

# RIP CURRENT DETECTION IN AN OPEN AREA AND ALONG JETTY USING AI

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The occurrence of drowning accidents on beaches is mainly caused by rip currents. In this study, we created a single AI model that can detect two types of rip currents with different characteristics: a flash rip current that occurs intermittently in open areas, and a fixed rip current that occurs along jetty. As a result of creating the AI model under various conditions, it was possible to detect the rip currents at each location with high accuracy at the stage of making the AI model. At the final point of the model's evolution, the accuracy, the precision and the recall rates of the rip current detection were 87 %, 48 % and 100 %, respectively. As a result of actually operating this AI model on the study beach, the single AI model could detect rip currents along the jetty and in the open area. However, it was confirmed that the AI model could not detect all rip currents which were continuously generated along the jetty.

*Keywords: rip current; flash rip; fixed rip; field observation; jetty; AI*

## INTRODUCTION

There are from 2,000 to 3,000 rescues including those of unconscious people every year on the beaches of Japan. Also, the occurrence of drowning accidents is mainly caused by the rip current, it accounts for 48% of drowning accidents (Ishikawa et al. 2014). Additionally, in Australia, the United States and the United Kingdom, more than 50 % of rescue accidents are caused by rip currents (Brighton et al., 2013). In order to reduce the rip current accidents, beach-goers need to recognize rip currents, then they have to avoid them using risk assessment. However, it is the difficulty of risk recognition and judgement under the momentary change in natural phenomenon for beach-goers. Especially, when almost all beach-goers understand the risk in the case of high wave conditions due to easy visual understanding, whereas they cannot understand rip currents the same way. On the other hand, the number of lifesavers is small at around one lifesaver compared to the thousands of beach-goers. In addition, swimming areas along the shore are limited, beach-goers sometimes enter unpatrolled areas. Therefore, we developed a new technology that can automatically detect the rip currents with the Artificial Intelligence, and notify beach-goers and lifesavers using the Internet of Things in 2019 (Ishikawa et al. 2021). In this system, the web cameras on the beach take photos of the surface image of a shooting range by three different cameras. Also, AI analyzes the image data in real time. At the time of occurrence of rip current, AI automatically informs it to the digital signage and beach-goer's smart phone. It is effective for the risk awareness of the beach-goers. Furthermore, if the beach-goers enters the rip current area, AI informs it to lifesaver's wearable device. Then, lifesavers can take early action. Therefore, AI has two primary functions which are the detection of rip currents and the detection of human entrance. The first study beach is located near Tokyo where flash rip currents are generated. As an actual example of rescue under the system operation, lifesavers could take early action by the AI detection, as a result, the life of the drowning person in the rip current area was saved in approximately 50 seconds. Thus, our first AI model for rip current detection can successfully detect rip currents in open areas. However, as a result of applying this AI model to other beaches, almost no rip current could be detected. On the other hand, there are many cases in which coastal structures generate fixed rip currents around themselves in Japan. In this study, we created a single AI model that can detect two types of rip currents with distinct characteristics: a flash rip current that occurs intermittently in open areas, and a fixed rip current that occurs along structures such as jetty.

## SUMMARY OF STUDY BEACH

The study beach is Wakasa-wada beach which is located on the west coast of Japan, as shown in Fig. 1. This beach is a pocket beach with a total length of about 1 km which is mainly composed of fine and medium-sized sand with a gentle seabed slope of 1/60 to 100. Rip currents are likely to occur along the eastside seawall and the two westside jetties. In addition, even in the open area where there are no structures, rip currents occur suddenly and intermittently depending on the waves and topographical conditions. In fact, there have been drowning accidents around these structures and open area in the past, as shown in Fig. 2. The red dots indicate the locations of recent drowning accidents. In order to confirm rip currents are actually occurring along jetty and in an open area, we carried out a color dye

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survey in February 24, 2021. The breaking wave height was approximately 0.5 m. Also, observed wave conditions were  $H_{1/3} = 1.15$  m and  $T_{1/3} = 7.8$  s at Tsuruga wave observatory which is located 53 km northeast of the study beach. Figure 3 shows the results of the color dye survey. It was actually confirmed that rip currents occurred at all areas even under relatively calm wave conditions. Therefore, we installed four web cameras on the beach so that these locations would be within the shooting range of the fixed-point camera. In the shooting range of the cameras 1 and 2 (Cam 1 and 2), rip currents occurring in an open area can be shot, and that of the cameras 3 and 4 (Cam 3 and 4), rip currents occurring along jetty A and B can be shot, as shown in Fig. 4.



Figure 1. Location of study beach.

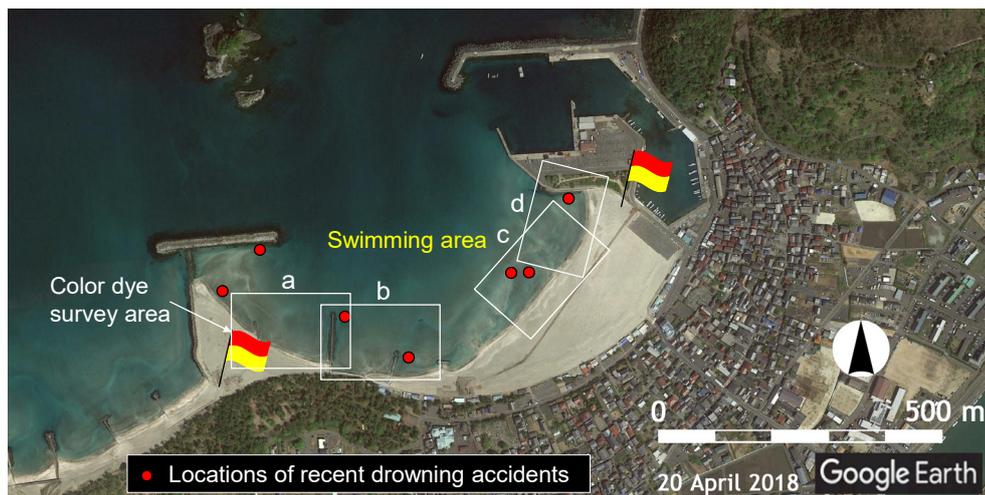


Figure 2. Locations of drowning accidents in recent years.

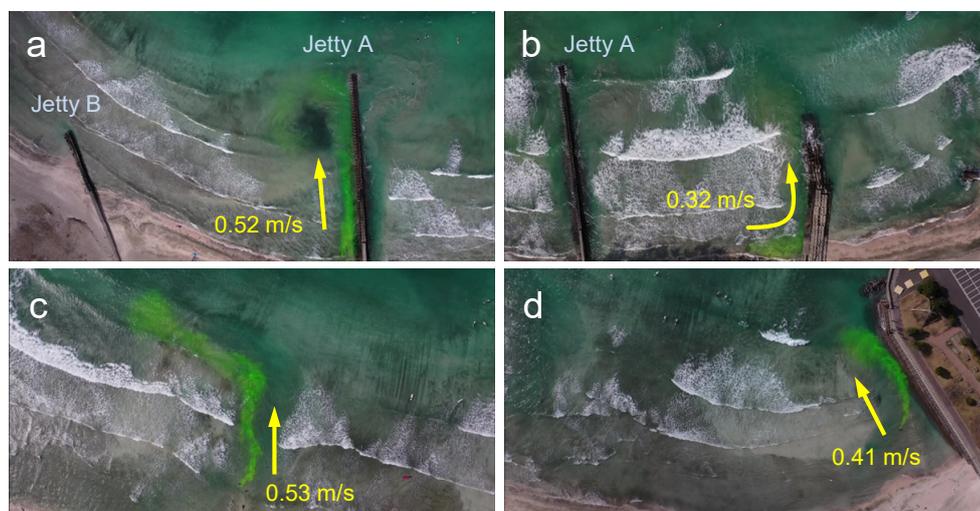


Figure 3. Results of color dye survey.

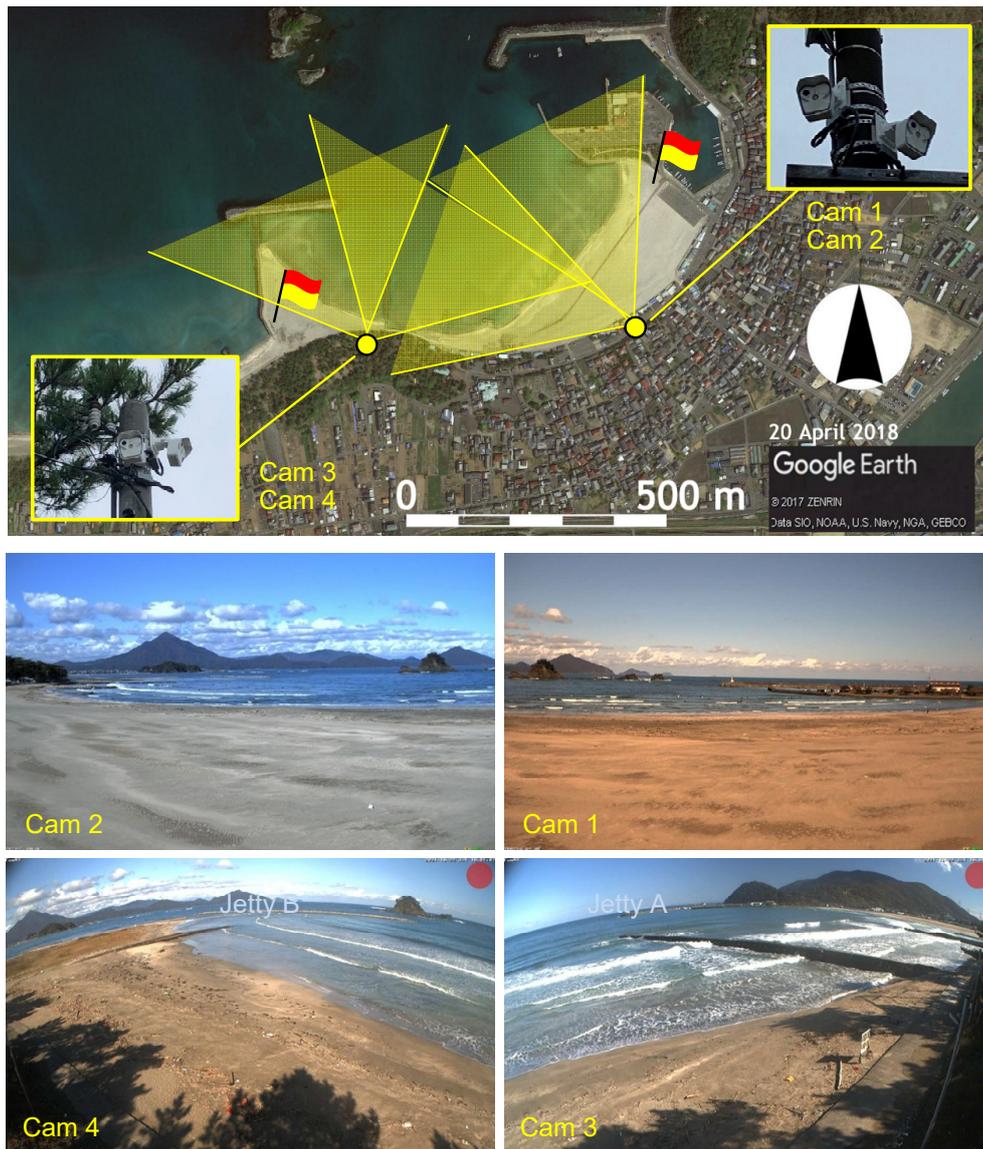


Figure 4. Images of shooting areas by 4 web cameras.

## CREATION OF AI MODEL

### AI learning Method

We created a single AI model that can detect two rip types with distinct characteristics using the surface image data of Cam 1, 3 and 4 from September 2020 to April 2021. Also, we didn't use images of Cam 2, because there were very few rip currents. Wave conditions during this period are shown in Fig. 5, high waves hit frequently during this period. Figure 6 shows the AI learning method and composition of data. For AI deep learning, we extracted 14 days for rip current annotations, and 9 days for images without rip currents by three experienced lifesavers. Then, we prepared 383 annotation videos of rip currents along jetties, and 79 annotation videos of the open area with different dates and times. In addition, 172 videos of jetties and 90 videos of the open area without rip current were prepared. Each video was shot between 7:00 and 17:00 and was 20 minutes long with a frame rate of three frames per second. Next, we set 697 videos for AI learning and 27 videos for testing. For training videos, we made more than 600,000 training samples with a different scale, random horizontal flip, hue, saturation, and brightness. These training samples with and without rip currents were split 8:2 for train samples and validation samples. About the feature extraction, we used the method of differences of three consecutive images as the feature extraction method for the rip current detection. Figure 7 shows an example of the feature extraction images of Cam 1 and 3. Pixels that have changed in three

consecutive frames are indicated by RGB values. Therefore, the rip current area is recognized as a no change or a small change area. Also, because three frames of image data are acquired per second, AI repeats the analysis at intervals of about one second. For AI learning, Tiny YOLO (Redmon and Farhadi 2017) was used as the AI object detector algorithm for rip current detection.

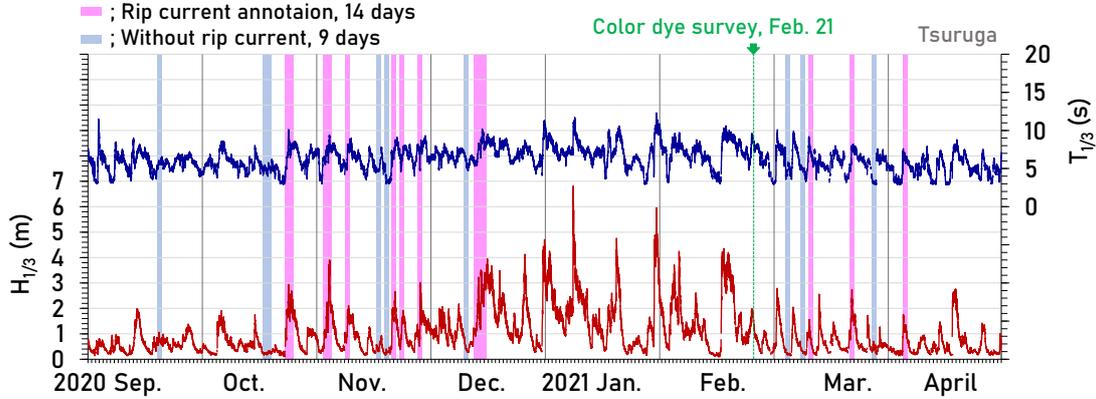


Figure 5. Wave conditions during image data acquisition period used for AI learning.

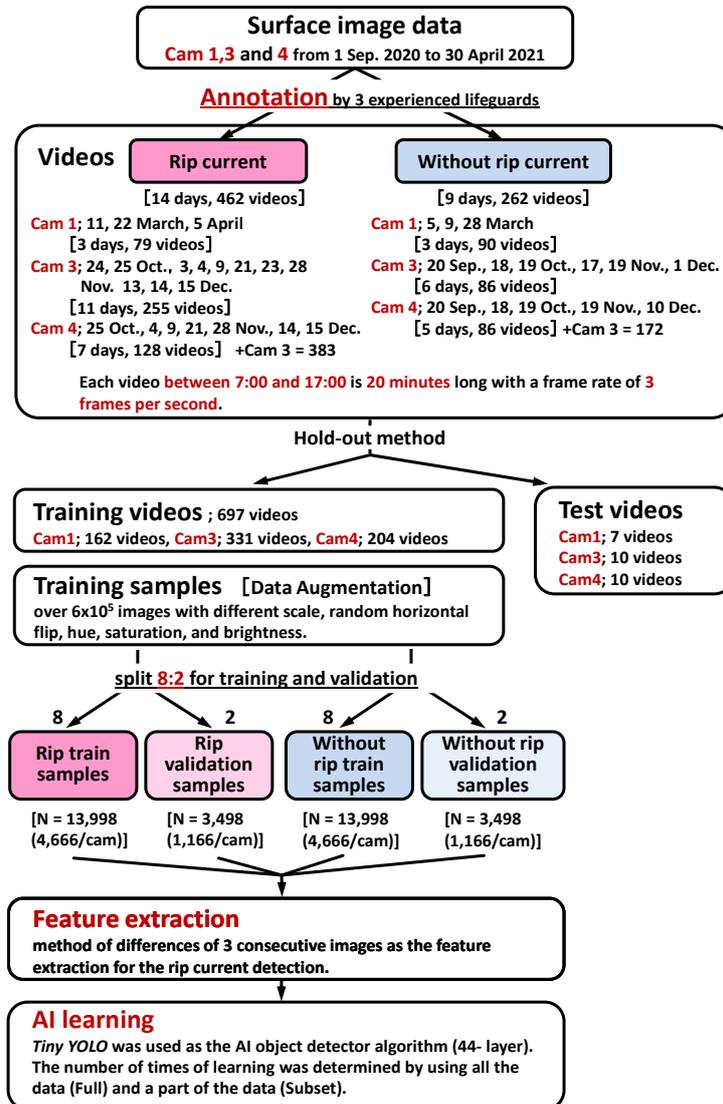


Figure 6. AI learning method and composition of data.

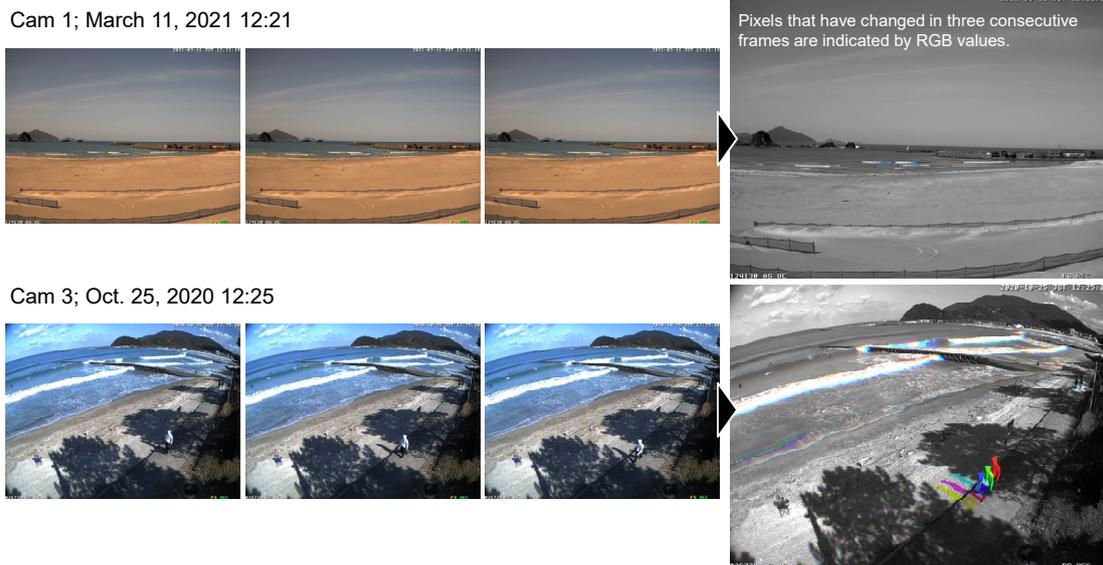


Figure 7. Examples of feature extraction images.

**Model Evaluation**

The AI model was evaluated by Accuracy, Precision, Recall and F-Measure values (Table 1). Precision is the percentage of rip currents that are actually detected as rip currents, and Recall is the percentage of correct detection of actual rip currents as rip currents. Also, True Positive (TP) means the number of a case in which the result of rip current occurrence by AI is correct, False Positive (FP) means the number of a case in which it is not correct. In addition, False Negative(FN) means a number of a case in which the result of rip current non-occurrence by AI is correct, True Negative(TN) means the number of a case in which it is not correct. Figure 8 shows a comparison example of the rip current detection area by AI and the annotation area, a blue area of detection by AI coincides well with a red area annotated by experienced lifesavers. According to these results, AI detected areas coincide well with annotated areas. As a result of creating the AI model under various conditions, it was possible to detect the rip currents at each location with high accuracy at the stage of making the AI model. Table 2 has the verification results of the created AI model at the final point of the model’s evolution, Accuracy, Precision and Recall rates of the rip current detection were 87 %, 48 % and 100 %, respectively. Also, Precision for Cam 1 had a high value, and both Cam 3 and 4 had low values. On the other hand, Recall of all cams were 100 %, which means that the rip current that actually occurred was not overlooked. If Recall is emphasized to prevent drowning accidents, the reliability of the model can be evaluated as high. Also, the final model used approximately 14,000 train-samples and 3,500 validation samples with and without rip currents, respectively. These numbers are about a quarter of the samples that were used when creating AI models in the past (Ishikawa et al. 2021).

Table 1. AI model evaluation method.	
Accuracy	Percentage of correctly detected rip currents and without rip currents. $(TP+TN) / (TP+FP+FN+TN)$
Precision	Percentage of correctly detected rip currents. $TP / (TP+FP)$
Recall	Percentage of correct detections for all test rip current data. $TP / (TP+FN)$
F measure	Harmonic Mean of Precision and Recall. $(2 \times Precision \times Recall) / (Precision + Recall)$

Table 2. Verification results of created AI model.				
data	Accuracy	Precision	Recall	F-Measure
All	0.87	0.48	1.00	0.65
Cam 1	0.84	0.71	1.00	0.83
Cam 3	0.86	0.19	1.00	0.32
Cam 4	0.89	0.23	1.00	0.37

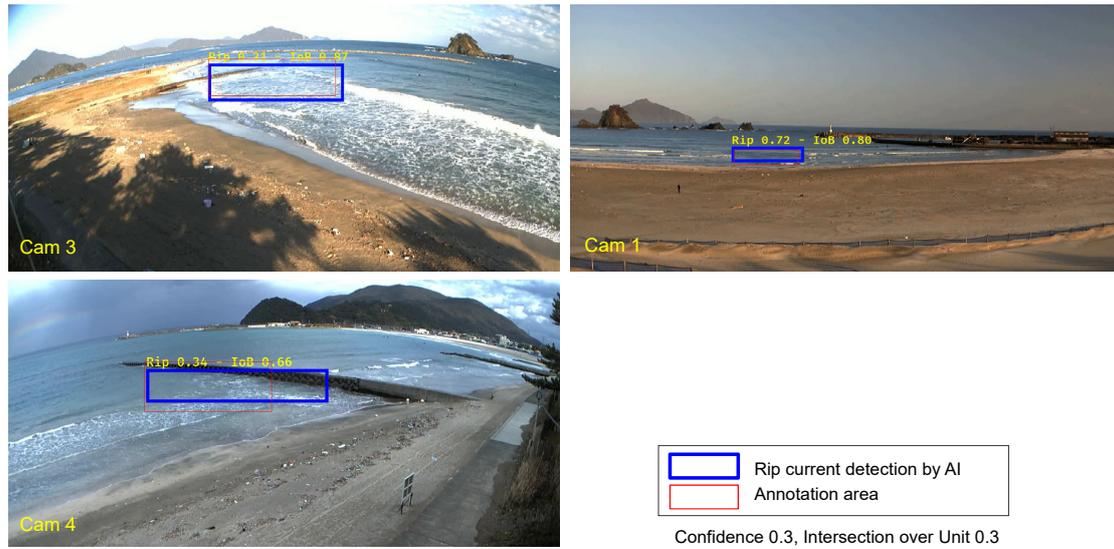


Figure 8. Comparison of the rip current detection by AI and the annotation area.

#### VALIDATION OF RIP CURRENT DETECTION BY AI

The created AI model was actually operated on the study beach from October 2021, and rip detection results by AI were verified using an image analysis. The log data was saved from October 15, 2021 to November 4, 2021, and from December 22 to 31, 2021, so the verification period was set to a total of 32 days within these periods. Figure 9 shows the wave conditions during the verification period. High waves were observed several times during the period. Figure 10 shows the number of daily rip current detections for Cam 1, 3 and 4 during the period. The increase and decrease in the number of rip current detection showed good correspondence with the change in wave height from October 15 to November 4. On the other hand, few rip currents were detected for Cam 4. The verification method was the image analysis, as well as a visual confirmation by the experienced lifesaver. In the image analysis, with or without rip currents is determined by image averaging (Lippmann and Holman 1989) using the characteristics of rip current areas where waves are less likely to break. At first, we made overlaid detection areas using an averaged image for each hour. As a result of visually confirming the captured images at the time when the rip current was detected, the occurrence of the rip current was actually confirmed in many images. As an example, Figure 11 shows the shooting image of Cam 1 and 3 at 12:00 on October 23 when AI detected a rip current, and detection areas overlaid an averaged image from 12:00 to 13:00. It can be confirmed that the detected rip current areas by AI were almost the same as the actual rip current areas. Similarly Figure 12 shows the results of Cam 3. The AI model could detect rip current areas along the jetty. Thus, it was clarified that a single AI model can detect rip currents with distinct characteristics even in actual operation.

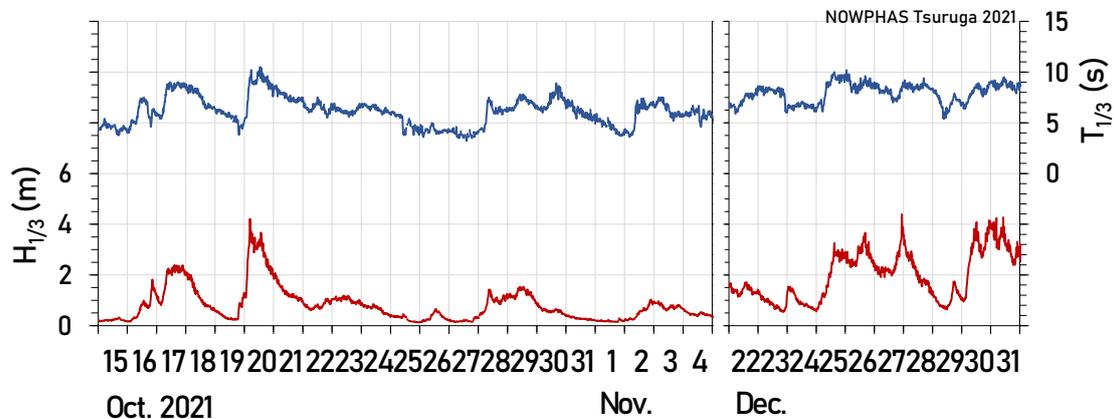


Figure 9. Wave conditions during the verification period for rip current detection by AI.

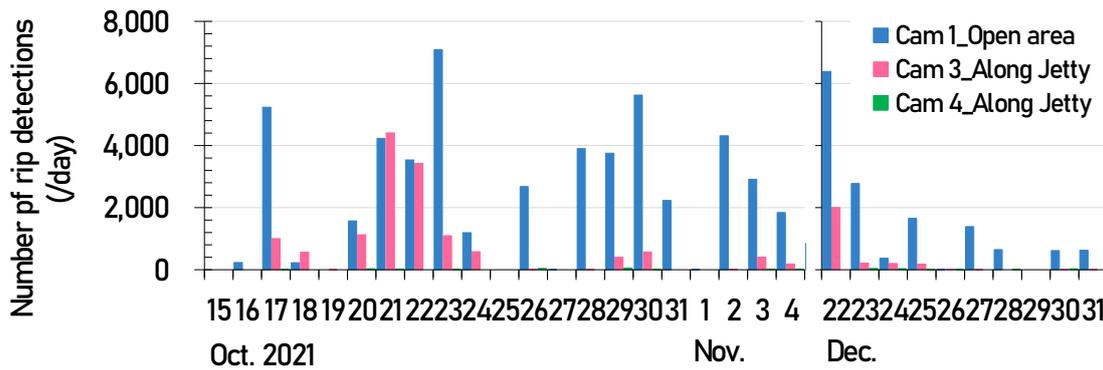


Figure 10. Daily rip detections by AI for Cam 1, 3 and 4 during the verification period.

(a) Shooting image 12:00, October 23, 2021



(b) Detection areas overlaid an averaged image from 12:00 to 13:00



Figure 11. Example of rip current detection results by AI of Cam 1.

(a) Shooting image 12:00, October 23, 2021



(b) Detection areas overlaid an averaged image from 12:00 to 13:00

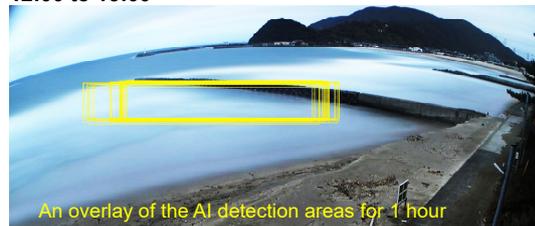


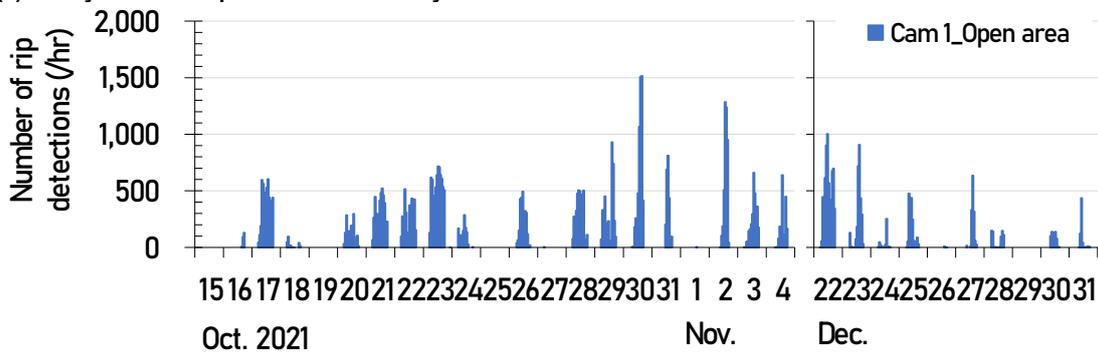
Figure 12. Example of rip current detection results by AI of Cam 3.

Next, we investigated whether the AI was able to detect the occurrence of actual rip currents during the period by a method using the image analysis. This method determines the occurrence of a rip current during the verification period from the difference in pixel values of comparison areas between the wave breaking zone and the rip current area in the averaged image (Shimada et al. 2022). Figure 13 shows comparison areas at the rip current area and the wave breaking zone of Cam 1. Each area was set at 60x20 pixels. In the averaged image, the rip current area where waves do not break easily has a lower brightness than the breaking wave zone, and the average pixel value approaches zero. On the other hand, the wave breaking zone is brighter than its surroundings, and the average pixel value approaches 255. Therefore, when the value obtained by subtracting the average pixel value of the rip current from that of the wave breaking zone is a positive value, it can be defined that a rip current was occurring. Figure 14(a) shows hourly results of rip current detection with a confidence of 0.3 for Cam 1. It was considered that the rip current occurred intermittently in the open area. Figure 14(b) shows the difference in average pixel values for each hour in the captured images of Cam 1. This result shows a good correspondence with the rip current detections by AI. Furthermore, the positive pixel value differences indicating the occurrence of rip currents was 176 hours of the 187 hours in total when rip currents were detected by AI. This means the AI could detect 94% of occurrence of rip currents for Cam 1. Thus, it was considered the created AI model can appropriately detect rip currents that occurred intermittently in the open area. On the other hand, it was 43% of cases where the AI judged that there was no rip current, actually there was no rip current. This means the AI could not detect 57% of occurrence of rip currents.



Figure 13. Pixel value comparison areas set for wave breaking zone and rip current area in the averaged image of Cam 1.

(a) Hourly results of rip current detection by AI



(b) Difference in Hourly average pixel values.

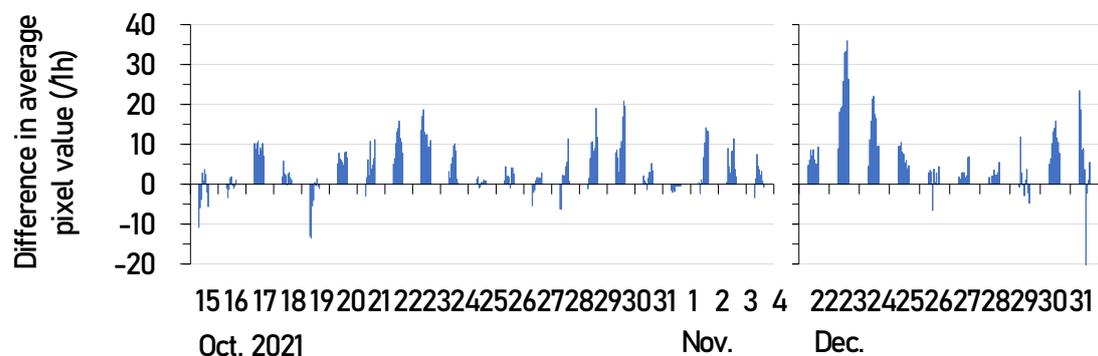


Figure 14. Results of image analysis for Cam 1.

The comparison areas at the rip current area and the wave breaking zone of Cam 3 is shown in Figure 15, and the results of image analysis for Cam 3 are shown in Fig. 16. The positive pixel value differences indicating the occurrence of rip currents was 128 hours at 98 % of the 130 hours in total when rip currents were detected by AI. On the other hand, it was estimated that rip currents occurred continuously along the jetty during the verification period according to Fig. 16(b). In 2% of cases where the AI judged that there was no rip current, actually there was no rip current. This means the AI could not detect 98% of occurrence of rip currents for Cam 3. Therefore, although the AI model was able to detect rip currents along jetty, it thought that the AI overlooked many rip currents. Figure 17 shows an example of an averaged image in which AI could not detect rip currents for images taken by Cam 3. It is thought that rip currents were occurring during this time. Figures 18 and 19 show comparison areas and results of image analysis for Cam 4. It was thought that the AI overlooked many rip currents similar to that of Cam 3. The AI overlooked many rip currents especially in December.



Figure 15. Pixel value comparison areas set for wave breaking zone and rip current area in the averaged image of Cam 3.

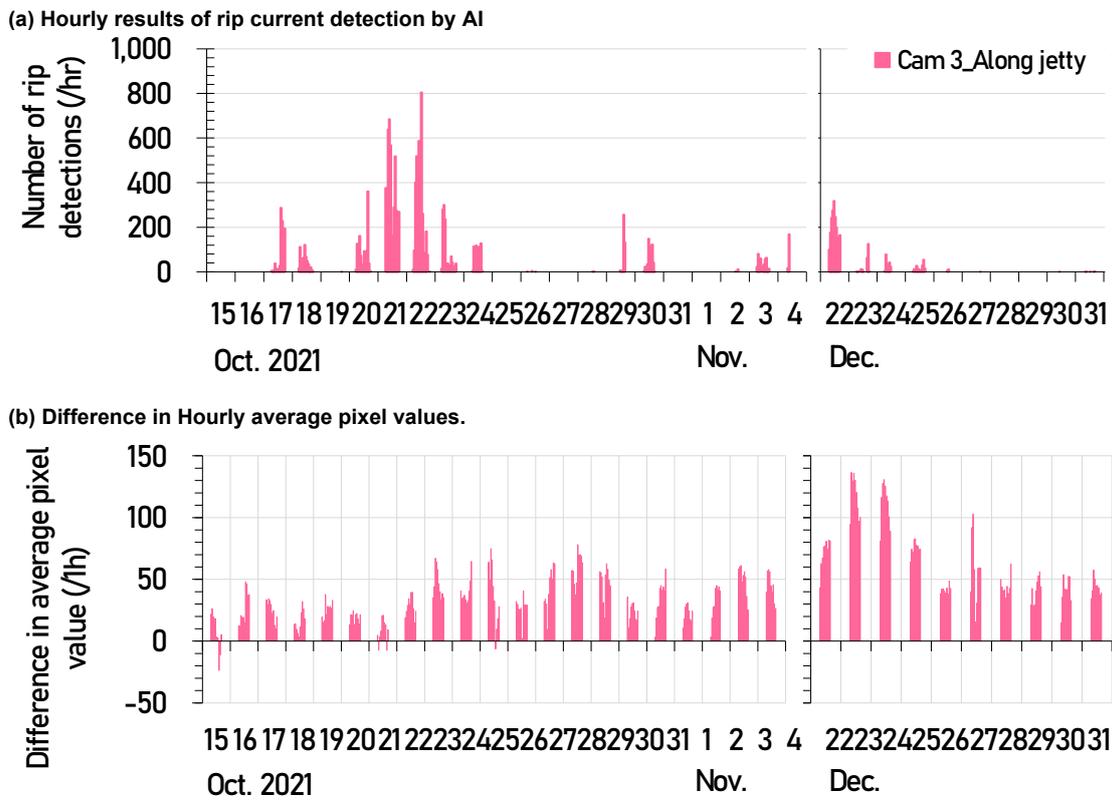


Figure 16. Results of image analysis for Cam 3.

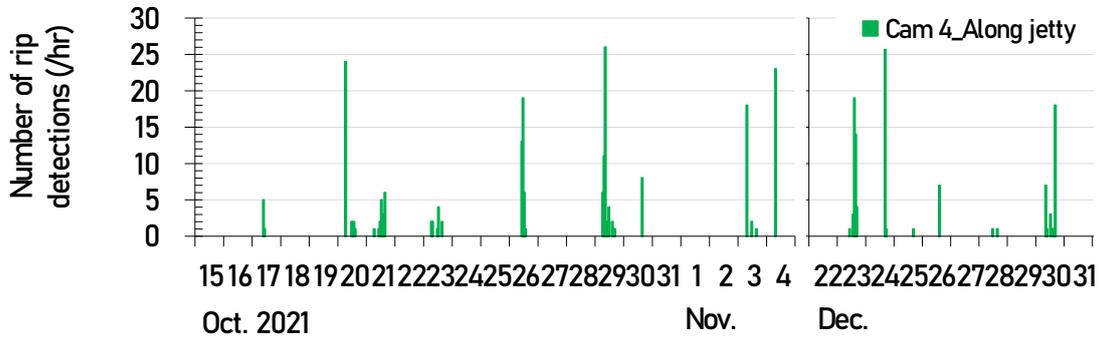


Figure 17. An example in which rip currents could not be detected in the image by Cam 3 (1 hour average image from 14:00 to 15:00 on October 28, 2021).



Figure 18. Pixel value comparison areas set for wave breaking zone and rip current area in the averaged image of Cam 4.

(a) Hourly results of rip current detection by AI



(b) Difference in Hourly average pixel values.

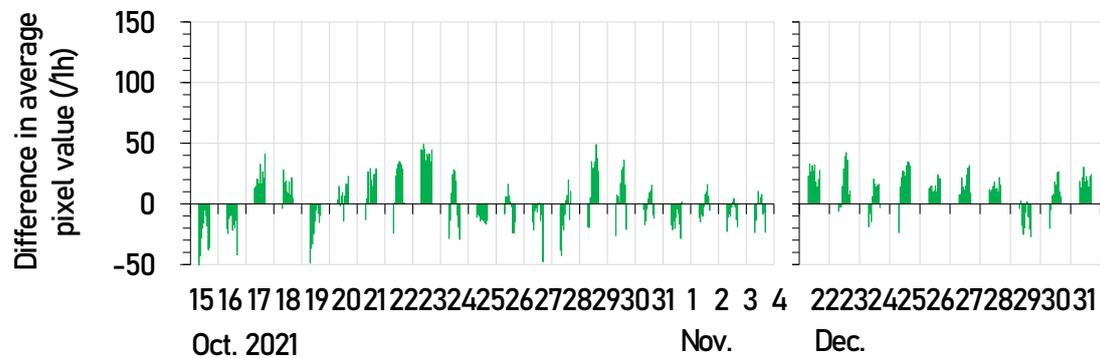


Figure 19. Results of image analysis for Cam 4.

Figure 20 shows the distribution of wave height and wave period. Although the wave height was slightly higher in December, the wave conditions during the verification period were roughly the same as for the AI learning data. On the other hand, there were rainy and snowy days in December, as shown in Figure 21. On rainy and snowy days, conditions different from AI learning, such as water droplets on the lens of Web cams and snowfall were confirmed, as shown in Fig. 22.

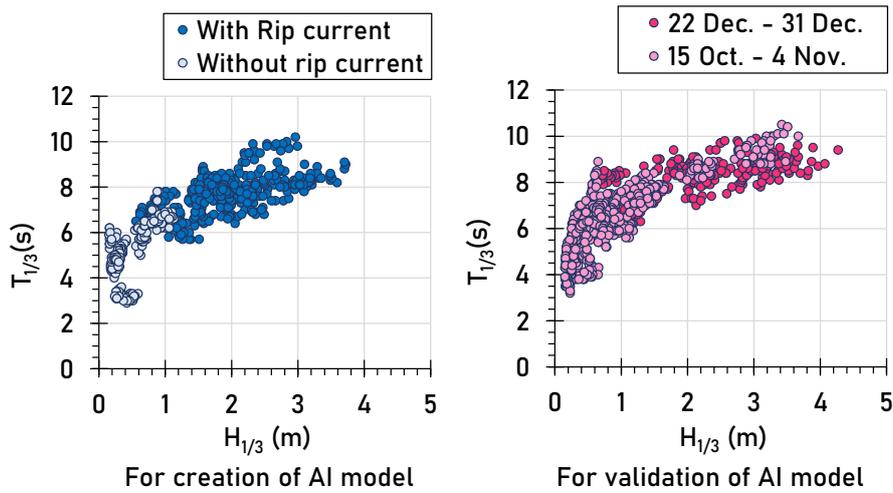


Figure 20. Distribution of Wave height and Wave period.

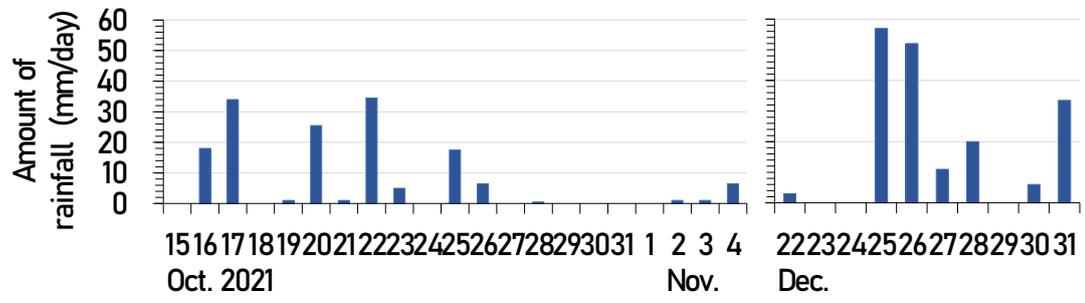


Figure 21. Amount of rainfall during the verification period.

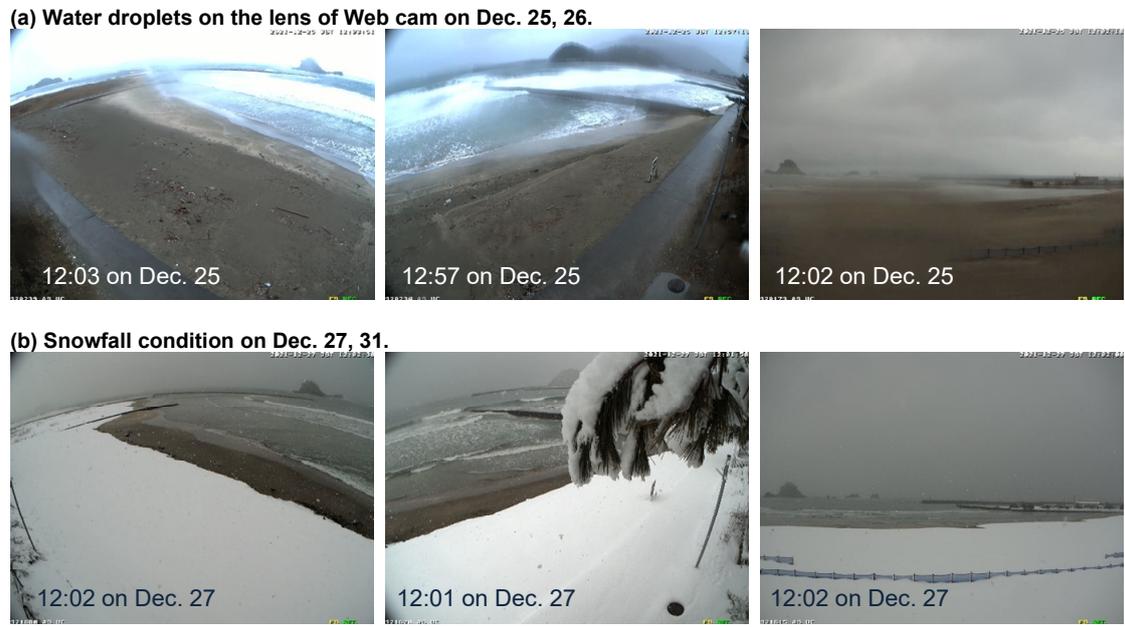


Figure 22. Examples of situations of rainfall and snowfall.

**CONCLUSIONS**

In this study, we created a single AI model that can detect two types of rip currents with distinct characteristics: a flash rip current that occurs intermittently in open areas, and a fixed rip current that

occurs along jetty. As a result of creating the AI model under various conditions, it was possible to detect the rip currents at each location with high accuracy at the stage of making the AI model. As a result of actually operating this AI model on the study beach, the single AI model could detect rip currents along the jetty and in the open area. However, it was confirmed that the AI model could not detect all rip currents which were generated along the jetty. However, the wave conditions were not unique during this verification period. On the other hand, it is difficult to detect with obstacles such as water droplets on the camera. Therefore, except in this situation, it is thought that the general purpose of the AI model can be increased with new training data added in which rip currents could not be detected by AI learning, or changing the condition of the AI confidence for rip current detection.

#### ACKNOWLEDGEMENTS

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