

Applicability of Object Detection to Microfossil Research: Implications from Deep Learning Models to Detect Microfossil Fish Teeth and Denticles Using YOLO-v7

Kazuhide Mimura¹, Kentaro Nakamura², Kazutaka Yasukawa³, Elizabeth Sibert⁴,
Junichiro Ohta³, Takahiro Kitazawa³, and Yasuhiro Kato³

¹Chiba Institute of Technology

²University of Tokyo

³The University of Tokyo

⁴Harvard University

June 05, 2024

Abstract

Microfossils of fish teeth and denticles, referred to as ichthyoliths, provide critical information for depositional ages, paleo-environments, and marine ecosystems, especially in pelagic realms. However, owing to their small size and rarity, it is time-consuming and difficult to analyze large numbers of ichthyoliths from sediment samples, limiting their use in scientific studies. Here, we propose a method to automatically detect ichthyoliths from microscopic images using a deep learning technique. We applied YOLO-v7, one of the latest object detection architectures, and trained several models under different conditions. The model trained under appropriate conditions with an original dataset achieved an F1 score of 0.87. We then enhanced the dataset efficiently using the pre-trained model. We validated the practical applicability of the model by comparing the number of ichthyoliths detected by the model with those counted manually. This revealed that the best model can predict the number of triangular teeth without manual check, and those of denticles and irregularly shaped teeth with manual check. This object detection method can extend the applicability of deep learning to a wider array of microfossils and has the potential to dramatically increase the spatiotemporal resolution of ichthyolith records for applications across disciplines.

1 **Applicability of Object Detection to Microfossil Research: Implications from Deep**
2 **Learning Models to Detect Microfossil Fish Teeth and Denticles Using YOLO-v7**

3 **K. Mimura^{1,2}, K. Nakamura^{3,2,1}, K. Yasukawa^{3,2}, E. C. Sibert⁴, J. Ohta^{3,5,1}, T. Kitazawa², Y.**
4 **Kato^{2,1,6}**

5 ¹Ocean Resources Research Center for Next Generation, Chiba Institute of Technology, 2-17-1
6 Tsudanuma, Narashino, Chiba 275-0016, Japan.

7 ²Department of Systems Innovation, School of Engineering, The University of Tokyo, 7-3-1
8 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan.

9 ³Frontier Research Center for Energy and Resources, School of Engineering, The University of
10 Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan.

11 ⁴Department of Geology & Geophysics, Woods Hole Oceanographic Institution, 266 Woods
12 Hole Rd MS 22, Woods Hole, MA 02543, USA.

13 ⁵Volcanoes and Earth's Interior Research Center, Research Institute for Marine Geodynamics,
14 Japan Agency for Marine-Earth Science and Technology (JAMSTEC), 2-15 Natsushima-cho,
15 Yokosuka, Kanagawa, 237-0061, Japan.

16 ⁶Submarine Resources Research Center, Research Institute for Marine Resources Utilization,
17 Japan Agency for Marine-Earth Science and Technology (JAMSTEC), 2-15 Natsushima-cho,
18 Yokosuka, Kanagawa, 237-0061, Japan.

19
20 Corresponding author: Kentaro Nakamura (kentaron@sys.t.u-tokyo.ac.jp)

21 **Key Points:**

- 22 • We trained object detection models under different conditions to detect microfossil fish
23 teeth and denticles from microscopic images.
- 24 • The best model can count teeth, denticles and irregularly shaped teeth from samples.
- 25 • Object detection may improve the observation efficiency of a wide array of microfossils.
26

27 **Abstract**

28 Microfossils of fish teeth and denticles, referred to as ichthyoliths, provide critical information
29 for depositional ages, paleo-environments, and marine ecosystems, especially in pelagic realms.
30 However, owing to their small size and rarity, it is time-consuming and difficult to analyze large
31 numbers of ichthyoliths from sediment samples, limiting their use in scientific studies. Here, we
32 propose a method to automatically detect ichthyoliths from microscopic images using a deep
33 learning technique. We applied YOLO-v7, one of the latest object detection architectures, and
34 trained several models under different conditions. The model trained under appropriate
35 conditions with an original dataset achieved an F1 score of 0.87. We then enhanced the dataset
36 efficiently using the pre-trained model. We validated the practical applicability of the model by
37 comparing the number of ichthyoliths detected by the model with those counted manually. This
38 revealed that the best model can predict the number of triangular teeth without manual check,
39 and those of denticles and irregularly shaped teeth with manual check. This object detection
40 method can extend the applicability of deep learning to a wider array of microfossils and has the
41 potential to dramatically increase the spatiotemporal resolution of ichthyolith records for
42 applications across disciplines.

43 **Plain Language Summary**

44 Fossils of fish teeth and denticles, referred to as ichthyoliths, can be used to study the
45 environmental changes of marine conditions throughout Earth's history. However, it is time-
46 consuming and difficult to analyze large numbers of ichthyoliths from sediment samples,
47 limiting their use in scientific studies. Here, we trained several artificial intelligence models to
48 automatically detect ichthyoliths from microscopic images. The best model is suitable for
49 counting the number of fish teeth, denticles, and irregularly shaped teeth fragments with minimal
50 human intervention. We propose that object detection, a deep learning technique used in this
51 study, can be applicable for the study of various microfossils, as well as for increasing the
52 spatiotemporal resolution of ichthyolith records.

53 **1 Introduction**

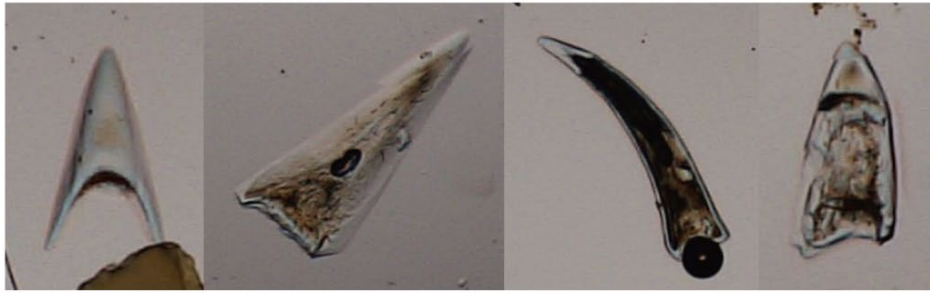
54 Microfossils such as foraminifers, coccolithophores, radiolaria, and diatoms, have been
55 used to constrain depositional ages and environments of various kinds of seafloor sediments, as
56 well as to provide high-resolution and detailed records of evolutionary processes (Armstrong &
57 Brasier, 2005). Among them, microfossil fish teeth and denticles, referred to as ichthyoliths, are
58 composed of calcium phosphate, which is resistant to dissolution on the deep seafloor (Doyle &
59 Riedel, 1985; Sibert et al., 2017). Therefore, ichthyoliths are observed from almost all types of
60 seafloor sediments, including pelagic clay, where other siliceous and calcareous microfossils are
61 rarely observed. Taking advantage of this, ichthyoliths have provided key constraints for
62 depositional ages (Doyle & Riedel, 1979, 1985; Ohta et al., 2020) and marine environments
63 and/or ecosystems (Britten & Sibert, 2020; Sibert et al., 2014, 2016, 2021) especially in pelagic
64 realms. In addition, ichthyoliths preserve a variety of geochemical systems, including strontium
65 and neodymium isotopes, which can provide additional age constraints on sediments (e.g.,
66 Gleason et al., 2002; Ingram, 1992) and insights into deep water circulation patterns and origin
67 of sedimentary components (e.g., Huck et al., 2016; Martin & Haley, 2000; Scher & Martin,
68 2004; Tanaka et al., 2022; Thomas et al., 2014). Oxygen isotopes in ichthyoliths have also been
69 used to reconstruct changes in ocean temperature (e.g., MacLeod et al., 2018). However,
70 traditional observation methods rely on “handpicking,” in which an observer picks fossils

71 individually under a stereomicroscope (Ohta et al., 2020; Sibert et al., 2017; Tanaka et al., 2022).
72 This process is time-consuming and can only be conducted by a skilled observer, making it
73 difficult to analyze large numbers of ichthyoliths from various sediment samples.

74 Computer vision technologies are developing rapidly. In particular, image processing
75 using deep learning has been applied to various fields, including earth science (Hoeser &
76 Kuenzer, 2020; Mimura et al., 2023a). Automating previous manual observation processes saves
77 time and provides opportunities for discoveries by increasing the number of fossils that can be
78 observed and processed. The application of deep learning techniques for the classification of
79 foraminifers (Hsiang et al., 2019) and radiolarians (Itaki et al., 2020b; Tetard et al., 2020;
80 Carlsson et al. 2022, 2023), and coccolithophores (Beaufort et al., 2022) is enhancing the
81 resolution in paleoenvironmental studies. These studies detect particles by thresholding and
82 recognize their classes using classification models. However, this method is difficult to directly
83 apply to ichthyoliths because it is sometimes challenging to identify the outline of ichthyoliths by
84 thresholding method (Figure 1). To solve this problem, we have proposed an automated
85 detection of ichthyoliths in microscopic images by combining the object detection model “Mask
86 R-CNN” (He et al., 2017) and image classification model “EfficientNet-V2,” both of which are
87 based on deep-learning techniques (Mimura et al., 2022). Although the system showed a good
88 performance, two problems remained. First, due to the scarcity of the learning dataset, the system
89 could only detect triangular teeth, leaving denticles and saw-toothed ichthyoliths undetected
90 (Figure 1). Second, there was a time loss in the combined system, as a well-trained object
91 detection model can distinguish classes without using the classification model.

92 Recently, we compared the performances of object detection models “Mask R-CNN” and
93 “YOLOv5” (Jocher et al., 2022) in detecting signals of hydrothermal activity in echo sounder
94 images (Mimura et al., 2023a) and showed that the YOLOv5 model achieved much higher
95 performance than that of the Mask R-CNN model. Here, with reference to this, we applied
96 “YOLOv7” (Wang et al., 2022), one of the latest versions of YOLO (You Only Look Once,
97 Redmon et al., 2016), to solve the problem of ichthyolith detection. To overcome the problems
98 associated with the previous system developed by us, we aimed to detect teeth, denticles, and
99 irregular shapes of teeth in a single step.

Tooth



(Challenging)



Denticle



Saw-toothed



100

101 **Figure 1.** Examples of ichthyolith images categorized into three classes used in this study.
102 Images of teeth considered challenging to detect under the thresholding-based method but can be
103 detected using object detection models are also shown.

104 2 Materials and Methods

105 2.1 Sample description

106 We used pelagic clay samples obtained from the Deep Sea Drilling Project (DSDP) Site
107 576, Ocean Drilling Program (ODP) Site 1149, Integrated Ocean Drilling Program (IODP) Sites
108 U1366 and U1370, and piston cores KR13-02 PC04 and MR14-E02 PC11. All cores were
109 recovered from the Pacific Ocean at water depths of more than 5,000 m (Table S1). We aimed to
110 cover a variety of depositional ages from the late Cretaceous to the present using
111 DSDP/ODP/IODP samples and to enhance the number of irregular teeth called *Rectangular saw-*
112 *toothed* (Figure 1) by collecting images from specific horizons of the two piston cores.

113 2.2 Slide preparation and imaging

114 Glass slides were prepared from the samples as described by Mimura et al. (2022).
115 Approximately 3–10 g of the sample was mixed well with deionized water and sieved using a
116 62- μm mesh. Larger particles were collected in a centrifuge, mixed with sodium polytungstate
117 with a specific gravity of approximately 2.8 g/cm³, and centrifuged at 1,000–1,500 rpm to collect
118 heavier particles, which were proposed by Sibert et al. (2017). The collected particles were
119 washed with deionized water, moved onto glass slides using a pipette, dried at 40 °C, and sealed
120 with a cover glass using a light-curing adhesive.

121 Imaging of glass slides was also performed as described previously (Mimura et al., 2022).
122 Using a digital microscope RX-100 (Hirox Co., Ltd.), the whole part of the observation realm
123 (~24×36 mm) was divided into ~1,000 squares (~1.15 × 1.15 mm / 1,200 × 1,200 pixels). The z-
124 stack images were automatically acquired using motorized x, y, and z stages. To capture as many
125 ichthyoliths as possible in a complete form, each image overlaps with adjoining images by 20%.

126 2.3 Generation of datasets

127 Out of more than 1 million (M) images of the microscopic field of view, 12,219 were
128 selected for “original” datasets. The locations and classes of the ichthyoliths within the images
129 were annotated manually. Ichthyoliths were classified into three classes (Figure 1): triangular
130 tooth (class name: “tooth”), denticle (“denticle”), and forms similar to *Rectangular saw-toothed*
131 (“saw-toothed”).

132 Two datasets were generated from these images and annotations. The dataset
133 “original_selected” comprised 6,945 images with ichthyoliths, and the dataset “original_all”
134 comprised 6,945 images with ichthyoliths and 5274 images without ichthyoliths (Mimura et al.,
135 2023b). The datasets contained 7,705 triangular teeth, 533 denticles, and 103 saw-toothed
136 shapes. The images and corresponding annotation files were randomly split into three subsets:
137 80% for training, 10% for validation, and 10% for testing. We note here that images in each
138 subset are the same between the two datasets, except for the image that does not contain
139 ichthyoliths. This enabled us to conduct performance tests on the same dataset (i.e., models
140 trained on the training subset of dataset original_selected can be tested by the testing subset of
141 the dataset original_all).

142 2.4 Tuning of hyperparameters

143 We conducted hyperparameter tuning by training the “YOLOv7” model under different
144 initial learning rates (“lr0” in YOLOv7’s parameter file) and the final one-cycle learning rates
145 (“lrf”). A stochastic gradient descent algorithm with a momentum fixed at 0.937 was applied for
146 training. The image size was fixed at 640×640 pixels and the batch size at 8. The models were
147 trained on a local Windows PC with a single graphic board with 16 GB of memory (GeForce
148 RTX 3080 Ti, NVIDIA Inc.).

149 2.5 Training conditions

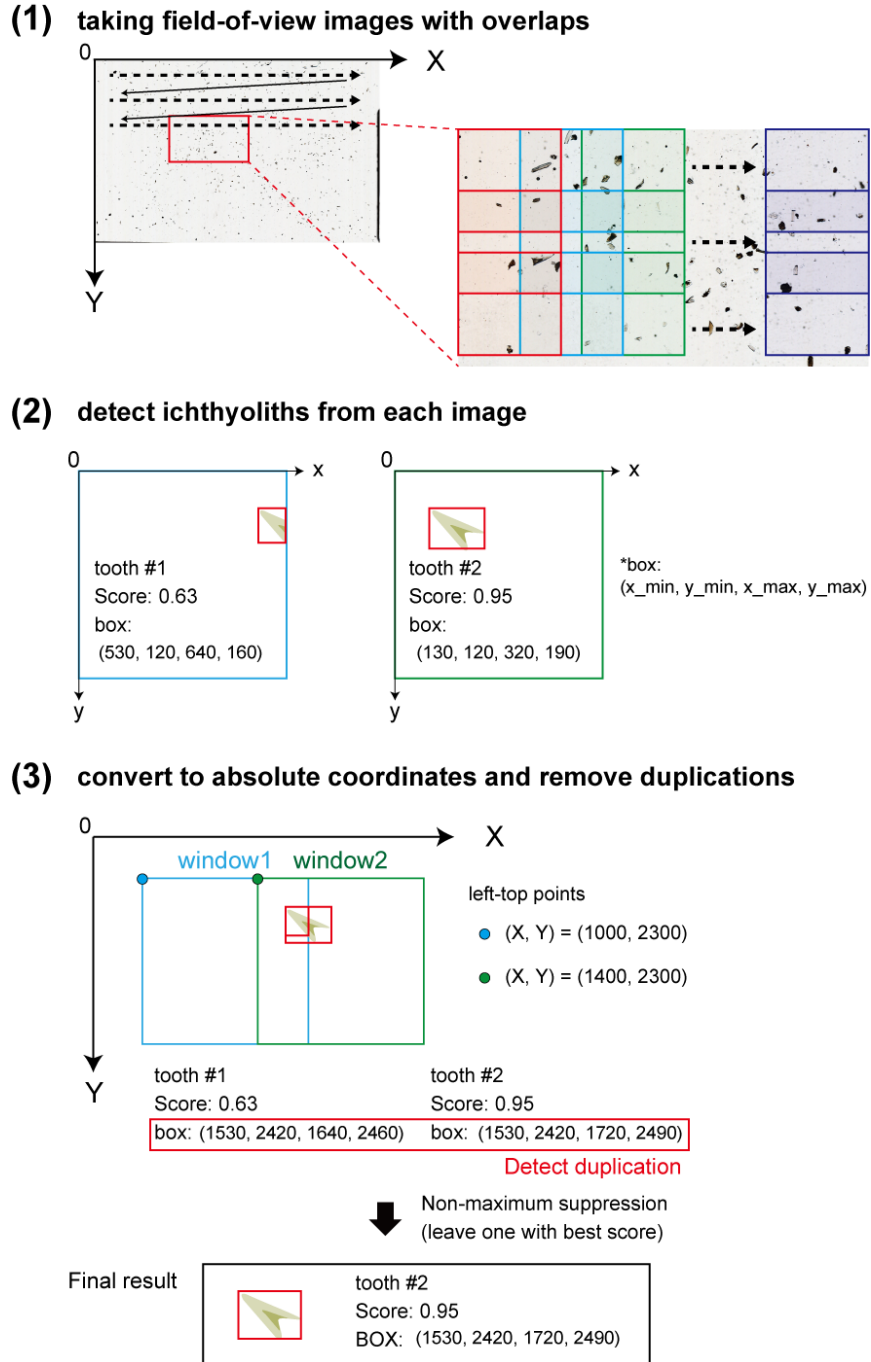
150 YOLOv7 provides several models with various numbers of trainable parameters. In this
151 study, we compared five models, “YOLOv7-tiny,” “YOLOv7,” “YOLOv7-X,” “YOLOv7-W6,”
152 and “YOLOv7-E6,” each having 6.2M, 36.9M, 71.3M, 70.4M, and 97.2M parameters,
153 respectively. Training of YOLOv7-tiny and YOLOv7 models was conducted on the local
154 Windows PC, while training of the higher models was conducted on the cloud computing
155 platform “Google Colaboratory” (Carneiro et al., 2018). The image size was set to 640×640
156 pixels. However, we also trained YOLOv7-W6 models with a larger image size set to $1,280 \times$
157 $1,280$ pixels, as Wang et al. (2022) proposed for larger models. In all training cases, the batch
158 size was fixed at 8. The models were trained on either the local Windows PC, a local Linux PC
159 with two graphic boards having 24 GB memory (GeForce RTX 3090 Ti, NVIDIA Inc.), or
160 Google Colaboratory (see Table 2).

161 Following YOLOv7’s online augmentation method, the images were randomly flipped
162 vertically and/or horizontally, and the colors, scales, and shear of the images were randomly
163 changed every time the training images were loaded.

164 2.6 Practical test

165 In the datasets described in Section 2.3, more than half of the images contained at least
166 one ichthyolith, whereas only tens to one hundred ichthyoliths are observed from $\sim 1,000$ images
167 in actual observation. We, therefore, conducted a practical test to evaluate the performance of the
168 trained models under more practical conditions.

169 Three samples at DSDP Site 576, not used in the original datasets described in Section
170 2.3 or the extended dataset described in Section 3.3, were selected for the practical test. The
171 models detected ichthyoliths from the whole field-of-view images (30,826 in total) taken from 28
172 slides. Since microscopic images were taken with overlap, duplicated detections were excluded
173 by calculating absolute coordinates in the entire slide (Figure 2). Simultaneously, the slides were
174 manually observed under a polarization microscope. We tested the practical applicability of the
175 trained models by comparing the number of ichthyoliths counted by the models with that
176 observed manually.



177

178 **Figure 2.** An illustration explaining the algorithm for excluding duplicate detections in this
179 study.

180 3 Results and Discussion

181 3.1 Hyperparameter tuning and iteration test

182 F1 scores of YOLOv7 models trained with different hyperparameters on dataset
 183 “original_all” are presented in Table 1. The initial learning rate of 0.0007 and final one-cycle
 184 learning rate of 0.05 were the most suitable conditions in this study. Under the same condition,
 185 we then conducted and evaluated five training iterations and observed that one standard error (1
 186 SE) of the F1 score was 0.008 (Table S2). When comparing the performance of the models in the
 187 following discussion, a difference in F1 scores greater than 2 SE (0.016) was considered
 188 significant.

189
 190 **Table 1.** F1 scores of the models trained on different hyperparameters of initial learning rate
 191 (“lr0”) and final one-cycle learning rate (“lrf”).
 192

F1 score		lrf		
		0.1	0.05	0.01
lr0	0.001	0.08	0.29	0.75
	0.0007	0.46	0.82	0.55
	0.0004	0.68	0.13	0.21

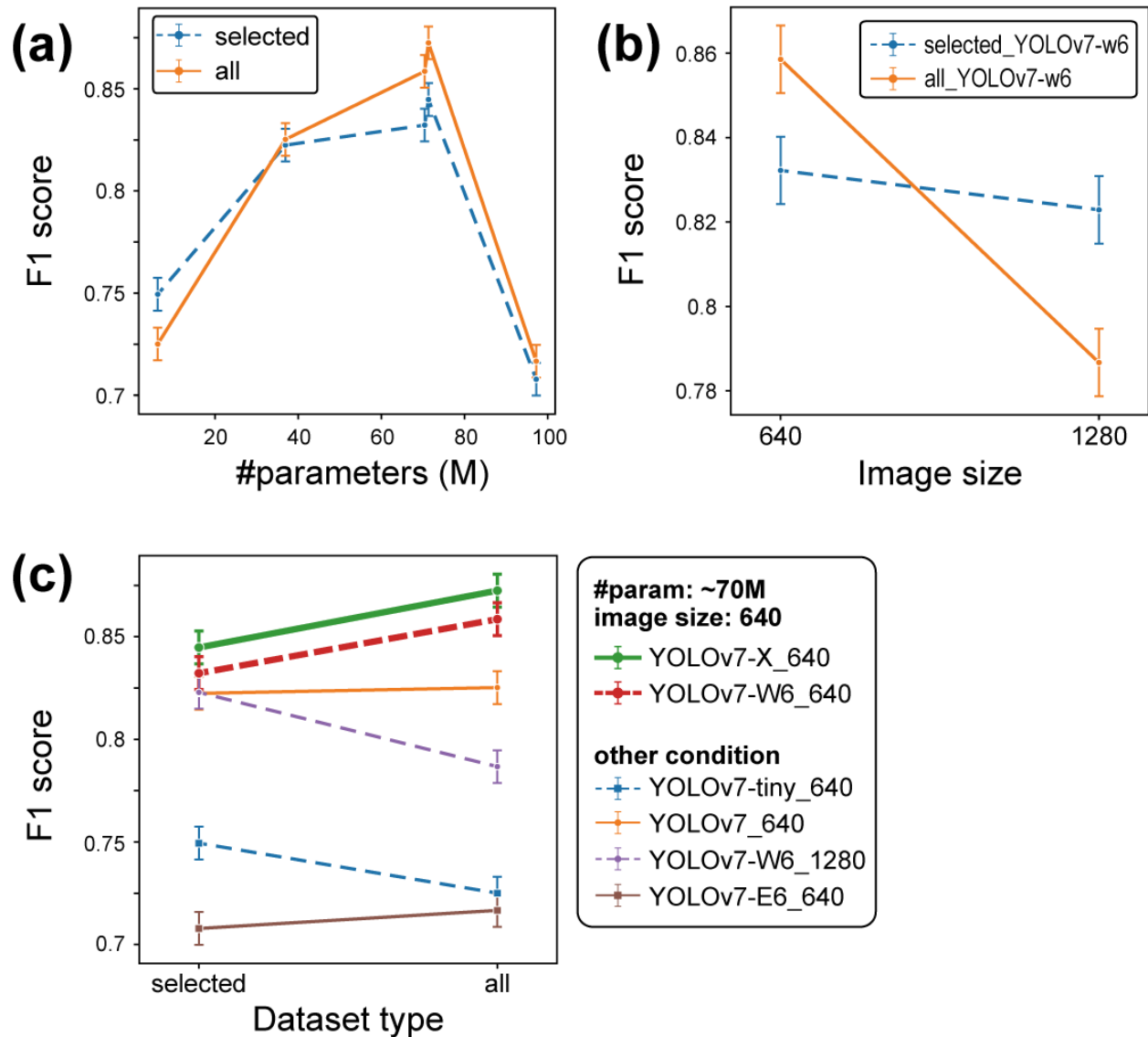
193

194 3.2 Comparison of performances under different training conditions

195 The performance of the models trained on different models and datasets is detailed in #1 to #12
 196 of Table 2. We evaluated the performance of models based on averaged F1 scores of the three
 197 classes (macro-F1 score). Comparing the number of parameters (Figure 3a), models with ~70M
 198 trainable parameters (YOLOv7-X, YOLOv7-W6) exhibited the highest F1 score, suggesting that
 199 these models are suitable for this study. Comparing the image sizes (Figure 3b), we observed that
 200 the models trained with the input image size set at 640 exhibited higher F1 scores than those
 201 trained with an image size of 1,280. Although the difference in the dataset “selected” is less than
 202 2SE, we suggest that the suitable input image size is 640, as larger input size increases the risk of
 203 overfitting (e.g., Sabottke and Spieler, 2020). Finally, comparing the dataset type (Figure 3c), the
 204 results exhibited a variety of trends. However, following the discussion above, if we focus on the
 205 cases with a number of parameters around 70M and input image size at 640, models trained on
 206 the dataset “all” showed higher F1 scores than those trained on the dataset “selected.” Thus, we
 207 concluded that the suitable training condition in this study is (1) to use models with ~70M
 208 parameters (YOLOv7-X or YOLOv7-W6), (2) to set the input image size at 640, and (3) to train
 209 on a dataset “all,” which is composed of both images containing ichthyoliths and images that do
 210 not contain ichthyoliths.

211 **Table 2.** Performances of the training with different models and datasets.

Case	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
Datas et	original_selected						original_all						extended_all		
Envir onme nt	Wind ows	Wind ows	Colab	Ubun tu	Ubun tu	Ubun tu	Wind ows	Wind ows	Colab	Ubun tu	Ubun tu	Ubun tu	Ubun tu	Ubun tu	
Condition	YOL Ov7- tiny	YOL Ov7	YOL Ov7- X	YOL Ov7- W6	YOL Ov7- W6	YOL Ov7- E6	YOL Ov7- tiny	YOL Ov7	YOL Ov7- X	YOL Ov7- W6	YOL Ov7- W6	YOL Ov7- E6	YOL Ov7- X	YOL Ov7- W6	
#Para m. (M)	6.2	36.9	71.3	70.4	70.4	97.2	6.2	36.9	71.3	70.4	70.4	97.2	71.3	70.4	
image size	640	640	640	640	1280	640	640	640	640	640	1280	640	640	640	
Precision	tooth dentic le	0.814	0.885	0.885	0.882	0.778	0.760	0.641	0.868	0.857	0.778	0.791	0.768	0.910	0.931
	saw- tooth ed	0.671	0.829	0.859	0.803	0.712	0.702	0.672	0.852	0.853	0.756	0.668	0.653	0.832	0.895
	avera ge	0.778	0.875	0.799	0.888	0.817	0.714	0.694	0.800	0.900	0.833	0.727	0.833	0.778	0.887
		0.754	0.863	0.848	0.858	0.769	0.725	0.669	0.840	0.870	0.789	0.728	0.751	0.840	0.904
Recall	tooth dentic le	0.789	0.832	0.857	0.850	0.907	0.862	0.880	0.859	0.896	0.908	0.916	0.870	0.843	0.813
	saw- tooth ed	0.755	0.837	0.869	0.776	0.857	0.755	0.837	0.776	0.831	0.918	0.857	0.776	0.878	0.878
	avera ge	0.699	0.698	0.800	0.800	0.893	0.500	0.682	0.800	0.899	0.999	0.797	0.500	0.700	0.800
		0.748	0.789	0.842	0.888	0.886	0.706	0.800	0.811	0.875	0.942	0.857	0.715	0.807	0.830
f1 score	tooth dentic le	0.801	0.858	0.871	0.866	0.838	0.808	0.742	0.863	0.876	0.838	0.849	0.816	0.875	0.868
	saw- tooth ed	0.711	0.833	0.864	0.789	0.778	0.728	0.745	0.812	0.842	0.829	0.751	0.709	0.854	0.886
	avera ge	0.736	0.777	0.799	0.842	0.853	0.588	0.688	0.800	0.899	0.908	0.760	0.625	0.737	0.841
		0.749	0.822	0.845	0.832	0.823	0.708	0.725	0.825	0.872	0.859	0.787	0.717	0.822	0.865



213

214 **Figure 3.** F1 scores compared by training conditions. The x-axis of each graph represents (a) the
 215 number of trainable parameters, (b) image sizes, and (c) the type of dataset. Error bars represent
 216 ± 1 SE.

217 3.3 Efficient production of training dataset using detection results

218 YOLOv7 can output results as text files in the same format as the training labels. Taking
 219 advantage of this, we enhanced the sizes of datasets by first predicting a trained model and then
 220 checking the result manually. Using the YOLOv7-X model trained on the dataset “all” with an
 221 image size of 640 (#9 of Table 2), the existence of ichthyoliths was predicted from $\sim 1,100,000$
 222 images generated from the six sites considered in this study. Images from three samples at Site
 223 576 used for the practical test were excluded. We collected 4,463 images in which the model
 224 predicted the existence of the class “denticle” or “saw-toothed,” which were relatively small
 225 compared to the class “tooth. After the manual check of detection results for the 4,463 images,
 226 2,528 images contained ichthyoliths, and 1,935 did not have ichthyoliths; of those containing

227 ichthyoliths, 1,657 teeth, 1,282 denticles, and 108 saw-toothed ichthyoliths were identified. Of
 228 these, the “denticle” was more than twice the number in the original dataset, and the “saw-
 229 toothed” was almost the same as the number in the original dataset. As well as the original
 230 datasets, images, and annotation information were randomly split into training (80%), validation
 231 (10%), and testing (10%) subsets.

232 The dataset “extended_all” was generated by combining the dataset collected by the
 233 above process and the dataset “original_all” (Mimura et al., 2023b). Considering the discussion
 234 in Section 3.2, we trained the two models, YOLOv7-X and YOLOv7-W6, on the dataset
 235 “extended_all” with an input image size set at 640. The performances of the trained models are
 236 shown in #13 and #14 of Table 2.

237 3.4 Practical test

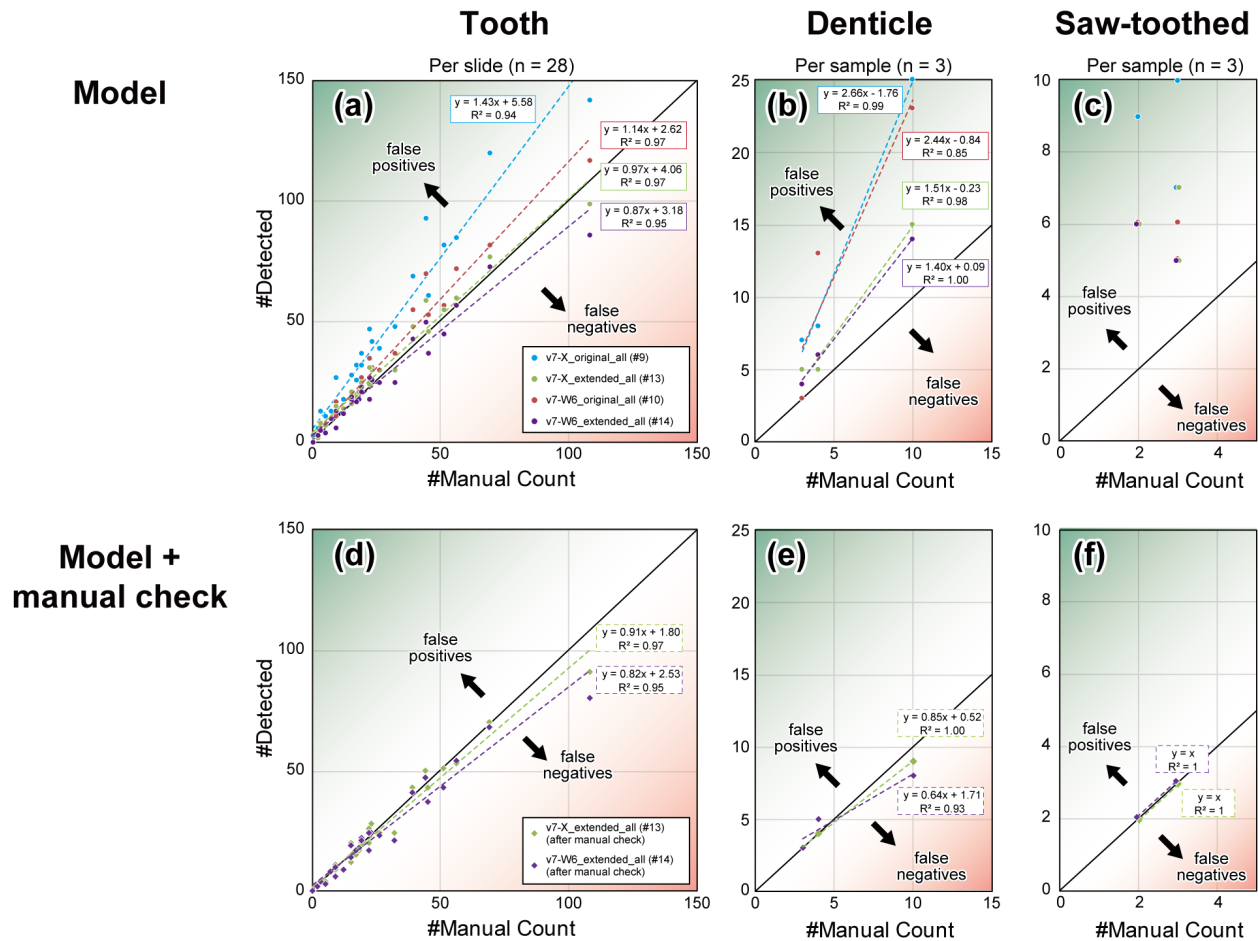
238 We conducted a practical test for the four models: YOLOv7-X trained on the datasets
 239 “original_all” (#9 of Table 2) and “extended_all” (#13), YOLOv7-w6 trained on the datasets
 240 “original_all” (#10) and “extended_all” (#14). The number of ichthyoliths detected by these
 241 models and that are manually counted are shown in Table S3. We also calculated the root mean
 242 square percentage error (RMSPE), using the following equation:

$$243 \quad RMSPE = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{\hat{y}_i - y_i}{y_i} \right)^2} \times 100 [\%] \dots (1)$$

244 where n , \hat{y}_i , and y_i indicate the number of samples, the predicted ichthyoliths, and the manually
 245 observed ichthyoliths, respectively.

246 Comparing the models trained on the dataset “original_all” (#9, #10) and “extended_all”
 247 (#13, #14), models trained on “extended_all” showed trends closer to $y = x$ for classes tooth and
 248 denticle (Figure 4a, b). The high performance of the model trained with the “extended_all”
 249 dataset may be attributed to the high variation of false patterns in practical conditions. We
 250 realized that models trained on the original dataset confused various triangular particles or
 251 patterns with teeth (Figure S1). Since the “extended_all” dataset contains many images that the
 252 preliminary model misdetected, the model trained with this dataset is considered to learn false
 253 positives efficiently. RMSPEs suggest that using the v7-w6_extended_all model (#14), the
 254 number of teeth and denticles from a sample can be estimated with $\sim 7\%$ and $\sim 24\%$ error rates,
 255 respectively. On the other hand, RMSPEs for the “saw-toothed” class are $> 70\%$. Furthermore,
 256 no clear trend was observed (Figure 4c), indicating that the number of “saw-toothed” cannot be
 257 accurately estimated based solely on the model’s detection result.

258 We also manually checked the images detected by models #13 and #14 and removed
 259 false positives and duplications that could not be excluded by the algorithm described in Figure
 260 2. After checking model #13’s detection, we observed a trend closer to $y=x$ (Figure 4d–f),
 261 indicating that combining manual review with model #13 is preferable. Model #13, with manual
 262 check, achieved an RMSPE of $\sim 3\%$, $\sim 9\%$, and almost no error for counting the number of teeth,
 263 denticles, and saw-toothed ichthyoliths, respectively (Table S3).



264

265 **Figure 4.** Comparison of the number of ichthyoliths counted manually and those detected by
 266 models trained in this study. The black solid lines indicate $y = x$, which means that the model's
 267 detections are identical to manual observations. Plots below and above the $y = x$ line indicate that
 268 the model made false negative and false positive errors, respectively. (a–c) Scatter diagram of the
 269 number of models' detection and manual count. Regression lines are only indicated in class
 270 "tooth" (a), as no clear trend was observed in class "denticle" (b) and class "saw-toothed" (c).
 271 (e–f) Comparison between the number of ichthyoliths that a human observer recounted after the
 272 best model's detection and the manually counted number. The numbers were compared per slide
 273 for teeth, but per sampling horizon for classes denticle and saw-toothed, particles in these slides
 274 were contained in only a few slides. Regression lines were obtained using Excel (Microsoft®
 275 Excel® for Microsoft 365 MSO, version 2310).

276 3.5 Advantages of object detection method using YOLO-v7

277 The application of deep learning to microfossil observations has attracted increasing
 278 attention recently (Hsiang et al., 2019; Salonen et al., 2019; Mitra et al., 2019; Romero et al.,
 279 2020; Itaki et al., 2020a; Marchant et al., 2020; Tetard et al., 2020; Classon et al., 2022, 2023). A
 280 commonly used method in particle detection is to apply rule-based thresholding to detect each
 281 particle and subsequently classify them using an image classification model. Although these
 282 methods require less work to prepare a dataset, deep learning-based detection has advantages
 283 over traditional methods in finding "challenging" particles. While traditional rule-based

284 thresholding methods struggle to detect particles that overlap, have drastic changes in brightness,
285 or have almost similar brightness to the background (Figure 1) in ichthyolith slides, deep
286 learning-based methods can accurately detect them. Therefore, we propose that object detection
287 would broaden the range of deep learning applications in microfossil studies.

288 Compared to our previous method (Mimura et al., 2022), which required two steps,
289 object detection by Mask R-CNN and image classification by EfficientNet-V2, the new method
290 can detect ichthyolith in a single step, which enhances the efficiency of observation. We
291 measured the detection times for processing 10,884 slide images using the two methods on
292 Google Colaboratory. While the previous method required 11,250 s in total, 7,230 s for detection
293 using Mask R-CNN, and 4,020 s for classification using EfficientNet-V2, the new method
294 required only 1,040 s in total process, indicating that the new method is approximately ten times
295 faster than the previous method.

296 3.6 Implications for biostratigraphic and paleoecological studies using ichthyoliths

297 We expect the new observation method to make the biostratigraphy of ichthyoliths more
298 precise, advancing progress in paleoceanography and resource geology related to pelagic (red)
299 clay. Pelagic clay covers over one-third of the global ocean (Dutkiewicz et al., 2015) and has
300 huge variation in bulk geochemistry (Dunlea et al., 2015; Mimura et al., 2019). Therefore,
301 pelagic clay is a good recorder of long-term and global/regional environmental changes (Zhou
302 and Kyte, 1992; Kyte et al., 1993; Tanaka et al., 2022; Yasukawa et al., 2023). Moreover,
303 pelagic clay is also attracting attention as a promising resource for rare-earth elements (Kato et
304 al., 2011; Yasukawa et al., 2014; Takaya et al., 2018; Ren et al., 2021). However, the scarcity of
305 microfossils except for ichthyoliths has hampered making precise age models of pelagic clay.
306 Letting machines perform much of the time-consuming observations, substantial amounts of
307 ichthyoliths can be observed, and more accurate age models will be established. This should
308 provide numerous insights into the evolution of pelagic environments from paleoceanographic
309 viewpoints, as well as the ore genesis and potential distributions of the prospective deep-sea
310 mineral resource.

311 We also expect that this tool will improve our understanding in biological and ecological
312 studies. As a demonstration, we show a downhole variation of denticle/tooth (D/T) ratios at
313 DSDP Site 576 in the western North Pacific Ocean (Table 3, Figure 5), which were generated
314 from the detection results of model #13 combined with manual check. D/T ratio is an index for
315 relative ratios of shark and ray-finned fish, an indicator of marine vertebrate community stability
316 (Sibert et al., 2016). By manual counting in a previous study (Sibert et al., 2016), three stages in
317 the D/T ratios from the late Cretaceous to the present were proposed. Cretaceous ocean (i.e.,
318 older than 66 Ma) was characterized by high D/T ratios, reflecting a relatively small number of
319 ray-finned fishes compared to the present ocean. Subsequently, Paleogene ocean (from 66 to ~20
320 Ma) showed moderate D/T ratios, reflecting the evolution of ray-finned fish after the K/Pg
321 boundary (Sibert and Norris, 2015). Finally, the modern ocean (from ~20 Ma to the present) is
322 characterized by low D/T ratios, which may reflect an extinction event of sharks in the early
323 Miocene (Sibert et al., 2020) and the consequent predominance of ray-finned fish. In the
324 previous study, the trend was clearly exhibited from the South Pacific (DSDP Site 596), but the
325 evidence from the North Pacific (ODP Site 886) was somewhat limited due to the huge hiatus in
326 the Paleogene (Figure 5). Using our deep learning-based image processing method, we found
327 D/T ratios results that were consistent with the previous study from DSDP Site 576 in the North

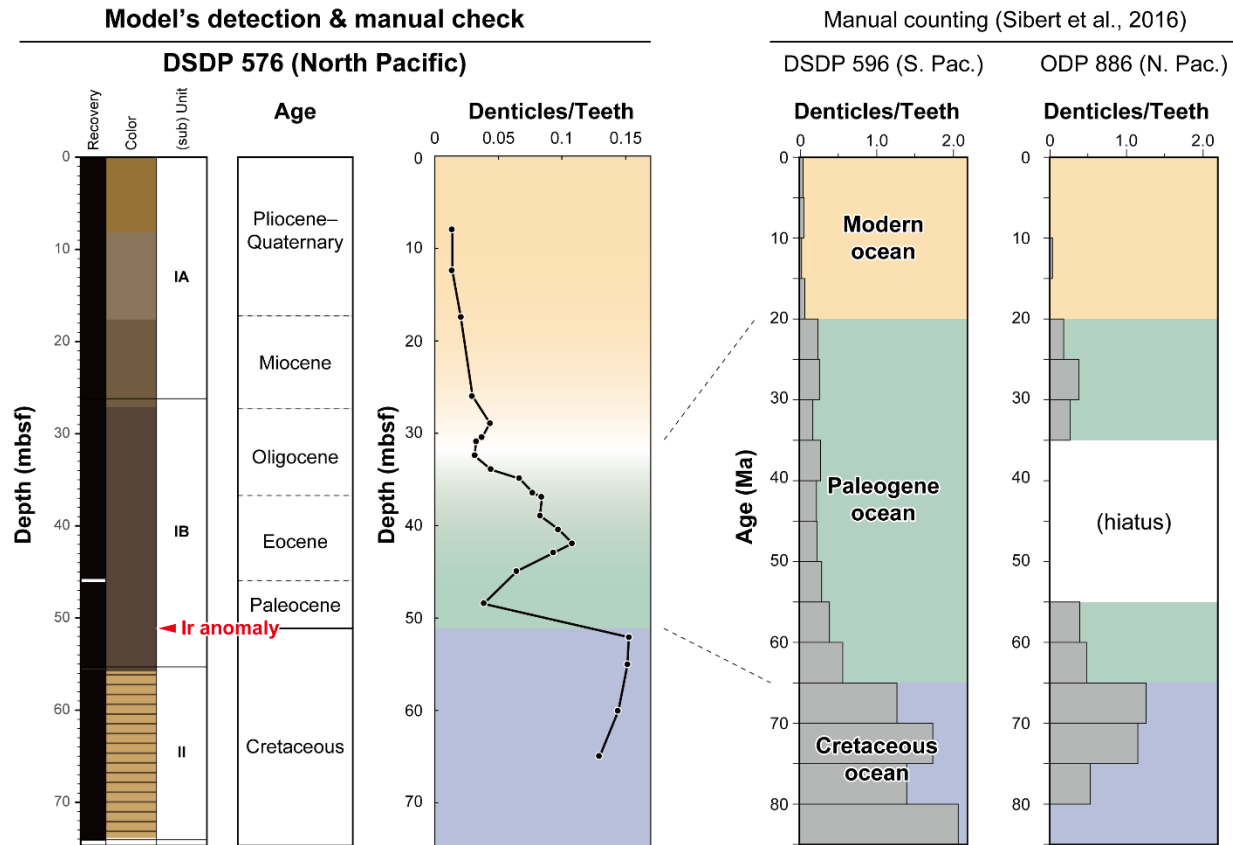
328 Pacific site that has continuous Paleogene sedimentation, supporting the pelagic vertebrate
 329 community structure proposed in Sibert et al. (2016). While this method is still developing, high
 330 throughput data collection provides the opportunity for elucidating the interaction between
 331 environmental change and the marine vertebrate community.

332

333 **Table 3.** The total count of ichthyoliths in the three classes was detected by model #13 (YOLOv7-X, trained on the
 334 dataset “extended_all” with an image size of 640. Results after the manual check are also provided.

Sample	depth (mbsf)	Age	weight (g)	v7x_extended_all			v7x_extended_all + manual check			Outlier
				tooth	denticle	sawToothed	tooth	denticle	sawToothed	
576B_01_02_77	2.28	P-Q ^a	2.53	2	1	0	2	0	0	1 ^b
576B_01_06_52	8.03	P-Q ^a	3.45	16	0	1	13	0	1	
576B_02_03_125	12.46	P-Q ^a	2.99	44	4	2	36	1	0	
576B_02_07_23	17.44	P-Q ^a	6.40	89	3	8	76	1	1	
576B_03_03_125	21.96	Miocene	2.19	12	1	0	9	0	0	1 ^b
576B_03_06_81	26.02	Miocene	3.81	123	5	5	101	3	3	
576B_04_01_75	27.96	Oligocene	2.72	38	3	2	31	2	1	1 ^b
576B_04_02_25	28.96	Oligocene	3.26	151	5	6	124	4	2	
576B_04_03_25	30.46	Oligocene	3.65	191	9	6	164	9	1	
576B_04_03_75	30.96	Oligocene	3.75	194	7	8	165	4	3	
576B_04_04_75	32.46	Oligocene	5.71	526	15	7	472	9	3	
576B_04_05_75	33.97	Oligocene	4.24	542	32	4	472	24	2	
576B_04_06_21	34.93	Oligocene	4.04	1099	78	17	969	61	3	
576B_04_07_27	36.485	Oligocene	4.84	517	46	3	451	39	1	
576B_05_01_25	36.96	Eocene	3.71	455	44	3	391	32	2	
576B_05_02_75	38.96	Eocene	5.29	497	40	1	417	35	1	
576B_05_03_75	40.47	Eocene	5.26	635	55	4	519	43	4	
576B_05_04_75	41.97	Eocene	4.43	115	13	0	96	12	0	
576B_05_05_25	42.97	Eocene	5.52	294	31	1	223	26	0	
576B_05_06_75	44.97	Eocene	4.63	413	21	0	345	13	0	
576B_06_02_75	48.47	Paleocene	2.85	373	16	0	330	13	0	
576B_06_04_23	50.95	Paleocene	3.89	28	10	0	23	8	0	1 ^b
576B_06_04_140	52.11	Cretaceous	3.42	438	52	1	357	47	0	
576B_06_06_140	55.11	Cretaceous	4.16	486	82	0	392	68	0	
576B_07_03_139	60.105	Cretaceous	4.51	444	53	0	308	46	0	
576B_07_07_30	65.01	Cretaceous	2.48	239	21	0	164	18	0	

Note. ^aPliocene–Quaternary. ^bToo small #tooth compared to uppler/lower horizons.



335

336 **Figure 5.** A downhole variation of denticle/teeth ratios at DSDP Site 576, hole 576B, obtained
 337 by the detection model proposed in this study. The age model at Site 576 is based on ichthyolith
 338 biostratigraphy (Shipboard Scientific Party, 1985) corrected by Ir anomaly (Kyte et al., 1995).
 339 The results of three samples with two small numbers of teeth compared to upper and lower
 340 horizons were excluded from the plot. D/T ratios obtained by manual counting at DSDP Site 596
 341 (South Pacific) and ODP Site 886 (North Pacific) are also shown.

342 **4 Conclusions**

343 In this study, we proposed a new and efficient method for the observation of ichthyoliths,
 344 which is approximately ten times faster than our previous method. Using this method, we expect
 345 that studies using ichthyoliths, including biostratigraphy, geochemistry, paleoecology, and the
 346 evolution of fishes, will become more precise due to improved sample throughput and
 347 identification. Conventional studies on ichthyolith stratigraphy have focused mainly on the
 348 presence or absence of each ichthyolith species. In contrast, ratios of the species were hardly
 349 considered, possibly due to the enormous amount of manual work required to count the total
 350 number of fossils in a discrete sediment sample under a microscope. Since the object detection
 351 method is capable of counting the total number of ichthyoliths in a sample, as well as classifying
 352 them to a particular type (here, teeth, denticles, or saw-toothed teeth), it can rapidly calculate a
 353 ratio of each ichthyolith species within an entire sample slide glass. This tool enables research
 354 focusing on quantitative changes in the occurrence of each ichthyolith morphotype, which in turn
 355 will provide more accurate depositional ages on pelagic clays, improve geochemical
 356 reconstructions, and open the possibilities for high-resolution ecological and evolutionary studies

357 of fish and sharks at significantly increased spatiotemporal resolution. Finally, while we focused
358 here on ichthyoliths, which are understudied compared to other microfossil groups, the
359 automated deep learning methods presented here can be applied broadly to a wide array of
360 microfossil groups, increasing the throughput of data across many fields of study.

361 **Acknowledgments**

362 The authors thank Prof. Richard Norris at the University of California San Diego for preliminary
363 discussions on ichthyolith analysis. This research used drill core samples collected by the Deep
364 Sea Drilling Project (DSDP), Ocean Drilling Program (ODP), and Integrated Ocean Drilling
365 Program (IODP). This research was funded by the Japan Society for the Promotion of Science
366 (JSPS) KAKENHI grant numbers 20H05658 to YK, 17H01361 to KN, 19J14560, 21K20354,
367 and 23K13192 to KM, and JST FOREST Program (Grant Number JPMJFR227A, Japan), as well
368 as National Science Foundation (NSF) grant number 2403839. The authors declare no conflict of
369 interest.

371 **Data Availability statement**

372 We named a series of program codes “yolov7-slideObservation” and made it available on
373 GitHub (<https://github.com/KazuhideMimura/yolov7-slideObservation>). The datasets for this
374 study can be accessed at figshare (Mimura et al., 2023b).

376 **References**

- 377 Armstrong, H. A., & Brasier, M. D. (2005). *Microfossils* (2nd edition). Oxford, UK: Blackwell
378 Publishing, 296 pp. <https://doi.org/10.1017/S001675680621238X>
- 379 Beaufort, L., Bolton, C. T., Sarr, A.-C., Suchéras-Marx, B., Rosenthal, Y., Donnadieu, Y., et al.
380 (2022). Cyclic evolution of phytoplankton forced by changes in tropical seasonality. *Nature*,
381 *601*(7891), 79–84. <https://doi.org/10.1038/s41586-021-04195-7>
- 382 Britten, G. L., & Sibert, E. C. (2020). Enhanced fish production during a period of extreme
383 global warmth. *Nature Communications*, *11*(1), 5636. [https://doi.org/10.1038/s41467-020-](https://doi.org/10.1038/s41467-020-19462-w)
384 [19462-w](https://doi.org/10.1038/s41467-020-19462-w)

- 385 Carneiro, T., Medeiros Da Nobrega, R. V., Nepomuceno, T., Bian, G., De Albuquerque, V. H.
386 C., & Filho, P. P. R. (2018). Performance analysis of Google colaboratory as a tool for
387 accelerating deep learning applications. *IEEE Access*, *6*, 61677–61685.
388 <https://doi.org/10.1109/ACCESS.2018.2874767>
- 389 Carlsson, V., Danelian, T., Boulet, P., Devienne, P., Laforge, A., & Renaudie, J. (2022).
390 Artificial intelligence applied to the classification of eight middle Eocene species of the genus
391 *Podocyrthis* (polycystine radiolaria). *Journal of Micropalaeontology*, *41*(2), 165–182.
392 <https://doi.org/10.5194/jm-41-165-2022>
- 393 Carlsson, V., Danelian, T., Tetard, M., Meunier, M., Boulet, P., Devienne, P., & Ventalon, S.
394 (2023). Convolutional neural network application on a new middle Eocene radiolarian dataset.
395 *Marine Micropaleontology*, *183*, 102268. <https://doi.org/10.1016/j.marmicro.2023.102268>
- 396 Doyle, P. S., & Riedel, W. R. (1985). Cenozoic and late Cretaceous ichthyoliths. In H. M. Bolli,
397 J. B. Saunders, & K. Perch-Nielsen (Eds.), *Plankton Stratigraphy* (pp. 965–995). Cambridge,
398 UK: Cambridge University Press.
- 399 Doyle, P. S., & Riedel, W. R. (1979). Ichthyoliths: Present status of taxonomy and stratigraphy
400 of microscopic fish skeletal debris. *Scripps Institution of Oceanography Reference Series*
401 (Report 79–16, pp. 1–231). La Jolla, CA: University of California Scripps Institute of
402 Oceanography.
- 403 Dunlea, A. G., Murray, R. W., Sauvage, J., Spivack, A. J., Harris, R. N., & D'Hondt, S. (2015).
404 Dust, volcanic ash, and the evolution of the South Pacific Gyre through the Cenozoic.
405 *Paleoceanography*, *30*(8), 1078–1099. <https://doi.org/10.1002/2015PA002829>

- 406 Dutkiewicz, A., Müller, R. D., O’Callaghan, S., & Jónasson, H. (2015). Census of seafloor
407 sediments in the world’s ocean. *Geology*, *43*(9), 795–798. <https://doi.org/10.1130/G36883.1>
- 408 Gleason, J. D., Moore, T. C., Rea, D. K., Johnson, T. M., Owen, R. M., Blum, J. D., Hovan, S.
409 A., & Jones, C. E. (2002). Ichthyolith strontium isotope stratigraphy of a Neogene red clay
410 sequence: calibrating eolian dust accumulation rates in the central North Pacific. *Earth and*
411 *Planetary Science Letters*, *202*(3–4), 625–636. [https://doi.org/10.1016/S0012-821X\(02\)00827-0](https://doi.org/10.1016/S0012-821X(02)00827-0)
- 412 He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2020). Mask r-cnn. In. *IEEE Transactions on*
413 *Pattern Analysis and Machine Intelligence*, IEEE International Conference on Computer Vision
414 (ICCV) 42(2), 386–397
- 415 Hoerer, T., & Kuenzer, C. (2020). Object detection and image segmentation with deep learning
416 on earth observation data: A review-Part I: Evolution and recent trends. *Remote Sensing*,
417 *12*(10),1667. <https://doi.org/10.3390/rs12101667>
- 418 Hsiang, A. Y., Brombacher, A., Rillo, M. C., Mleneck-Vautravers, M. J., Conn, S., Lordsmith,
419 S., et al. (2019). Endless Forams: > 34,000 modern planktonic foraminiferal images for
420 taxonomic training and automated species recognition using convolutional neural networks.
421 *Paleoceanography and Paleoclimatology*, *34*(7), 1157–1177.
422 <https://doi.org/10.1029/2019PA003612>
- 423 Huck, C. E., van de Flierdt, T., Jiménez-Espejo, F. J., Bohaty, S. M., Röhl, U., & Hammond, S.
424 J. (2016). Robustness of fossil fish teeth for seawater neodymium isotope reconstructions under
425 variable redox conditions in an ancient shallow marine setting. *Geochemistry, Geophysics,*
426 *Geosystems*, *17*(3), 679–698. <https://doi.org/10.1002/2015GC006218>

- 427 Ingram, B. L. (1992). Ichthyolith strontium isotopic stratigraphy of deep-sea clays: Sites 885 and
428 886 (North Pacific Transect). *Proceedings of the Ocean Drilling Program: Scientific Results*.
429 <https://doi.org/10.2973/odp.proc.sr.145.130.1995>
- 430 Itaki, T., Taira, Y., Kuwamori, N., Maebayashi, T., Takeshima, S., & Toya, K. (2020a).
431 Automated collection of single species of microfossils using a deep learning–micromanipulator
432 system. *Progress in Earth and Planetary Science*, 7(19), 1–7. [https://doi.org/10.1186/s40645-](https://doi.org/10.1186/s40645-020-00332-4)
433 [020-00332-4](https://doi.org/10.1186/s40645-020-00332-4)
- 434 Itaki, T., Taira, Y., Kuwamori, N., Saito, H., Ikehara, M., & Hoshino, T. (2020b). Innovative
435 microfossil (radiolarian) analysis using a system for automated image collection and AI-based
436 classification of species. *Scientific Reports*, 10, 21136. [https://doi.org/10.1038/s41598-020-](https://doi.org/10.1038/s41598-020-77812-6)
437 [77812-6](https://doi.org/10.1038/s41598-020-77812-6)
- 438 Jocher, G., Chaurasia, A., Stoken, A., Borovec, J., Nanocode012, Kwon, Y., et al. (2022).
439 [software] ultralytics/yolov5: v7.0 - YOLOv5 SOTA Realtime Instance Segmentation (v7.0).
440 *Zenodo*. <https://doi.org/10.5281/zenodo.7347926>
- 441 Kato, Y., Fujinaga, K., Nakamura, K., Takaya, Y., Kitamura, K., Ohta, J., Toda, R., Nakashima,
442 T., & Iwamori, H. (2011). Deep-sea mud in the Pacific Ocean as a potential resource for rare-
443 earth elements. *Nature Geoscience*, 4, 535–539. <https://doi.org/10.1038/ngeo1185>
- 444 Kyte, F. T., Leinen, M., Heath, G. R., & Zhou, L. (1993). Cenozoic sedimentation history of the
445 central North Pacific: Inferences from the elemental geochemistry of core LL44-GPC3.
446 *Geochimica et Cosmochimica Acta*, 57(8), 1719–1740. [https://doi.org/10.1016/0016-](https://doi.org/10.1016/0016-7037(93)90109-A)
447 [7037\(93\)90109-A](https://doi.org/10.1016/0016-7037(93)90109-A)

- 448 Kyte, F. T., Bostwick, J. A., & Zhou, L. (1995). Identification and characterization of the
449 Cretaceous/Tertiary boundary at ODP Sites 886 and 803 and DSDP Site 576. In I. A. Basov, D.
450 W. Scholl, & J. F. Allan (Eds.) *Proceedings of the ODP*, sci. results, 145 (pp. 427–434). Rea:
451 D.K. TX: College Station. <https://doi.org/10.2973/odp.proc.sr.145.132.1995>
- 452 MacLeod, K. G., Quinton, P. C., Sepúlveda, J., & Negra, M. H. (2018). Postimpact earliest
453 Paleogene warming shown by fish debris oxygen isotopes (El Kef, Tunisia). *Science*, 360(6396),
454 1467–1469. <https://doi.org/10.1126/science.aap8525>
- 455 Marchant, R., Tetard, M., Pratiwi, A., Adebayo, M., & de Garidel-Thoron, T. (2020). Automated
456 analysis of foraminifera fossil records by image classification using a convolutional neural
457 network. *Journal of Micropalaeontology*, 39(2), 183–202. [https://doi.org/10.5194/jm-39-183-](https://doi.org/10.5194/jm-39-183-2020)
458 2020
- 459 Martin, E.E., & Haley, B.A. (2000). Fossil fish teeth as proxies for seawater Sr and Nd isotopes.
460 *Geochimica et Cosmochimica Acta* 64(5): 835–847. [https://doi.org/10.1016/S0016-](https://doi.org/10.1016/S0016-7037(99)00376-2)
461 7037(99)00376-2
- 462 Mitra, R., Marchitto, T. M., Ge, Q., Zhong, B., Kanakiya, B., Cook, M. S., Fehrenbacher, J. S.,
463 Ortiz, J. D., Tripathi, A., & Lobaton, E. (2019). Automated species-level identification of planktic
464 foraminifera using convolutional neural networks, with comparison to human performance.
465 *Marine Micropaleontology*, 147, 16–24. <https://doi.org/10.1016/j.marmicro.2019.01.005>
- 466 Mimura, K., Nakamura, K., Yasukawa, K., Machida, S., Ohta, J., Fujinaga, K., & Kato, Y.
467 (2019). Significant impacts of pelagic clay on average chemical composition of subducting
468 sediments: New insights from discovery of extremely rare-earth elements and yttrium-rich mud

469 at Ocean Drilling Program Site 1149 in the western North Pacific Ocean. *Journal of Asian Earth*
470 *Sciences*, 186, 104059. <https://doi.org/10.1016/j.jseae.2019.104059>

471 Mimura, K., Minabe, S., Nakamura, K., Yasukawa, K., Ohta, J., & Kato, Y. (2022). Automated
472 detection of microfossil fish teeth from slide images using combined deep learning models.
473 *Applied Computing and Geosciences*, 16, 100092. <https://doi.org/10.1016/j.acags.2022.100092>

474 Mimura, K., Nakamura, K., Takao, K., Yasukawa, K., & Kato, Y. (2023a). Automated detection
475 of hydrothermal emission signatures from multi-beam echo sounder images using deep learning.
476 *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 16, 2703–
477 2710. <https://doi.org/10.1109/JSTARS.2023.3247467>

478 [Dataset] Mimura, K., Nakamura, K., Yasukawa, K., Sibert, E. C., Ohta, J., Kitazawa, T., & Kato,
479 Y. (2023b) Image datasets for training, validating and testing deep learning models to detect
480 microfossil fish teeth and denticles called ichthyolith using YOLOv7. *figshare*.
481 <https://doi.org/10.6084/m9.figshare.22736609.v1>

482 Ohta, J., Yasukawa, K., Nozaki, T., Takaya, Y., Mimura, K., Fujinaga, K., Nakamura, K., Usui,
483 Y., Kimura, J.-I., Chang, Q., & Kato, Y. (2020). Fish proliferation and rare-earth deposition by
484 topographically induced upwelling at the late Eocene cooling event. *Scientific Reports*, 10, 9896.
485 <https://doi.org/10.1038/s41598-020-66835-8>

486 Ren, J., Liu, Y., Wang, F., He, G., Deng, X., Wei, Z., & Yao, H. (2021). Mechanism and
487 influencing factors of REY enrichment in deep-sea sediments. *Minerals*, 11(2), 196.
488 <https://doi.org/10.3390/min11020196>

- 489 Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-
490 time object detection. In *Proceedings of the IEEE conference on computer vision and pattern*
491 *recognition* (pp. 779–788). <https://doi.org/10.1109/CVPR.2016.91>
- 492 Romero, I. C., Kong, S., Fowlkes, C. C., Jaramillo, C., Urban, M. A., Oboh-Ikuenobe, F.,
493 D’Apolito, C., & Punyasena, S. W. (2020). Improving the taxonomy of fossil pollen using
494 convolutional neural networks and superresolution microscopy. *Proceedings of the National*
495 *Academy of Sciences*, *117*(45), 28496–28505. <https://doi.org/10.1073/pnas.2007324117>
- 496 Sabottke, C. F., & Spieler, B. M. (2020). The effect of image resolution on deep learning in
497 radiography. *Radiology: Artificial Intelligence*, *2*(1), e190015.
498 <https://doi.org/10.1148/ryai.2019190015>
- 499 Salonen, J. S., Korpela, M., Williams, J. W., & Luoto, M. (2019). Machine-learning based
500 reconstructions of primary and secondary climate variables from North American and European
501 fossil pollen data. *Scientific Reports*, *9*(1), 15805. <https://doi.org/10.1038/s41598-019-52293-4>
- 502 Scher, H. D., & Martin E. E. (2004). Circulation in the Southern Ocean during the Paleogene
503 inferred from neodymium isotopes. *Earth and Planetary Science Letters*, *228*(3–4), 391–405.
504 <https://doi.org/10.1016/j.epsl.2004.10.016>
- 505 Shipboard Scientific Party (1985). Site 576. In *Initial Reports of the Deep Sea Drilling Project*,
506 (Vol. 86, pp. 51–90).
- 507 Sibert, E. C., Hull, P. M., & Norris, R. D. (2014). Resilience of Pacific pelagic fish across the
508 Cretaceous/Palaeogene mass extinction. *Nature Geoscience*, *7*(9), 667–670.
509 <https://doi.org/10.1038/NGEO2227>

510 Sibert, E. C., & Norris, R. D. (2015). New Age of Fishes initiated by the Cretaceous–Paleogene
511 mass extinction. *Proceedings of the National Academy of Sciences*, *112*(28): 8537–8542.

512 <https://doi.org/10.1073/pnas.1504985112>

513 Sibert, E. C., Norris, R. D., Cuevas, J., & Graves, L. (2016). Eighty-five million years of Pacific
514 Ocean gyre ecosystem structure: Long-term stability marked by punctuated change. *Proceedings*
515 *of the Royal Society B: Biological Sciences*, *283*(1831), 20160189.

516 <https://doi.org/10.1098/rspb.2016.0189>

517 Sibert, E. C., Cramer, K. L., Hastings, P. A., & Norris, R. D. (2017). Methods for isolation and
518 quantification of microfossil fish teeth and elasmobranch dermal denticles (ichthyoliths) from
519 marine sediments. *Palaeontologia Electronica*, *20*(1), 1–14. <https://doi.org/10.26879/677>

520 Sibert, E. C., & Rubin, L. D. (2021). An early Miocene extinction in pelagic sharks. *Science*,
521 *372*(6546), 1105–1107. <https://doi.org/10.1126/science.aaz3549>

522 Takaya, Y., Yasukawa, K., Kawasaki, T., Fujinaga, K., Ohta, J., Usui, Y., et al. (2018). The
523 tremendous potential of deep-sea mud as a source of rare-earth elements. *Scientific Reports*, *8*,
524 5763. <https://doi.org/10.1038/s41598-018-23948-5>

525 Tanaka, E., Yasukawa, K., Nakamura, K., Ohta, J., Miyazaki, T., Vaglarov, B. S., Machida, S.,
526 Fujinaga, K., Iwamori, H., & Kato, Y. (2022). Secular variations in provenance of sedimentary
527 components in the western North Pacific Ocean constrained by Sr isotopic features of deep-sea
528 sediments. *Geochemistry, Geophysics, Geosystems*, *23*, e2021GC009729. [https://doi.](https://doi.org/10.1029/2021GC009729)

529 [org/10.1029/2021GC009729](https://doi.org/10.1029/2021GC009729)

- 530 Tetard, M., Marchant, R., Cortese, G., Gally, Y., de Garidel-Thoron, T., & Beaufort, L. (2020).
531 Technical note: A new automated radiolarian image acquisition, stacking, processing,
532 segmentation and identification workflow. *Climate of the Past*, 16(6), 2415–2429.
533 <https://doi.org/10.5194/cp-16-2415-2020>
- 534 Thomas, D. J., Korty, J., R., Huber, M., Schubert J. A., & Haines, B. (2014). Nd isotopic
535 structure of the Pacific Ocean 70–30 Ma and numerical evidence for vigorous ocean circulation
536 and ocean heat transport in a greenhouse world. *Paleoceanography*, 29(5), 454–469.
537 <https://doi.org/10.1002/2013PA002535>
- 538 Wang, C-Y., Bochkovski, A., & Liao, H-Y. M. (2022). YOLOv7: Trainable bag-of-freebies
539 sets new state-of-the-art for real-time object detectors. arXiv preprint arXiv:2207.02696.
540 <https://doi.org/10.48550/arXiv.2207.02696>
- 541 Yasukawa, K., Liu, H., Fujinaga, K., Machida, S., Haraguchi, S., Ishii, T., Nakamura, K., &
542 Kato, Y. (2014). Geochemistry and mineralogy of REY-rich mud in the eastern Indian Ocean.
543 *Journal of Asian Earth Science*, 93, 25–36. <https://doi.org/10.1016/j.jseaes.2014.07.005>
- 544 Yasukawa, K., Tanaka, E., Miyazaki, T., Vaglarov, B. S., Chang, Q., Nakamura, K., Ohta, J.,
545 Fujinaga, K., Iwamori, H., & Kato, Y. (2023). High-Dimensional Chemostratigraphy of Pelagic
546 Clay in the Western North Pacific Ocean Revealed via an Unsupervised Clustering Approach.
547 *Paleoceanography and Paleoclimatology*, 38(7), e2023PA004644.
548 <https://doi.org/10.1029/2023PA004644>

549 Zhou, L., & Kyte, F. T. (1992). Sedimentation history of the South Pacific pelagic clay province
550 over the last 85 million years inferred from the geochemistry of Deep Sea Drilling Project Hole
551 596. *Paleoceanography*, 7(4), 441–465. <https://doi.org/10.1029/92PA01063>

Geochemistry, Geophysics, Geosystems

Supporting Information for

Applicability of Object Detection to Microfossil Research: Implications from Deep Learning Models to Detect Microfossil Fish Teeth and Denticles Using YOLO-v7

K. Mimura^{1,2}, K. Nakamura^{3,2,1}, K. Yasukawa^{3,2}, E. C. Sibert^{4,5}, J. Ohta^{3,6,1}, T. Kitazawa², Y. Kato^{2,1,7}

¹Ocean Resources Research Center for Next Generation, Chiba Institute of Technology, 2-17-1 Tsudanuma, Narashino, Chiba 275-0016, Japan.

²Department of Systems Innovation, School of Engineering, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan.

³Frontier Research Center for Energy and Resources, School of Engineering, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan.

⁴Department of Earth & Planetary Sciences, Yale University, P.O. Box 208109, New Haven, CT 06511, USA

⁵Department of Geology & Geophysics, Woods Hole Oceanographic Institution, 266 Woods Hole Rd MS 22, Woods Hole, MA 02543, USA.

⁶Volcanoes and Earth's Interior Research Center, Research Institute for Marine Geodynamics, Japan Agency for Marine-Earth Science and Technology (JAMSTEC), 2-15 Natsushima-cho, Yokosuka, Kanagawa, 237-0061, Japan.

⁷Submarine Resources Research Center, Research Institute for Marine Resources Utilization, Japan Agency for Marine-Earth Science and Technology (JAMSTEC), 2-15 Natsushima-cho, Yokosuka, Kanagawa, 237-0061, Japan.

Contents of this file

Figure S1

Tables S1 to S2

Additional Supporting Information (Files uploaded separately)

Caption for Table S3: Total number of ichthyoliths counted by manual observation and those detected by four models trained in this study. The total counts after manual checks are also shown.

Introduction

Figure S1 contains some images showing examples of particles or patterns misdetected by a model trained with the original dataset. Table S1 shows locations and water depths of the sites analyzed in this study. Table S3 shows the total number of ichthyoliths counted by manual observation and those detected by four models trained in this study. Please note that Tables S3 is provided in a separate file.

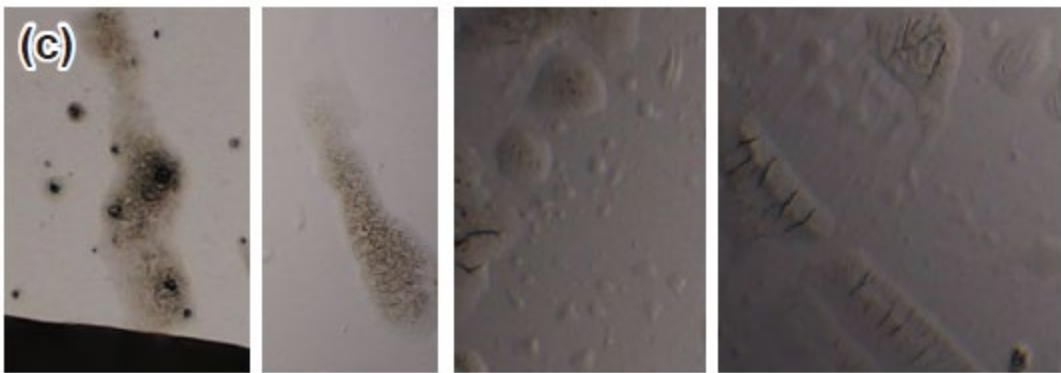
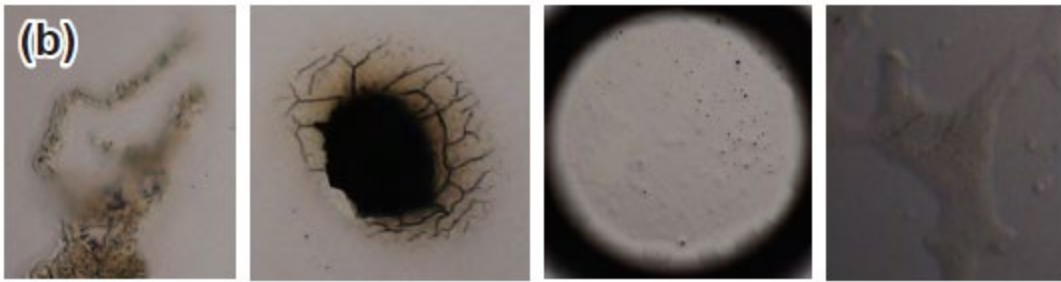
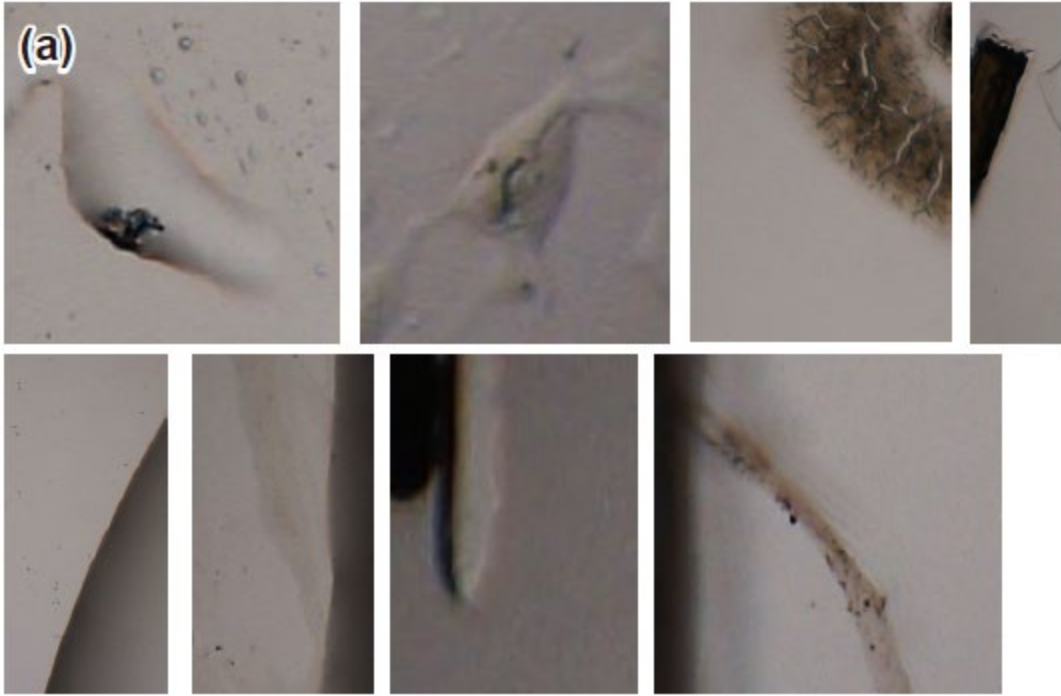


Figure S1. Examples of particles or patterns that were misdetected as (a) tooth, (b) denticle and (c) saw-toothed by a YOLOv7-X model trained on “original_all” dataset.

Cruise	Site	Hole	Latitude	Longitude	Water depth [m]
DSDP Leg 76	576	B	32°21.37' N	164°16.52' E	6,219
ODP Leg 185	1149	A	31°20.52' N	143°21.07' E	5,818
		B	31°20.52' N	143°21.06' E	5,818
IODP Expedition 329	U1366	C	26°03.08' S	156°53.67' W	5,130
		U1370	41°51.12' S	153°06.38' W	5,073
KR13-02	PC04	-	21°56.11' N	152°39.51' E	5,720
MR14-E02	PC11	-	22°59' N	154°01' E	5,647

Table S1. Locations and water depths of the analyzed sites.

iteration	1 (#8)	2	3	4	5	Average	1SD	1SE	
Precision	tooth	0.868	0.861	0.89	0.881	0.921	0.884	0.023	0.010
	denticle	0.852	0.771	0.805	0.828	0.869	0.825	0.039	0.017
	saw-toothed	0.8	0.89	0.873	0.875	0.781	0.844	0.050	0.022
	average	0.84	0.844	0.856	0.861	0.857	0.852	0.009	0.004
Recall	tooth	0.859	0.884	0.868	0.871	0.938	0.884	0.031	0.014
	denticle	0.776	0.837	0.816	0.786	0.816	0.806	0.025	0.011
	saw-toothed	0.8	0.894	0.7	0.7	0.811	0.781	0.082	0.037
	average	0.811	0.872	0.795	0.786	0.855	0.824	0.038	0.017
f1 score	tooth	0.863	0.872	0.879	0.876	0.929	0.884	0.026	0.012
	denticle	0.812	0.803	0.810	0.806	0.842	0.815	0.016	0.007
	saw-toothed	0.800	0.892	0.777	0.778	0.796	0.808	0.048	0.021
	average	0.825	0.858	0.824	0.822	0.856	0.837	0.018	0.008

Table S2. Standard deviation and standard error of evaluation parameters calculated by iteration of training under the same condition for five times.

(Tables S3 is provided in a separate file.)

Table S3. Total number of ichthyoliths counted by manual observation and those detected by four models trained in this study. Total counts after manual check is also shown.

sample	slide	Manual count			v7x_original_all (#9)			v7-x_extended_all (#13)			v7-w6_original_all (#10)			v7-w6_extended_all (#14)			v7x_extended_all + manual check			v7-w6_extended_all + manual check		
		tooth	denticle	saw-toothed	tooth	denticle	saw-toothed	tooth	denticle	saw-toothed	tooth	denticle	saw-toothed	tooth	denticle	saw-toothed	tooth	denticle	saw-toothed	tooth	denticle	saw-toothed
576B_03_06_81	1	17	0	0	32	1	0	19	1	0	18	0	0	17	0	0	15	0	0	17	0	0
	2	2	0	1	6	1	1	4	0	1	3	0	1	3	0	1	2	0	1	2	0	1
	3	18	1	0	21	1	0	20	1	0	21	1	0	18	1	0	17	1	0	18	1	0
	4	7	0	0	13	2	0	10	0	0	10	0	1	10	1	0	8	0	0	8	0	0
	5	9	0	0	27	0	3	15	0	2	17	0	2	13	0	2	11	0	0	10	0	0
	6	23	1	2	42	1	3	30	1	2	31	1	1	26	1	2	28	1	2	24	1	2
	7	19	1	0	32	1	0	25	2	0	27	1	0	23	1	0	20	1	0	22	1	0
Total	95	3	3	173	7	7	123	5	5	127	3	5	110	4	5	101	3	3	101	3	3	
576B_04_02_25	1	0	0	0	3	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
	2	5	0	0	11	0	0	7	0	0	7	0	0	4	0	0	4	0	0	3	0	0
	3	2	0	0	4	0	0	2	0	0	2	0	0	3	0	0	2	0	0	2	0	0
	4	3	0	0	13	0	1	8	0	0	7	0	0	5	1	1	4	0	0	4	0	0
	5	15	1	2	20	1	3	16	0	3	18	1	3	18	0	3	12	0	2	14	0	2
	6	19	2	0	37	4	3	23	4	1	23	6	0	21	4	0	19	3	0	21	4	0
	7	22	0	0	27	2	0	24	0	0	25	2	1	18	0	1	20	0	0	17	0	0
	8	15	1	0	28	1	1	21	1	1	20	2	0	19	1	0	20	1	0	19	1	0
	9	22	0	0	47	0	0	31	0	0	35	0	0	27	0	0	26	0	0	24	0	0
	10	17	0	0	26	0	1	19	0	1	19	0	2	17	0	1	17	0	0	17	0	0
Total	120	4	2	216	8	9	151	5	6	156	13	6	132	6	6	124	4	2	121	5	2	
576B_04_04_75	1	12	0	0	18	0	0	14	0	0	13	1	0	12	0	0	9	0	0	9	0	0
	2	9	0	1	17	1	1	13	1	1	11	2	1	6	0	1	9	0	1	6	0	1
	3	26	2	1	39	5	2	25	4	1	30	5	2	25	3	1	24	2	1	23	2	1
	4	32	1	0	48	7	1	30	4	1	37	3	1	25	3	0	24	1	0	21	1	0
	5	44	3	0	93	5	2	59	3	0	70	3	0	50	2	0	50	3	0	47	2	0
	6	69	2	0	120	2	2	77	1	2	82	2	1	73	1	1	70	1	0	68	1	0
	7	39	0	0	69	0	0	48	0	0	55	1	0	43	0	0	43	0	0	41	0	0
	8	45	0	0	61	2	0	46	0	0	53	2	0	43	2	0	43	0	0	37	0	0
	9	56	1	1	85	2	1	60	1	1	72	1	1	57	2	1	53	1	1	54	1	1
	10	108	1	0	142	1	1	99	1	1	117	3	0	86	1	1	91	1	0	80	1	0
	11	51	0	0	82	0	0	55	0	0	57	0	0	45	0	0	51	0	0	43	0	0
Total	491	10	3	774	25	10	526	15	7	597	23	6	459	14	5	467	9	3	429	8	3	
RMSPE	-	-	-	42.8%	74.7%	147.1%	13.3%	29.0%	83.1%	16.7%	86.6%	77.8%	6.6%	24.1%	73.7%	3.3%	9.0%	0%	4.7%	10.7%	0%	