Abstract—Urban rivers provide a water environment that influences residential living. River surface monitoring has become crucial for making decisions about where to prioritize cleaning and when to automatically start the cleaning treatment. We focus on the organic mud, or “scum” that accumulates on the river’s surface and gives it its peculiar odor and external economic effects on the landscape. Because of its feature of a sparsely distributed and unstable pattern of organic shape, automating the monitoring has proved difficult. We propose a patch-wise classification pipeline to detect scum features on the river surface using mixture image augmentation to increase the diversity between the scum floating on the river and the entangled background on the river surface reflected by nearby structures like buildings, bridges, poles, and barriers. Furthermore, we propose a scum index covered on rivers to help monitor worse grades online, collecting floating scum and deciding on chemical treatment policies. Finally, we show how to use our method on a time series dataset with frames every ten minutes recording river scum events over several days. We discuss the value of our pipeline and its experimental findings.

Keywords—River surface detection, Image augmentation, Patch-wise monitoring, Scum-cover-ratio, Scaled heatmap.

I. INTRODUCTION
A. Related Works
The automated garbage collector and river cleaning robot have been the center of the river manager assisted robotics research for the past decade [1, 2]. Additionally, the river surface monitoring has become crucial to decide which areas are the worst and to automatically begin the cleaning process. Since 1991, there have been numerous studies for understanding the scum formation mechanism in-house experiments [3, 4], field observations regarding organic sludge and odor [5, 6], and automatic scum behavior monitoring using river surface computer vision [7][8]. Owing to the complex events and intertwined phenomena that include physical, chemical, biological, and hydrological features, it is not widely known how to fundamentally solve the river scum problem.

After a few days of rainfall, combined sewer overflows (CSOs) have suddenly occurred at the upstream of the river owing to scum and the highly dispersed residential living environment. The river’s odor and external economic effects on the landscape are then caused by organic mud, or “scum” that appears on the river’s surface. Mizuta et al. [8] proposed a method for monitoring scum in urban river’s tidal area. The 805 split lattice color images with a 20 \times 20 pixel size were automatically used by the fixed point camera to determine whether or not scum was present. The accuracy to identify the scum ranged from 58 to 88 percent using this straightforward neural network model with one hidden layer. The input variables include the 45 features of statistics and 25, 50, and 75 percentiles for each pixel’s RGB components. Additionally, they included input features like bridges and fences as reflected background features that were visible on the water surface. Although this was a preliminary version of the scum monitoring method, there is still room for accuracy enhancement and generalization to deep learning algorithms for pixel-by-pixel classification, also known as semantic segmentation, such as the U-Net [9]. Nakatani et al. [10] studied detailed observations of scum using multiple cameras and sediment surveys in a tidal river to understand the generation and floating behavior of scum using the U-Net. They discovered evidence that the local flow may have a significant impact on the spatial-temporal behavior of the scum owing to the tide level. Semantic segmentation is unquestionably a possible option for a roughly scum monitoring method. If we use the marine debris object type [11, 12], which includes bottle, can, hook, and tire, the U-Net with the ResNet34 backbone was still the best performing model. However, it has not always high accuracy with a value of Intersection of Union 0.748.

However, the scum feature has sparsely distributed and unstable pattern, making it difficult to improve the semantic segmentation accuracy. The scum segmentation on the river surface still has an over-prediction issue, and it is insufficiently accurate for scum monitoring on the river water surface. The area of interest, the scum, was obscured by the water surface, which was frequently reflected by the nearby background features such as building, bridge, pole, sign, sky, and trees. The authors propose a patch-wise classification method using image augmentation to improve the precise recognition of the river scum.

B. Pixel-wise Segmentation vs Patch Classification
First, we debate whether supervised learning such as used in classification, object detection, and semantic segmentation, is a better deep learning approach. We can select the semantic segmentation or classification if the target feature of the scum is not categorized into object context. It becomes challenging to annotate the scum feature on the pixel-wise region of interest (ROI) within the river surface in the case of the semantic segmentation. The scum features are sparsely dispersed, and the pattern is unstable and complex. The training results would be low precision and the false negative error, which
predict scum but actually background, would increase if we attempted to annotate one of the filled regions with multiple scum features. Therefore, the authors proposed a patch-wise classification approach rather than the pixel-wise semantic segmentation. The patch size is 128 × 256. In contrast, we can consider an approach from unsupervised learning like the generator and anomaly detection such as the Variational Auto-Encoder (VAE) [13].

As illustrated in Fig.1, we demonstrated how to train the three classes of conditional VAE [14] using a dataset that was defined by C0: early scum, C1: grow-thick scum, and C2: background. Here, the bridge z-space contains 256 elements. Using t-SNE, we could dimension-reduce the z-mean and z-variance into plots of two and three dimensions. Hence, the three classes of river water surface, scum-generated feature, and a background that includes the building, train, bridge, barrier, pole, and tree, were not independent of each other. Here, a fake scene was reflected on the river’s water surface with a mirrored background rather than an actual image. Thus, river water surface images are very complex and dependent on the water surface class and the target scum feature. Therefore, we will not select the generative learning and pixel-wise segmentation approaches. We discovered that it is not fitted to the dataset of river scum images for accurate scum detection. To tackle the low precision problem, this study proposed a patch-wise classification approach using mixture image augmentation.

C. Overview of Pipeline

As shown in Fig.2, we give an overview of the pipeline from the offline training stage to the online prediction and computing scum index. The first three components of the training stage are 1) data preparedness, 2) mixture image augmentation, 3) patch classification deep learning. The data preparation process involves cropping a rectangle without the far region’s top and extracting four rows by five columns of patch images. Mixture image augmentation [15] transforms into diversified images using multiple raw images, such as the mixup [16,17], Cutout [18], and RICAP [19]. A convolutional neural network, such as the ResNet50, ResNet101, and Inception-v3 are practically used in deep learning for patch classification. Secondly, the prediction stage using the pretrained deep network includes the following steps: 1) predict 20 patch probabilities; 2) combine their probabilities into a matrix; 3) create a scaled heatmap; 4) binarize the mask image; and 5) calculate the pixel count of the scum region. The prediction brings the total number of patch probabilities taken from the raw input frame to 20. Their probability values are combined into a matrix. The matrix with four rows by five columns is transformed into a scaled heatmap with a grayscale intensity range of 0 to 255. The heatmap can binarize a mask image with pixels set to 0 or 1. The scum region pixel with a value of one on the mask image can be counted. Finally, the temporal scum index at a time stamp is computed as the value we call "scum-cover-ratio" whose scum region pixel count is divided by the river region pixel count, ranging from 0 to 100 percent. Here, the river region can count pixels without a background. The background region is constant when the camera angle is fixed, allowing us to set the river region’s pixel count. We can repeatedly calculate the scum-cover-ratio using the raw input frame image collected every ten minutes. We can visualize the time series of scum-cover-ratio and draw the color heatmap ranging from blue to red.

To distinguish between the floating scum feature and the entangled background on the river surface mirrored close to structures like buildings, bridges, poles, and barriers, we propose a patch classification pipeline to detect scum regions on the river surface using mixture augmentation. We also proposed a "scum-on-river" ratio index to help with online scum appearance degradation and decision-making regarding collecting floating scum and chemical treatment policy. Finally, we demonstrated how to use our pipeline on a time series of frames every ten minutes, recording the river scum vision for several days at an urban river in Japan 2021.

II. RIVER SURFACE DETECTION METHOD

A. Crop Far Region and Patch Classification

The first three steps of the training stage are data preparation, mixture image augmentation, and deep learning patch classification. The data preparation operates to crop a rectangle without the top of the far region and to extract four rows by five columns of patch images. The size of the river vision camera used in this study is 1,280 pixels wide by 720 pixels high. We precisely cut the top of the rectangle at 1,280 pixels in width and 108 pixels in height, because this relatively remote
area has extremely low resolution and the background noise from the bridge, building, pole and barrier. The remaining image is therefore $128 \times 256$ in size and $512$ by a width $1,280$; hence, we can extract it based on a patch image. We can thus create a patch image with four rows by five columns. We define the scum condition on the river surface: C0: early scum, C1: grow-thick scum, and C2: background. Convolutional neural networks (CNNs) can be used to implement deep learning to classify patch images into 3 classes as a supervised learning e.g. the ResNet18, ResNet50 [20], MobileNetv2 [21] and self-supervised and unsupervised learning [22]. We chose the ResNet50, ResNet101, and Inception-v3 as the practical CNN of supervised classification model; this deep network is frequently used to facilitate transfer learning.

B. Mixture Augmentation for Variety and Disentanglement

The past decade has seen renewed importance of augmented image data for deep learning [13]. Image data augmentation is categorized into two i.e., basic image manipulation and deep learning approaches. The former augmentation includes 1) kernel filters, 2) geometric transformations, 3) random erasing, 4) mixing images, and 5) color space transformations. The latter consists of three components: 1) adversarial training, 2) neural style transfer, and 3) GAN model-based transformation. Particularly, geometric transformation, image blending, and neural style transfer have contributed to meta learning [15]. The deep learning-based augmentation could not be fitted to the target dataset of the river surface because of the features entangled between the region of interest in the scum and the background mirroring the building, bridge, pole and barrier. This study proposes the fundamental image manipulations, such as mixing and random erasing of images. To detangle the river surface feature, the random erasing technique is straightforward and efficient as the regional dropout in the training images. We also believe that the augmentation of mixing images diversifies the river water surface feature. Using multiple raw images, the mixture image augmentation creates diversified images, like the mixup [16,17], Cutout [18], and RICAP [19]. Convolutional neural network deep learning is used for a patch classification.

As illustrated in Fig.3, the mixup is a linear combination manipulation using two randomly sampled images $X_i, X_j$. Here, we set the random weight parameter $\lambda \in [0, 1]$. This weight parameter is randomly generated from the Beta distribution $Beta(\alpha, \alpha)$ where it takes a value between $[0, 1]$. It is generated from the uniform distribution when $\alpha = 1.0$. When $\alpha = 0.2, 0.4$, the peakiness on both sides increases in a bustab-like shape. Therefore, we can write the following two equations to represent the mix-up image augmentation.

\[
\tilde{M} = \lambda X_i + (1 - \lambda) X_j \quad (1)
\]

\[
\tilde{C}_{\text{mixup}} = \lambda z_i + (1 - \lambda) z_j \quad (2)
\]

Here, two randomly selected images from different classes are labeled $z_i, z_j$, and the augmented new label $\tilde{C}_{\text{mixup}}$ results in one-hot encoding. Notably, the mixup augmentation never enhances the overall performance of classification deep learning, even if two images were randomly selected from the same class.

As shown in Fig.4, the Cutout is a straightforward regularization technique that involves random masking out square input regions during training. Inspired by the dropout regularization mechanisms, this is an extremely easy implementation, but it could be combined with the existing form of data augmentation to further enhance model performance. To apply to situations like occlusion, the Cutout image augmentation has been labeled "regional dropout". This regional dropout has been used with the drop rate $d \in \{0.4, 0.5, 0.6\}$ in the past experimental studies on natural image recognition datasets. The complex entangled features on the river surface could be disentangled using the Cutout regularization. The entangled features included the scum floating organ and mirrored sky, bridge, building, and pole backgrounds.

As illustrated in Fig.5, the random image cropping and patching (RICAP) technique involves mixing four randomly cropped images, respectively, and concatenating them into a new augmented image. The RICAP greatly expands the variety of images and prevents overfitting of deep convolutional neural networks. Image data manipulation is done in three steps. First, we can randomly select four images $m \in \{1, 2, 3, 4\}$ from the practice dataset. On the upper left $(m = 1)$, upper right $(m = 2)$, lower left $(m = 3)$, and lower right sides $(m = 4)$, we patch them in that order. Second, we can crop the images separately. $\bar{w}$ and $h$ denotes the width and height of the training image, respectively. We can randomly set the boundary position $(\bar{w}, h)$ of the four images $m$ from a uniform distribution. This is known as the variant anywhere-RICAP.

\[
w \sim U(0, \bar{w}), h \sim U(0, \bar{h}) \quad (3)
\]

Then we can automatically obtain the cropping sizes $(w_m, h_m)$ of the image $m$. i.e., $w_1 = w_3 = \bar{w}$, $w_2 = w_4 = \bar{w} - w$, $h_1 = h_3 = \bar{h}$, $h_2 = h_4 = \bar{h} - h$.
In the prediction stage using the pre-trained deep network, it includes the following steps: 1) predict 20 patch probabilities; 2) combine their probabilities into a matrix; 3) create a scaled heatmap; 4) binarize the mask image; and 5) pixel count of scum region. The prediction brings the total number of patch probabilities extracted from the raw input frame to 20. Their probabilities’ values are combined into a matrix. The matrix with four rows by five columns is transformed into a scaled heatmap with a grayscale intensity range of 0 to 255. The heatmap can binarize a mask image with pixels set to 0 or 1. The translated binary mask image and the gray scaled heatmap from patch probability matrix are shown together in Fig.6.

The scum region pixel whose value is one on the mask image can be counted. Finally, the temporal scum index at a time stamp is calculated as the value, we call “scum–cover” ratio whose scum region pixel count is divided by the river region pixel count, ranging from 0 to 100 percent.

\[
\text{ratio} = \frac{\text{pixels(scum)}}{\text{pixels(I - background)}} = \frac{\text{pixels(scum)}}{\text{pixels(river)}}
\]  

Here, I denotes the cropped raw input image without remote area of upper rectangle. The river region can count the pixels without background. When the camera angle is fixed, the background area remains constant, allowing us to set the river region’s pixel count.

Fig. 6. Example of Binarized Mask Images from Patch Probability Scaled Heatmap

III. APPLIED RESULTS

A. Data Preparedness and Transfer Learning

River scum is a rare occurrence, and it is difficult to collect its appearance before it gets too thick. We prepared a time series dataset to focus on the weeks when the scum first appeared, and we extracted frames per ten minutes from some recorded videos at an urban river around a densely populated area. A combined sewer station operates upstream of the city river. We show how to apply our method on two weekly time series with a frame every ten minutes, where river scum events have been occurring for several days.

For training classification, used 884 frame images scum occurrence in 2021. The 13 cameras were continuously recording the scum conditions along an urban river and monitor the scum condition. We divided the training and test images in a 9:1 ratio. The image is 720 × 1,280 in both height and width. We have prepared 14,404 patches for the deep learning model’s training, and the 1,470 patches for evaluating test accuracy.

B. Training Results and Test Accuracy

We trained the ResNet50, ResNet101, and Inception-v3 using a baseline model and several image augmentations such as mixup, Cutout, and RICAP. We implemented transfer learning using the Adam, whose frozen rate is 80 percent from the input layer in the deep network. We set the number of mini-batch 64 and computed 20 epochs iterations.

The test accuracy comparison of the patch classification and mixture image augmentation is shown in Table I. Here, we define the three classes of river surface conditions, C0: early scum, C1: grow-thick scum, and C2: background. At the three rows of the mixup augmentation, it never achieves
a higher level of accuracy than the baseline ResNet50 model. The linear mixing strategy was inefficient to generalize performance. However, it outperformed the baseline model with test accuracy + 0.6 and on the precision + 1.7 when displaying the three rows of the Cutout augmentation. The highest score among ablation studies was achieved by the drop rate $d = 0.6$. However, the recall accuracy was the same as in the baseline model. The RICAP augmentation + 0.5 outperformed the recall accuracy than the baseline model. The RICAP has improved the test accuracy and the precision over the baseline model by + 0.3 and + 0.4, respectively. For scum detection and monitoring to decrease the scum-positive false error, where predict negative scum but actually scum, the recall accuracy is essential. Therefore, we think that the RICAP is practically the best result among these ResNet50 + augmentation studies.

As shown in Table II, at the three rows of the mixup augmentation, it achieves a higher precision of accuracy than the baseline ResNet101 model. But the recall of accuracy never improved. When displaying the three rows of the Cutout augmentation, it outperformed the baseline model with test accuracy + 1.5 and on the precision + 3.3, and also the recall + 1.3. The highest score among ablation studies was achieved by the drop rate $d = 0.6$. The RICAP augmentation has improved the test accuracy and the precision over the baseline model by + 0.3 and + 2.4, respectively. But the recall never improved. Therefore, the Cutout($d = 0.4$) is actually the best result among these Inception-v3 + augmentation studies.

Thus, we chose the ResNet101 + Cutout($d = 0.6$) result using the regional dropout of augmentation strategy from the three model’s ablation studies, setting the pre-trained network to predict the patch probabilities and computing the scum-cover-ratio.

As shown in Table III, the mixup augmentation never improved every accuracies than the baseline Inception-v3 model. When displaying the three rows of the Cutout augmentation, it outperformed the baseline model with test accuracy + 0.9 and on the precision + 0.7, and also the recall + 3.2. The highest score among ablation studies was achieved by the drop rate $d = 0.4$. The RICAP augmentation has improved the test accuracy and the recall over the baseline model by + 0.1 and + 0.7, respectively. But the precision never improved. Therefore, the Cutout($d = 0.4$) is actually the best result among these Inception-v3 + augmentation studies.

C. Qualitative Analysis and U-Net Similarity

We demonstrated to apply our patch-wise detector method and existing pixel-wise segmentation into 884 images that contains 13 cameras monitoring tidy river. As depicted in Fig.8 and Fig.9, compared to the state-of-the-art of semantic segmentation approach using the U-Net, we visualized montage examples including 6 columns per camera on the river viewing 12 cameras. It depicts in the right, 1) raw image cropped the upper background, 2) U-Net prediction output, 3) scum-cover prediction output(ours), 4) semantic segmentation overlaid, 5) scaled heatmap based on the patch probabilities of scum class (ours), 6) fusion of two predictions.
Fig. 8. Comparison of U-Net Segmentation and Patch Classification (in the right, raw image, U-Net prediction, scum-cover output (ours), segmentation overlayed, scaled heatmap (ours), fusion of two predictions)

comparing the U-Net and our patch-wise detector. Here, we demonstrated the U-Net with 46 layers whose loss function is dice, and we annotated 200 images randomly selected from one camera H5 and also trained 100 epochs that took 10 hours. The accuracy scores are mIoU 0.785, scum class IoU 0.613, and background class IoU 0.958 as a reference study. Thus, the patch classification prediction output has first order approximately covered the pixel-wise segmentation output at each camera. At the 6 columns of fusion, the white region indicates that two method’s outputs are completely matched. The green region denotes the less precision and the magenta region stands for the less recall accuracy.

Fig. 9. Similarity Score of the U-Net Segmentation and Our Patch Classification (boxplots in the right, Jaccard similarity, Dice similarity, Structural Similarity (SSIM))

As drawn in Fig. 10, it shows the similarity score of the pixel-wise segmentation and our patch classification, whose boxplots are in the right, Jaccard similarity, Dice similarity, Structural Similarity (SSIM). The median scores has been 0.138, 0.242, 0.616 respectively, whose 75 percent quantile values are 0.261, 0.414, 0.775 and furthermore 25 percent quantile scores are 0.033, 0.065, 0.424 respectively. Although, the patch-wise classification has not completely match the pixel-wise segmentation method, but our patch classification predictor has been first order approximately similar with the pixel-wise segmentation in 61.6 percent as the SSIM score.

D. Visualize Temporal Scum-cover-Ratio for Monitoring

As shown in Fig. 10, we demonstrated to compute the scum-cover-ratio of a monitoring camera H5 viewing river surface. This plots temporal scum-cover-ratios for model comparison between the ResNet50, ResNet101, Inception-v3 with mixture augmentation. The augmented ResNet50 model sometimes performs sky rocketed. Therefore, the augmented ResNet101 model has been more stable than others.

Fig. 10. Results of Temporal Scum-cover-Ratio Index (model comparison, ResNet50, ResNet101, Inception-v3)

IV. CONCLUDING REMARK

A. Experimental Studies and Lessons

We suggested using image augmentation to increase the variety and disentangled regularization in a patch-wise detector to identify scum features on river surfaces. We precisely trained the practical deep network’s baseline. We have enhanced river surface images using the mixup, Cutout, and RICAP for accuracy comparison. We found that the ResNet101 + Cutout ($d = 0.6$) outperformed the baseline model and other augmentations in terms of recall accuracy, 94.9 percent and precision 99.8 percent. We also discovered that the mixture strategy could improve the best recall by 95.1 percent in the ResNet50 + RICAP augmentation. Furthermore, we provided an assisted metric to make it possible to compute a scum-cover-ratio index for river scum monitoring and heatmap visualization. With the grow-thick scum class, we could set the average probability’s bottom line to 0.01, insignificant probability that prevented an unstable scale heatmap. Using this setting, we could illustrate a scum-on-river ratio of greater than five percent when we implemented experimental studies to our river surface dataset. Finally, we demonstrated how to use our pipeline to images from urban cameras. The dataset of time series frames every ten minutes included scum growing events and thick conditions on two weeks, May, July, and September 2021 in Japan. We found that the limitation that background noise such as building reflections on the surface, and light rain waves on the river’s surface influenced the false positive error. We also discovered the feasibility of detecting
the scum appearance in the early morning hours. Furthermore, we demonstrated to apply our patch-wise detector and the pixel-wise segmentation approach using the U-Net into the dataset of 13 cameras monitoring tidy river. We discovered that our patch-wise detector has been first order approximately similar with the pixel-wise segmentation in 61.6 percent from point of the structural similarity score.

B. Future Works

The off-line training and prediction results are limited in this study. Several obstacles for on-line assisted river managers address the water surface vision problem. First, it reduces rain noise in relation to rain reflection on the river surface on rainy days. Second, we should monitor the river surface during the night, in the early morning five o’clock and after 19 o’clock because the scum growing event could have occurred at night. Third, it becomes crucial to forecast the scum excess time more than the water quality level. We can collect additional time series datasets such as temperature, rainfall, and river water level. Using these temporal variables, we can multi-mode learning to forecast the growing scum trend and the peak of scum index level. Fourth, the rare frequency of scum events makes the supervised training too much time and the data collecting cost. So we exploit the self-supervised and unsupervised approach to create more general pipeline. River water environment will still impact urban life around the world. We will attempt to automate river water vision monitoring that assists for water environment cleaning.

APPENDIX A

DATASET AND CLASS DEFINITION

A. Training Image Examples for Patch Classification

The authors have prepared the river scum image dataset whose total number was 14,404 for training. On the other hand, we prepared another unseen test dataset whose number of images was 1,470. The test image dataset has contained that each class C0, C1, C2 number of images were 533, 467, 470 respectively. Here, we illustrate the examples of each class patch images that is randomly sampled 40. The size of patch image is $128 \times 256$ with the height and width.

As illustrated in Fig.13, we show the C0 class of images for classicification training whose number of images is 5,576 in the C0 class. Here, we randomly sampled 40 patch images from the C0 ”early scum” class of dataset. The C0 class has been the domain of zero scum on river surface, or the small scum on river initially whose mixture were zero scum and extremely small scum on river.

In addition, as illustrated in Fig.14, we show the C1 class of images for classicification training whose number of images is 4,520 in the C1 class. We randomly sampled 40 patch images from the C1 ”grow-thick scum” class. The C1 class has been the domain whose scum was growing, or that has been thick scum on river surface whose mixture image on river surface has been reflecting mirror these neighbor structure such as bridge, building, barrier, pole. In sunny day, sky and cloud have reflected the scum growing on river surface.

Furthermore, as illustrated in Fig.15, we show the C2 class of images for classicification training whose number of images is 4,308 in the C2 class. Here, we randomly sampled 40 patch images from the C2 ”background” class of dataset. The C2 class has been the domain where all of image was background concrete structure, steel pipe and tree. Furthermore, there has been mixture images between zero scum on river and those structure at some dark situation under the bridge.

APPENDIX B

SPECTRAL K-MEANS CLUSTERING RIVER VIEW CAMERA

As drawn in Fig.16, we applied the $k$-means clustering from the RGB elements of river viewing camera. Those results differ from the number of clusters in the right, $k = 3, 5, 8, 12, 20, 30$. After a preprocess to mask the background at the upper region, it enables to focus only the region of interest, that is the river surface. Herein, the ripples spread on multiple layers, and there are complex features such as the reflection of poles and buildings, a lot of variants on the water surface. We will tackle to extract the scum floating organ or that sank in the river surface for tidy river environment monitoring. Therefore it has limitation to extract the target scum feature floating organ on the river surface using image processing by RGB elements, so that it needs another deep learning algorithms.
ACKNOWLEDGMENT

We thank Takuji Fukumoto and Shinichi Kuramoto (Math-Works Japan) who contributed to support the MATLAB resources on Image Data Augmentation for Deep Learning.

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