 4. Comparison of prediction results by this study method and actual drowning accidents in test data.

		Actual drowning accidents		
		Occurred	Not Occurred	Total
AI prediction	Red	31	5	36
	Yellow	0	3	3
	Blue	0	70	70
	Total	31	78	109

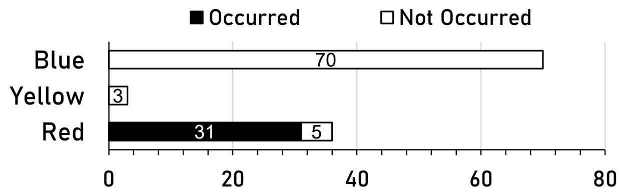


Figure 15. Comparison of prediction results by this study method and actual drowning accidents in test data.

Interpretation of the model

As the scope of AI application has been rapidly expanding in recent years, national governments are required to ensure the reliability of AI. In Japan, the AI utilization guidelines issued by the Ministry of Internal Affairs and Communications (MIC) specify two principles for considering the reliability of AI: the principle of transparency and the principle of accountability. The former is to pay attention to the accountability of the results of AI decisions. The latter is that AI users should strive to be accountable to their stakeholders. Furthermore, the principles of fairness, accountability, and transparency are clearly stated in the Principles for a Human-Centered AI Society issued by the Cabinet Office. Other countries have also developed guidelines, such as the Ethically Adjusted Designs published by the IEEE in the U.S. and the EU General Data Protection Regulation (GDPR) adopted in the EU. These principles are considered to be aimed at preventing the problem of operating AI as a black box. On the other hand, the learning algorithm of the AI created by the authors uses LightGBM, which improves prediction accuracy by combining multiple decision trees, and therefore, a black box problem is pointed out. Explainable AI (XAI) has been proposed for the black box problem of AI with complex internals. So, an increasing number of studies have attempted to interpret AI constructed using XAI (Arrieta et al. 2020). We investigated the reliability of XAI to deal with the black box problem by attempting to interpret AI created using XAI.

In order to solve the black box problem of AI with complex internals, we have used SHAP (Scott Lundberg et al. 2017) which is one of the explainable AI methods to identify which features the created AI emphasizes in the process of prediction. It is possible to determine the contribution of each feature to the predicted value of each piece of data by SHAP values. Specifically, we interpreted which features the AI model we created focused on when predicting the probability of drowning accidents. Furthermore, the relationship between the model predictions and features were analyzed using SHAP and compared quantitatively with the characteristics of the occurrence of rip current accidents based on statistical analysis. In this study, TreeSHAP (Scott Lundberg et al. 2018) was used to efficiently calculate SHAP values.

SHAP values for one of the training data

Figure 16 shows the SHAP values for one of the training data at 12:00 on July 16, 2014. The average predicted value $E[f(x)]$ for all data is 0.277, and the predicted value $f(x)$ for this data is 0.837. The difference between this predicted value and the average is broken down into SHAP values for each feature, arranged in descending order starting with the feature with the largest absolute SHAP value. For example, when the number of rescuers the day before is 3, that increases the predicted value by 0.24. But when the number of users is 150, it decreases the predictive value by 0.03. The combination of a decrease and an increase finally resulted in a predicted value of 0.837, which was determined to be red.

On the other hand, Figure 17 shows the SHAP values for one of the training data at 12:00 on July 19, 2014. The predicted value of $f(x)$ for this data is 0.798. In the case of this data, the number of rescuers on the previous day was 0.24, which is a large positive factor for the predicted value of this data. In contrast, the precipitation between 12:00 and 15:00 is 0.11, which is a negative factor. The results in a predicted value was 0.798, which was determined to be red. Thus, by using the SHAP value, the contribution of each feature to the predicted value of each piece of data can be determined.

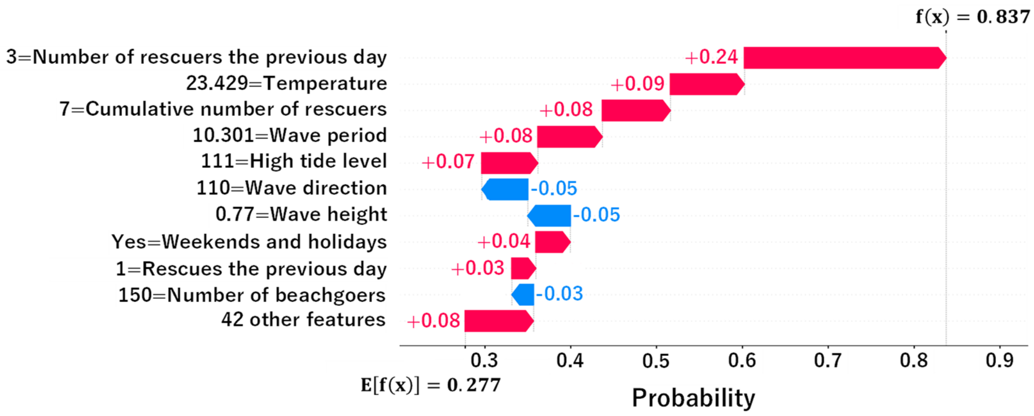


Figure 16. SHAP values for one of the training data at 12:00 on July 16, 2014.

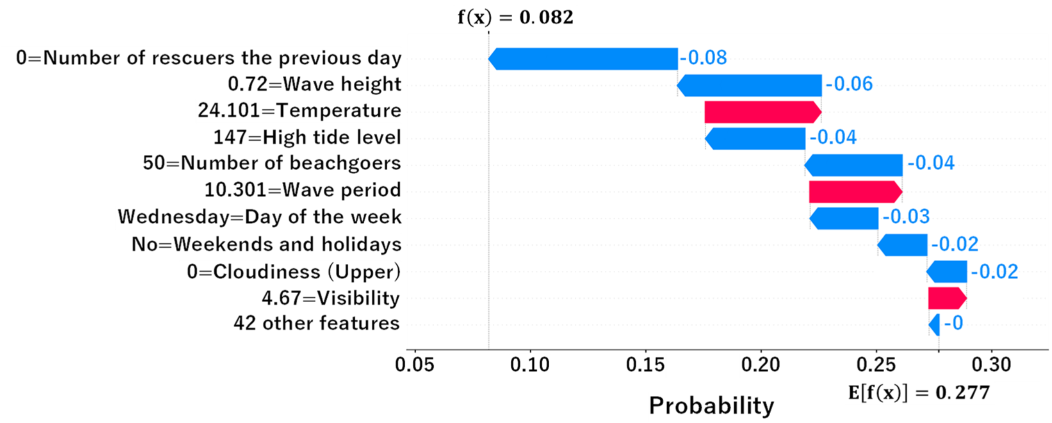
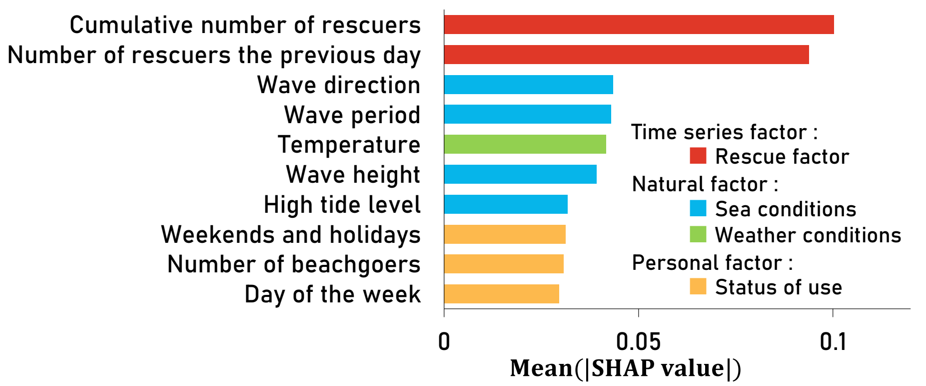


Figure 17. SHAP values for one of the training data at 12:00 on July 19, 2014.

Features of importance

The average contribution of each feature called feature importance can be interpreted by calculating the average of the absolute values across the data for each feature.

The reason for taking absolute averages is that it allows us to see the degree of influence of the feature, whether it increases or decreases the predicted value. Figure 18 shows the top 10 features of importance calculated by SHAP. Red is the time-series factor of the rescue factor, blue is the natural factor of sea conditions, green is that of weather conditions and yellow is the personal factor of status of use. It was newly found that time-series rescue factors were emphasized, which had not been considered as a factor in the occurrence of drowning accidents and that are not related to the main cause of drowning accidents on the study beaches, rip currents as shown Fig. 3.



* Cumulative number of rescuers from the first day of beach opening to the previous day in each year.

Figure 18. Top 10 feature importance by SHAP.

Relationship between the predicted values

In Figure 19, the relationship between the predicted values and features were examined by plotting the value of the feature on the x-axis and the SHAP value on the y-axis for each of the data. When the SHAP value increases with the value of the feature of interest, an increase in the value of the feature contributes to an increase in the probability of drowning, and when the SHAP value decreases with an increase in the value of the feature, an increase in the feature contributes to a decrease in the predicted value. The interval of the SHAP values on the vertical axis is aligned so that we can compare the magnitude of the variance, but the cumulative number of rescues and the number of rescues on the previous day had a large vertical variation. This suggests that these features influenced each other with other features.

These areas mean that they contribute to the increase in the predicted value. In the time series factors, the SHAP value was higher where the cumulative number of rescuers was between 80 and 120 and where the number of rescuers the day before was between 5 and 11. In the natural factors, the SHAP values were higher where the wave direction was between southeast to south southeast, where the wave period was between 10 to 11 s, where the temperature was at 25°C, where the wave height was between 1.1 to 1,3 m and the high tide level was between 1.2 to 1.3 m. In the personal factors, the SHAP values were higher where the holidays and Obon were Yes, where the number of beachgoers were between 400-1,500, and where the day of the week was Sunday.

According to a previous study that investigated the factors that cause the occurrence of rip current accidents through statistical analysis, rip current accidents are more likely to occur when the wave height is 1.5 to 2 m, the period is 10 to 11 s, the wave direction is S, SE, and the number of beachgoers is 500 or more (Shimada, R. et al., 2019). Therefore, focusing on the SHAP values corresponding to these conditions, we found that wave heights of 1.1 to 1.3 m, wave periods of 10 to 11 s, wave directions of 135 to 160 degrees (SE to SSE), and the number of beachgoers is 500 to 1,500 contributed significantly to the increase in the model's predicted values. These results indicate that the conditions for the occurrence of drowning accidents based on statistical analysis and the conditions for increasing the probability of drowning accidents based on AI are similar.

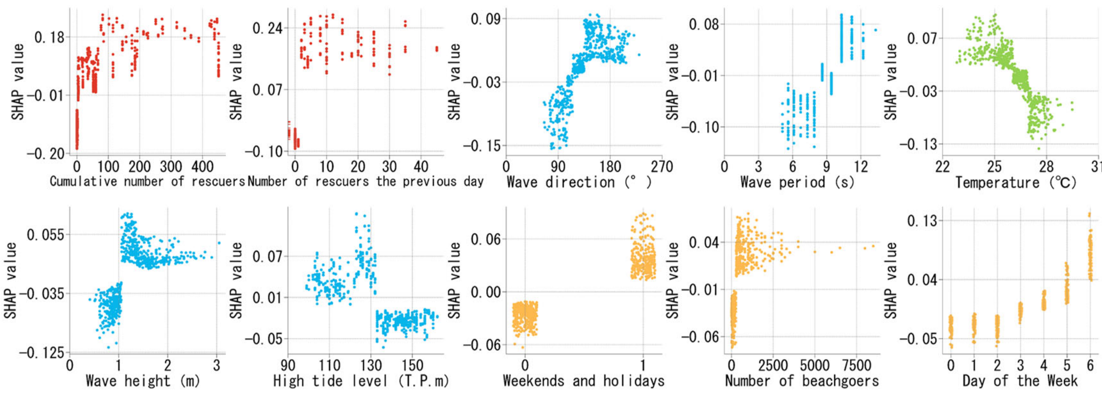


Figure 19. Relationship between the predicted values.

Investigation of model versatility

It was tested whether the probability of drowning accidents could be predicted with high AUC and whether drowning accidents could be prevented at the two beaches which are verification beach A and B on either side of the study beach as shown Fig. 2.

Accuracy of the model

Figure 20 shows the AUC of AI model for each verification beach, beach B was able to predict the probability of drowning accidents with a high AUC, but beach A could not.

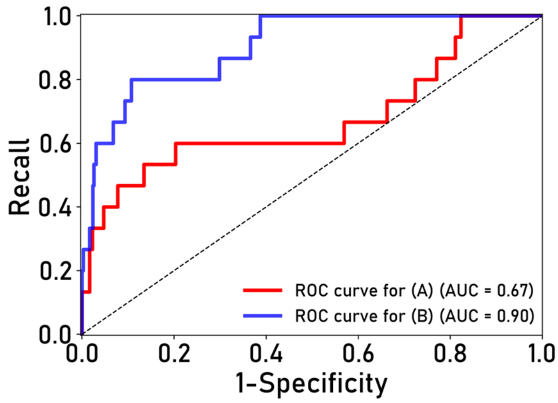


Figure 20. AUC of AI model for each verification beach.

Usefulness of the method

Table 5,6 and Fig. 21, 22 shows the comparison between the prediction results and the actual drowning accidents. The model mostly predicted the test data with drowning accidents being red. Especially on beach B, many drowning accidents were prevented. There was a large amount of data showing that AI predicted the swimming condition was red even though no drowning accidents had occurred at either of the two beaches.

Table 5. Comparison of prediction results by this study method and actual drowning accidents at verification beach A.

		Actual drowning accidents		
		Occurred	Not Occurred	Total
AI prediction	Red	7	49	56
	Yellow	1	26	27
	Blue	7	417	424
	Total	15	492	507

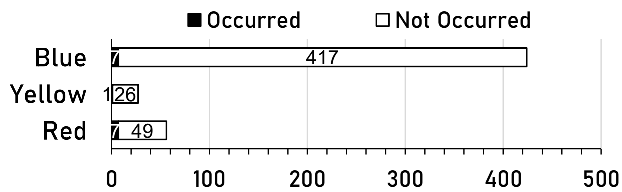


Figure 21. Comparison of prediction results by this study method and actual drowning accidents at verification beach A.

Table 6. Comparison of prediction results by this study method and actual drowning accidents at verification beach B.

		Actual drowning accidents		
		Occurred	Not Occurred	Total
AI prediction	Red	12	35	47
	Yellow	0	23	23
	Blue	3	371	374
	Total	15	429	444

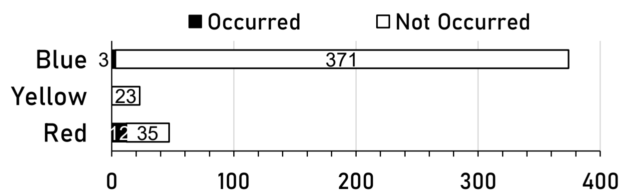


Figure 22. Comparison of prediction results by this study method and actual drowning accidents at verification beach B.

Cause analysis of results

The reason for the decreased accuracy of the model was identified by investigating the features that were working for prediction using SHAP. Figure 23, 24 shows the top 10 features of importance calculated by SHAP at verification beaches. It was found that personal factors, which were not often taken into account when predicting test data, were given more importance. The results show that the time-series trend of drowning accidents at these validation beaches differ from that of the train data at the study beach. The ratio of data where a drowning accident occurred to data where no drowning accident occurred was 1:2.603 for the training data, but 1:32.8 for verification beach A and 1:28.6 for verification beach B. Regarding the much less accurate verification beach A, it is possible that the cumulative number of rescuers may not have had much of a predictive. Furthermore, it was thought to be caused by differences in the natural environment such as waves and wind.

Figure 25, 26 shows the relationship between the predicted values at verification beaches. Compared to the train data from the study beaches, the data from these beaches had fewer drowning accidents, and the smaller cumulative number of rescues and the number of rescues the previous day were considered to have influenced the prediction.

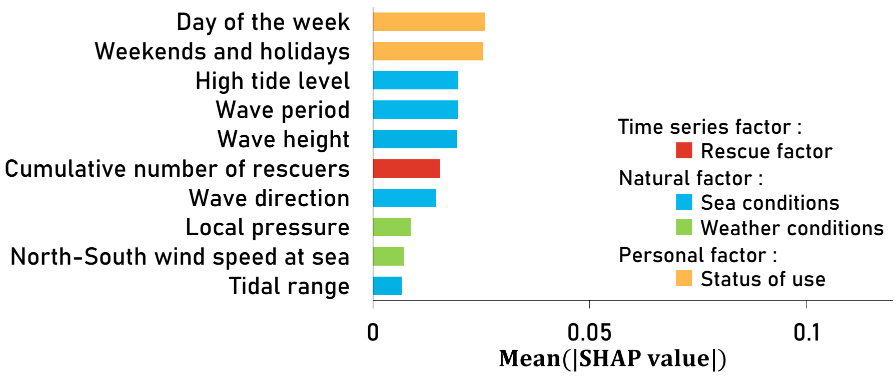


Figure 23. Top 10 feature importance by SHAP at verification beach A.

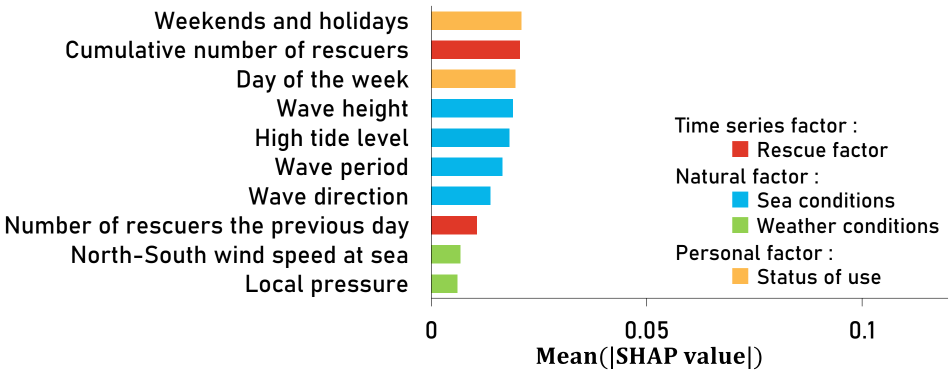


Figure 24. Top 10 feature importance by SHAP at verification beach B.

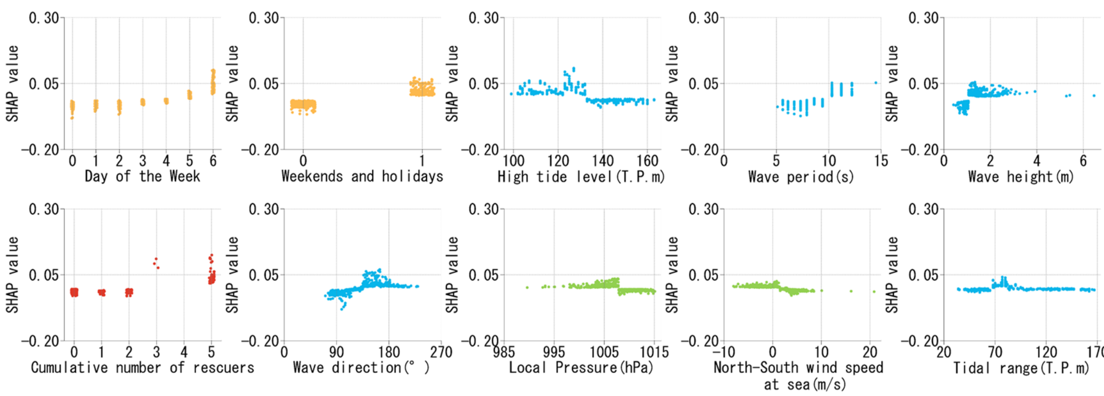


Figure 25. Relationship between the predicted values at verification beach A.

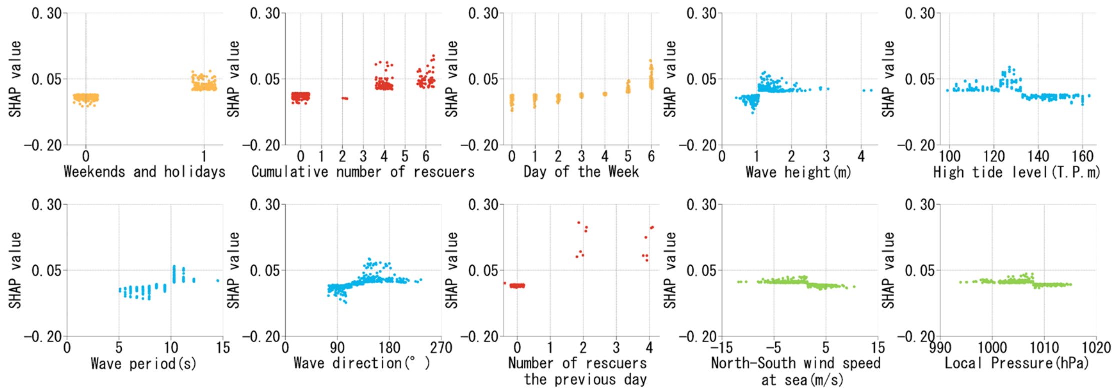


Figure 26. Relationship between the predicted values at verification beach B.

CONCLUSIONS

In this study, we examined a method for objectively determining swimming conditions based on the probability of drowning accidents. Test data was applied to the constructed model to verify the accuracy of the prediction results and the usefulness of the method. As a result, the probability of drowning was predicted with high accuracy (AUC = 1.0). For the determination of swimming conditions using the probability of drowning accidents, a threshold was calculated using *Youden's index*. As a result of using this threshold, swimming conditions were determined appropriately. So, it was suggested that the beach safety flags could be set appropriately and that drowning accidents could be prevented by applying this method to the study beach.

Furthermore, the black box problem of the AI model created using SHAP, was examined. It was investigated that there was an importance of features in predicting the probability of drowning accidents. As a result, it was newly found that time-series rescue factors were emphasized, which had not been considered as a factor in the occurrence of drowning accidents. Therefore, in order to prevent drowning accidents, lifesavers need to pay attention not only to weather and ocean conditions and usage conditions, but also to time-series rescue records. Analysis of the relationship between the predicted values of the AI model and the features showed that the conditions that increase the probability of drowning accidents are similar to the conditions for the occurrence of rip current accidents based on statistical analysis. In the actual operation of AI, it is necessary to consider accident prevention measures in light of the new findings revealed in this study.

Finally, in order to inbestigate model versatility, we applied created AI to other beaches, the AUC decreased, and the usefulness of the method was not confirmed. In the future, it is needed to create a generic AI by doing A and B.

APPENDIX

Hyperparameters of the model with the highest accuracy in the validation data as shown Table 7.

Table 7. Results of optimizing the hyperparameters of each model.

Model	Hyperparameters
LightGBM	*colsample_bytree* = 0.901, *max_depth* = 8, *min_child_samples* = 58, *min_child_weight* = 2.22, *num_leaves* = 20, *subsample* = 0.933, *subsample_freq* = 13, *random_state* = 0
XGBoost	*colsample_bytree* = 0.383, *max_depth* = 8, *min_child_weight* = 2.07, *random_state* = 0, *subsample* = 0.615, *random_state* = 0
Random Forest	*class_weight* = 0, *criterion* = 1, *max_depth* = 5, *max_leaf_nodes* = 14, *min_samples_leaf* = 58, *min_samples_split* = 10, *n_estimators* = 10, *random_state* = 0
Decision Tree	*max_depth* = 8, *min_samples_leaf* = 82, *min_samples_split* = 2, *random_state* = 0
MLP	*activation* = 1, *alpha* = 882, *batch_size* = 88, *hidden_layer_sizes* = 1, *Learning_rate* = 0, *max_iter* = 46, *solver* = 2, *early_stopping* = True, *random_state* = 0
K-NN	*leaf_size* = 56, *n_neighbors* = 30, *p* = 1
SVC	*C* = 0, *max_iter* = 108, *random_state* = 0
Logistic Regression	*C* = 1.62, *fit_intercept* = 0, *intercept_scaling* = 9.54, *max_iter* = 3.0, *random_state* = 0

* Other hyperparameters are default values

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