Adversarial Bayesian Augmentation for Single-Source Domain Generalization Supplementary Material

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The appendix contains the details of Living17 dataset, additional results on PACS dataset and more visualizations.

1. Details of Living17

We show the partition of the source domain and the target domain in Table 1. The dataset contains 17 superclasses. Each superclass has four subclasses. We select two of the four for the source domain and the remaining two as the target domain. The partition follows [4]. The class id in the table follows the setting from the ImageNet dataset [1].

Super Class	Class IDs	
	Source Domain	Target Domain
salamander	27, 29	26, 28
turtle	37, 34	33, 35
lizard	41, 44	47, 38
snake, serpent, ophidian	60, 57	65, 61
spider	76, 72	74, 77
grouse	81, 83	82, 80
parrot	88, 90	87, 89
crab	118, 120	119, 121
dog, domestic dog, Canis familiaris	163, 154	257, 157
wolf	272, 271	270, 269
fox	280, 279	277, 278
domestic cat, house cat, Felis domesticus, Felis catus	282, 285	283, 284
bear	297, 295	296, 294
beetle	305, 306	302, 303
butterfly	325, 321	324, 322
ape	368, 365	366, 367
monkey	377, 380	381, 379

Table 1: The partition of Living17 for source domain and target domain. For each superclass, the source domain contains two subclasses and the target domain contains two subclasses.

2. Details results of PACS

We show the detailed results, including the standard deviation for our model on the PACS dataset. We compare our model with ERM, Augmix [3], and Convolutional-based augmentations, such as RandConv [5] and ALT [2]. Results are shown in Table 2, 3, 4, 5, corresponding to Photo, Art painting, Cartoon and Sketch as the source domain.

3. Visualizations

We show the additional qualitative results. Figure 1, 6, 7 show the augmented images by our method on the source domain of Digits dataset, Living17 dataset and Camelyon17 respectively. Figure 2, 3, 4, 5 show the augmented images as photo, art painting, cartoon and sketch as source domain. The first row shows the input images, and the second row shows the augmented image by our methods. Similarly, we illustrate the diversity introduced by our methods in comparison to the source distribution, the target distribution, and the distribution of RandConv, ALT augmentations, as shown in Figure 8, 9, 10. For PACS dataset, we adopt 1-layer ALT and ABA, while for Living17 and Camelyon, we adopt 5-layer ALT and ABA. For PACS dataset, the Photo domain is the source domain, and the Sketch domain is the target domain. For Camelyon17 dataset, the combination of Hospital 1,2,3 is the source domain, and Hospital 4 is the target domain. We observe that in both datasets, the distribution of our augmented method is spread widely across the tSNE space, consistent with the result from the Digits dataset in Figure 3 of the main paper.

References

[1] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 248–255, 2009. 1

[2] Tejas Gokhale, Rushil Anirudh, Jayaraman J Thiagarajan, Bhavya Kailkhura, Chitta Baral, and Yezhou Yang. Improving diversity with adversarially learned transformations for

Method	**Photo***	**Art**	**Cartoon**	**Sketch**	**Target Avg.**	**All Avg.**
ERM	-	64.1	23.6	29.1	38.9	-
Augmix	99.532 (0.438)	68.633 (0.950)	33.788 (1.205)	36.304 (2.801)	46.242 (1.122)	59.564 (0.930)
1-layer convolutional-based augmentations						
RandConv	96.407 (0.757)	61.309 (2.316)	37.577 (2.257)	50.463 (9.018)	49.783 (4.255)	61.439 (3.217)
ALT$_{\text{1-layer}}$	99.298 (0.438)	70.000 (0.399)	39.761 (2.443)	42.728 (5.928)	50.830 (2.127)	62.947 (1.689)
ALT$_{\text{1-layer+RandConv}}$	99.298 (0.438)	69.941 (0.213)	38.874 (1.686)	47.905 (0.924)	52.240 (0.820)	64.005 (0.660)
ABA$_{\text{1-layer}}$	99.123 (0.292)	**70.667 (0.517)**	**42.129 (1.813)**	**50.681 (3.094)**	**54.492 (1.352)**	**65.650 (1.047)**
ABA$_{\text{1-layer+RandConv}}$	99.064 (0.286)	70.303 (0.843)	40.546 (1.612)	46.114 (3.697)	52.321 (1.823)	64.007 (1.375)
3-layer convolutional-based augmentations						
ABA$_{\text{3-layer}}$	98.713 (0.234)	67.041 (0.687)	**46.698 (1.267)**	**62.825 (1.625)**	**58.855 (0.828)**	**68.819 (0.661)**
ABA$_{\text{3-layer+RandConv}}$	99.061 (0.610)	**68.353 (0.842)**	44.830 (2.606)	57.682 (2.520)	56.958 (0.801)	67.482 (0.491)
5-layer convolutional-based augmentations						
ALT$_{\text{5-layer}}$	99.064 (0.286)	**68.770 (0.932)**	43.387 (1.142)	50.832 (2.937)	54.330 (1.078)	65.513 (0.757)
ALT$_{\text{5-layer+RandConv}}$	98.947 (0.234)	68.740 (0.702)	40.828 (2.517)	56.024 (2.009)	55.197 (0.498)	66.135 (0.330)
ALT$_{\text{5-layer+Augmix}}$	99.298 (0.438)	68.506 (0.836)	43.507 (2.615)	53.271 (4.149)	55.094 (1.876)	66.145 (1.387)
ABA$_{\text{5-layer}}$	98.480 (0.286)	67.197 (0.485)	**47.381 (2.023)**	**62.566 (2.638)**	**59.048 (1.429)**	**68.906 (1.084)**
ABA$_{\text{5-layer+RandConv}}$	98.830 (0.002)	67.881 (0.935)	45.990 (3.440)	58.916 (2.640)	57.595 (1.263)	67.904 (0.947)
ABA$_{\text{5-layer+Augmix}}$	98.830 (0.477)	66.243 (0.403)	46.573 (1.660)	60.813 (1.209)	57.876 (0.221)	68.115 (0.115)

Table 2: SSDG performance on PACS for the P $\rightarrow$ ACS. *Source Domain. **bold**: best result.

Method	**Photo**	**Art***	**Cartoon**	**Sketch**	**Target Avg.**	**All Avg.**
ERM	95.2	-	62.3	49.0	68.8	-
Augmix	95.317 (0.422)	93.077 (1.276)	64.061 (0.361)	55.027 (2.195)	71.469 (0.637)	76.871 (0.581)
1-layer convolutional-based augmentations						
RandConv	87.281 (0.796)	85.437 (0.532)	61.143 (2.752)	60.519 (4.050)	69.648 (2.152)	73.595 (1.582)
ALT$_{\text{1-layer}}$	**95.365 (0.285)**	92.500 (1.239)	64.462 (1.018)	61.792 (3.433)	73.873 (1.314)	78.530 (1.043)
ALT$_{\text{1-layer+RandConv}}$	94.766 (0.409)	91.442 (1.532)	64.480 (1.083)	61.140 (3.971)	73.462 (1.288)	77.957 (0.836)
ABA$_{\text{1-layer}}$	94.311 (0.273)	91.442 (1.439)	**65.239 (1.436)**	67.228 (3.555)	75.593 (1.563)	79.555 (1.289)
ABA$_{\text{1-layer+RandConv}}$	94.515 (0.449)	91.346 (1.426)	65.162 (1.258)	**67.661 (3.889)**	**75.779 (1.636)**	**79.671 (1.123)**
3-layer convolutional-based augmentations						
ABA$_{\text{3-layer}}$	92.635 (0.386)	91.346 (1.325)	**64.625 (0.576)**	**68.745 (1.789)**	75.335 (0.889)	79.338 (0.976)
ABA$_{\text{3-layer+RandConv}}$	**93.592 (0.36)**	91.443 (2.050)	64.601 (0.710)	67.849 (1.485)	**75.341 (0.520)**	**79.372 (0.713)**
5-layer convolutional-based augmentations						
ALT$_{\text{5-layer}}$	**94.934 (0.269)**	91.058 (0.720)	63.524 (1.821)	63.813 (2.249)	74.090 (1.086)	78.332 (0.845)
ALT$_{\text{5-layer+RandConv}}$	93.593 (0.328)	92.596 (1.036)	64.044 (0.635)	65.991 (1.130)	74.543 (0.537)	79.056 (0.609)
ALT$_{\text{5-layer+Augmix}}$	93.174 (0.437)	91.442 (0.638)	**65.683 (1.656)**	**68.226 (2.453)**	**75.694 (1.214)**	79.631 (0.856)
ABA$_{\text{5-layer}}$	92.108 (0.442)	91.827 (1.426)	64.872 (0.994)	67.172 (1.135)	74.717 (0.757)	78.995 (0.518)
ABA$_{\text{5-layer+RandConv}}$	93.210 (0.402)	92.212 (0.981)	65.580 (1.326)	68.068 (2.521)	75.619 (1.015)	**79.767 (0.695)**
ABA$_{\text{5-layer+Augmix}}$	92.255 (0.539)	90.545 (1.379)	64.022 (0.625)	67.829 (2.017)	74.702 (0.968)	78.663 (0.834)

Table 3: SSDG performance on PACS for the A $\rightarrow$ PCS. *Source Domain. **bold**: best result.

domain generalization. In *IEEE Winter Conference on Applications of Computer Vision*, pages 434–443, 2023. 1

[3] Dan Hendrycks*, Norman Mu*, Ekin Dogus Cubuk, Barret Zoph, Justin Gilmer, and Balaji Lakshminarayanan. Augmix: A simple method to improve robustness and uncertainty under data shift. In *International Conference on Learning Representations*, 2020. 1

[4] Shibani Santurkar, Dimitris Tsipras, and Aleksander Madry. {BREEDS}: Benchmarks for subpopulation shift. In *International Conference on Learning Representations*, 2021. 1

[5] Zhenlin Xu, Deyi Liu, Junlin Yang, Colin Raffel, and Marc Niethammer. Robust and generalizable visual representation learning via random convolutions. In *International Conference on Learning Representations*, 2021. 1

Method	**Photo**	**Art**	**Cartoon***	**Sketch**	**Target Avg.**	**All Avg.**
ERM	83.6	65.7	-	60.7	70.0	-
Augmix	84.599 (0.997)	68.281 (2.085)	96.287 (0.940)	71.097 (0.609)	74.659 (1.088)	80.066 (0.897)
1-layer convolutional-based augmentations						
RandConv	73.677 (1.814)	57.051 (1.764)	91.660 (0.876)	**72.855 (2.314)**	67.861 (1.550)	73.810 (1.317)
$\mathrm{ALT}_{\text{1-layer}}$	85.018 (0.874)	67.764 (1.195)	95.865 (0.977)	72.232 (1.039)	75.005 (0.620)	80.220 (0.530)
$\mathrm{ABA}_{\text{1-layer+RandConv}}$	84.683 (0.997)	68.232 (1.247)	94.937 (0.755)	72.553 (1.159)	75.156 (0.672)	80.101 (0.622)
$\mathrm{ABA}_{\text{1-layer}}$	84.575 (0.881)	69.463 (1.429)	95.274 (0.560)	72.792 (1.505)	75.610 (0.894)	80.526 (0.636)
$\mathrm{ABA}_{\text{1-layer+RandConv}}$	**85.377 (0.743)**	**70.371 (1.078)**	95.190 (0.430)	72.298 (1.828)	**76.016 (0.559)**	**80.809 (0.468)**
3-layer convolutional-based augmentations						
$\mathrm{ABA}_{\text{3-layer}}$	**85.269 (1.077)**	71.660 (0.977)	95.274 (0.413)	**75.531 (0.791)**	**77.487 (0.573)**	**81.934 (0.427)**
$\mathrm{ABA}_{\text{3-layer+RandConv}}$	85.191 (0.922)	**72.034 (1.215)**	95.112 (0.578)	74.413 (1.162)	77.219 (0.853)	81.681 (0.630)
5-layer convolutional-based augmentations						
$\mathrm{ALT}_{\text{5-layer}}$	84.575 (1.047)	68.867 (2.126)	94.768 (0.430)	74.421 (0.441)	75.954 (1.119)	80.658 (0.929)
$\mathrm{ALT}_{\text{5-layer+RandConv}}$	83.916 (0.510)	68.086 (1.901)	95.190 (0.686)	**74.487 (0.505)**	75.496 (0.799)	80.420 (0.644)
$\mathrm{ALT}_{\text{5-layer+Augmix}}$	**85.964 (1.098)**	71.943 (1.234)	94.599 (0.560)	74.172 (0.752)	**77.360 (0.734)**	81.670 (0.667)
$\mathrm{ABA}_{\text{5-layer}}$	85.413 (0.885)	71.660 (0.635)	95.359 (0.462)	74.426 (1.393)	77.166 (0.347)	81.715 (0.312)
$\mathrm{ABA}_{\text{5-layer+RandConv}}$	84.647 (0.498)	71.152 (0.814)	94.937 (0.462)	74.192 (0.950)	76.664 (0.237)	81.232 (0.170)
$\mathrm{ABA}_{\text{5-layer+Augmix}}$	85.888 (0.707)	**73.470 (1.122)**	95.781 (0.911)	72.512 (0.818)	77.290 (0.786)	**81.913 (0.569)**

Table 4: SSDG performance on PACS for the C $\rightarrow$ PAS. *Source Domain. **bold**: best result.

Method	**Photo**	**Art**	**Cartoon**	**Sketch***	**Target Avg.**	**All Avg.**
ERM	35.6	28.0	54.5	-	39.4	-
Augmix	46.731 (2.916)	37.852 (1.878)	58.575 (1.747)	94.221 (0.711)	47.719 (1.723)	59.345 (1.268)
1-layer convolutional-based augmentations						
RandConv	46.132 (4.879)	**52.168 (1.623)**	**63.942 (2.219)**	94.264 (0.673)	**54.081 (1.959)**	**64.126 (1.465)**
$\mathrm{ALT}_{\text{1-layer}}$	46.024 (3.148)	38.154 (2.171)	59.334 (1.35)	94.422 (0.432)	47.838 (1.947)	59.484 (1.423)
$\mathrm{ALT}_{\text{1-layer+RandConv}}$	49.030 (3.242)	38.770 (2.128)	59.829 (1.358)	94.673 (0.293)	49.210 (2.142)	60.576 (1.672)
$\mathrm{ABA}_{\text{1-layer}}$	**52.587 (2.390)**	43.643 (5.125)	62.287 (2.124)	94.523 (0.293)	52.839 (2.804)	63.260 (2.150)
$\mathrm{ABA}_{\text{1-layer+RandConv}}$	49.713 (3.434)	39.199 (1.736)	61.715 (1.382)	94.673 (0.700)	50.209 (1.934)	61.325 (1.471)
3-layer convolutional-based augmentations						
$\mathrm{ABA}_{\text{3-layer}}$	52.587 (2.967)	**45.635 (3.936)**	**63.063 (1.511)**	94.623 (0.201)	**53.762 (2.457)**	**63.977 (1.804)**
$\mathrm{ABA}_{\text{3-layer+RandConv}}$	**52.780 (1.472)**	44.764 (1.767)	63.022 (0.815)	94.822 (0.694)	53.523 (0.900)	63.842 (0.736)
5-layer convolutional-based augmentations						
$\mathrm{ALT}_{\text{5-layer}}$	49.305 (2.775)	39.658 (3.423)	61.109 (1.853)	94.573 (0.466)	50.024 (2.408)	61.161 (1.726)
$\mathrm{ALT}_{\text{5-layer+RandConv}}$	51.305 (0.866)	41.787 (1.174)	62.773 (1.089)	94.724 (0.527)	51.955 (0.791)	62.647 (0.571)
$\mathrm{ALT}_{\text{5-layer+Augmix}}$	49.078 (2.072)	40.186 (2.494)	62.901 (0.358)	94.271 (0.624)	50.721 (1.414)	61.609 (1.103)
$\mathrm{ABA}_{\text{5-layer}}$	49.461 (2.584)	45.576 (4.069)	**64.522 (0.425)**	94.171 (0.801)	53.186 (2.072)	63.433 (1.662)
$\mathrm{ABA}_{\text{5-layer+RandConv}}$	**52.982 (1.960)**	**46.299 (2.702)**	63.106 (0.651)	93.719 (0.449)	**54.129 (1.334)**	**64.026 (0.970)**
$\mathrm{ABA}_{\text{5-layer+Augmix}}$	51.377 (0.240)	43.335 (0.610)	62.351 (0.747)	94.472 (0.001)	52.354 (0.034)	62.884 (0.026)

Table 5: SSDG performance on PACS for the S $\rightarrow$ PAC. *Source Domain. **bold**: best result.

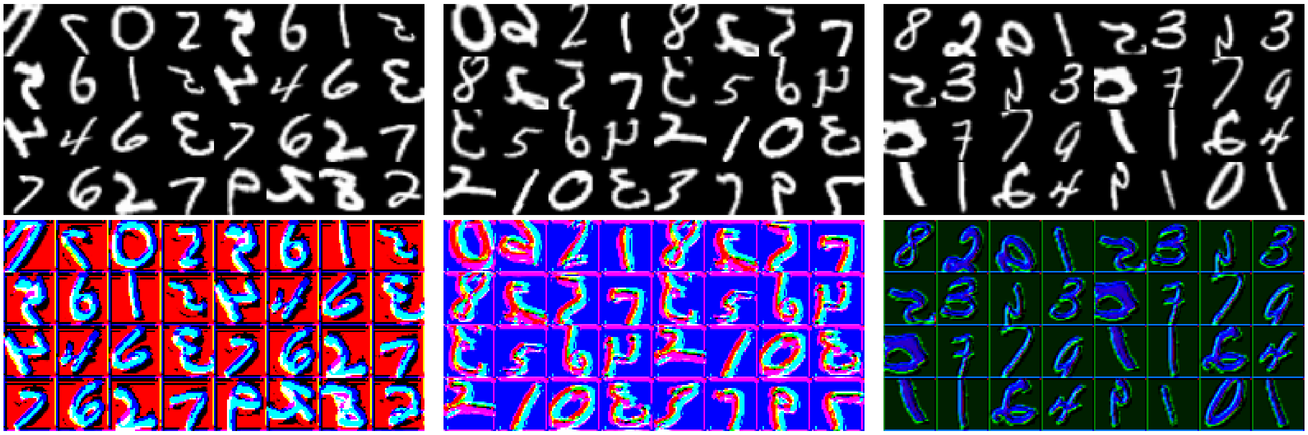

Figure 1: Digits: Images augmented by ABA$_{\text{3-layer}}$ with MNIST-10K as source dataset.

Figure 2: PACS: Images augmented by ABA$_{\text{3-layer}}$ with photo as source dataset.

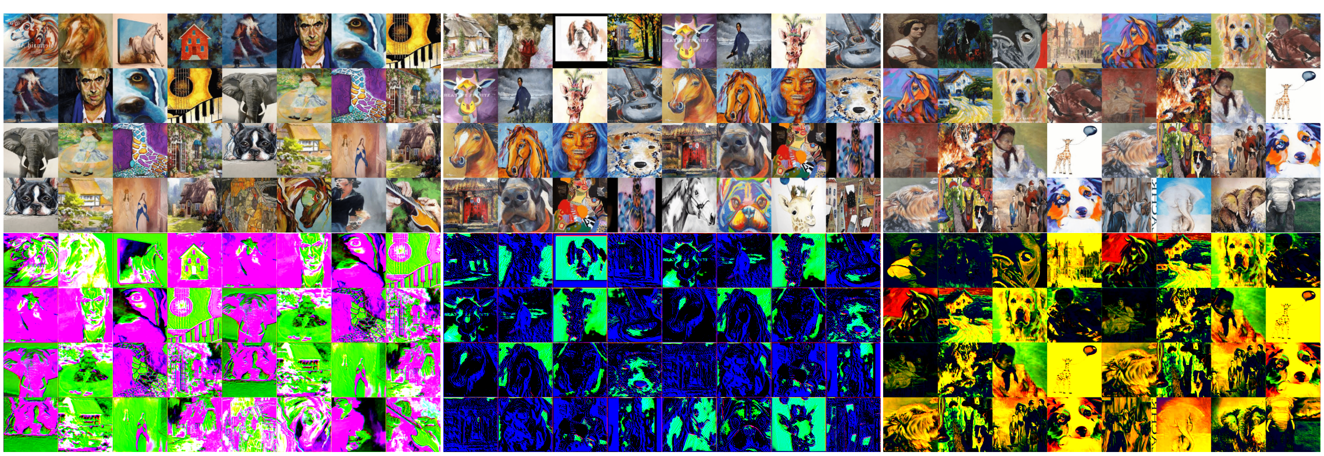

Figure 3: PACS: Images augmented by ABA$_{\text{3-layer}}$ with art painting as source dataset.

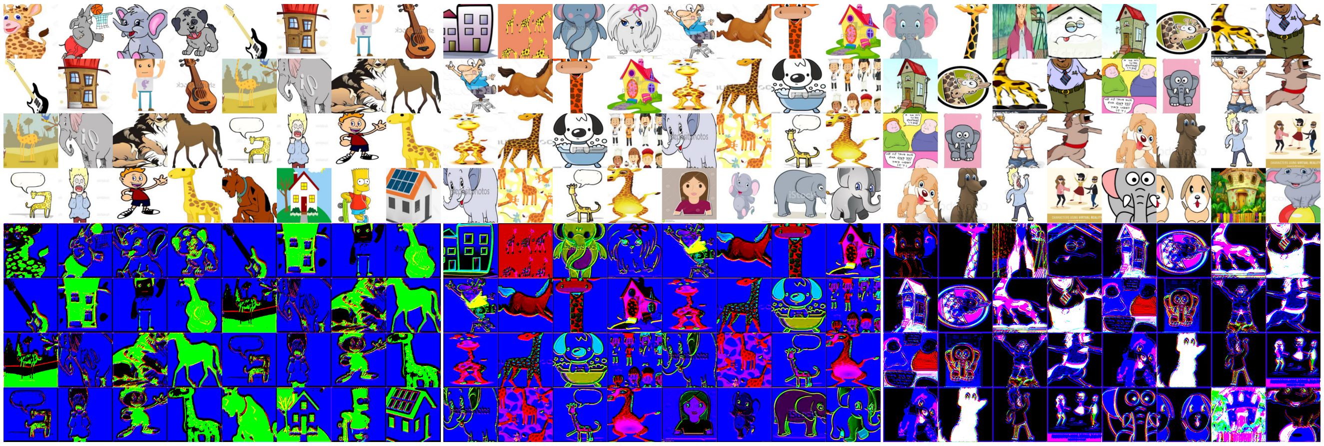

Figure 4: PACS: Images augmented by $ABA_{3\text{-layer}}$ with cartoon as source dataset.

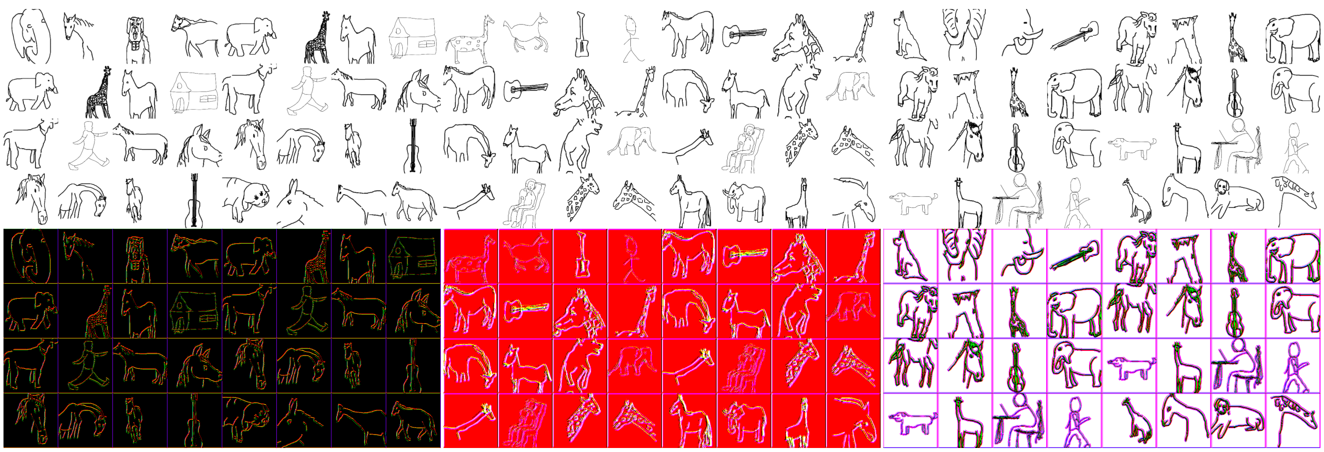

Figure 5: PACS: Images augmented by $ABA_{3\text{-layer}}$ with sketch as source dataset.

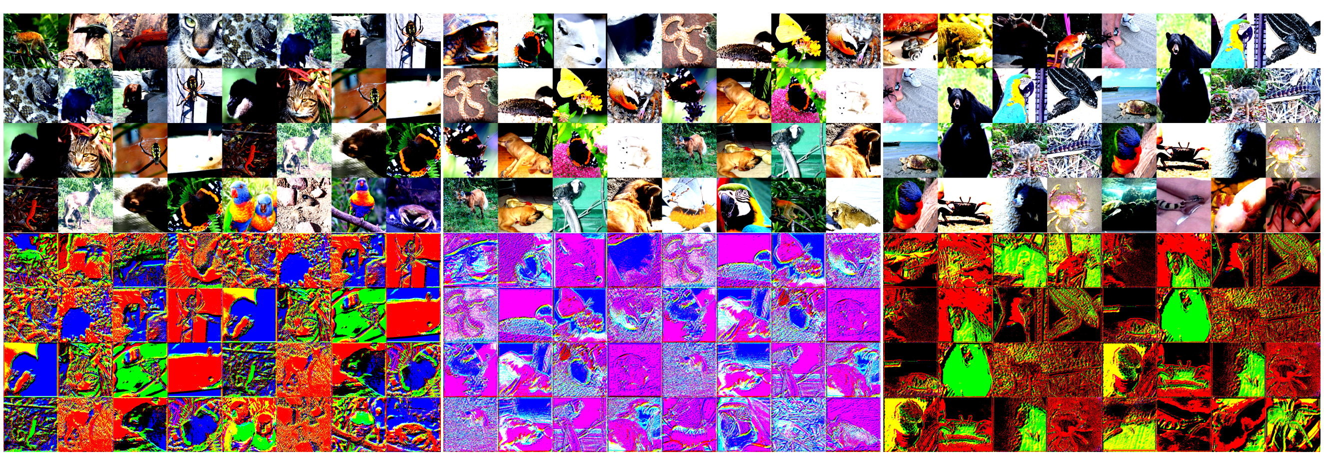

Figure 6: Living17: Images augmented by $ABA_{5\text{-layer}}$.

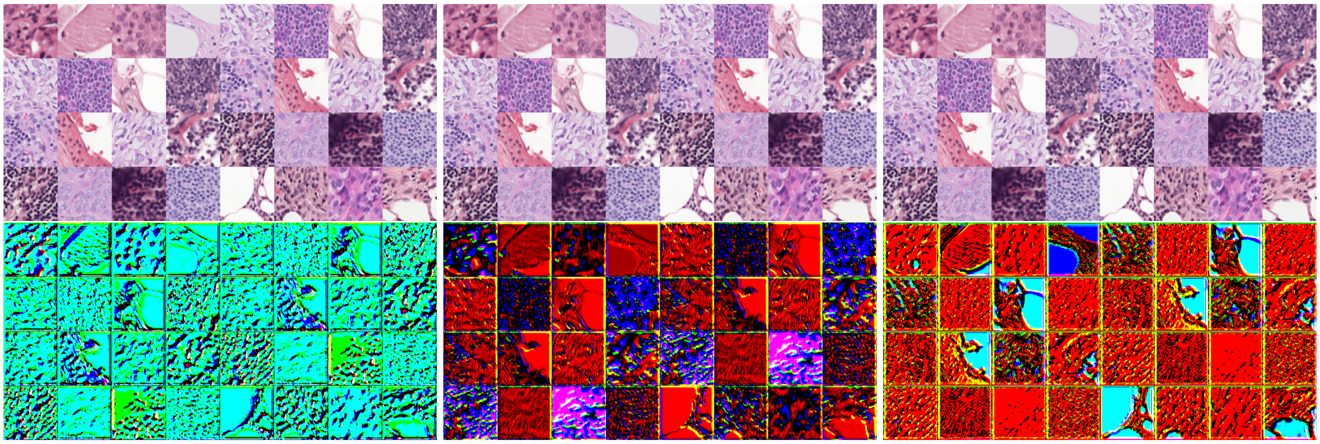

Figure 7: Camelyon17: Images augmented by $\text{ABA}_{\text{5-layer+RandConv}}$.

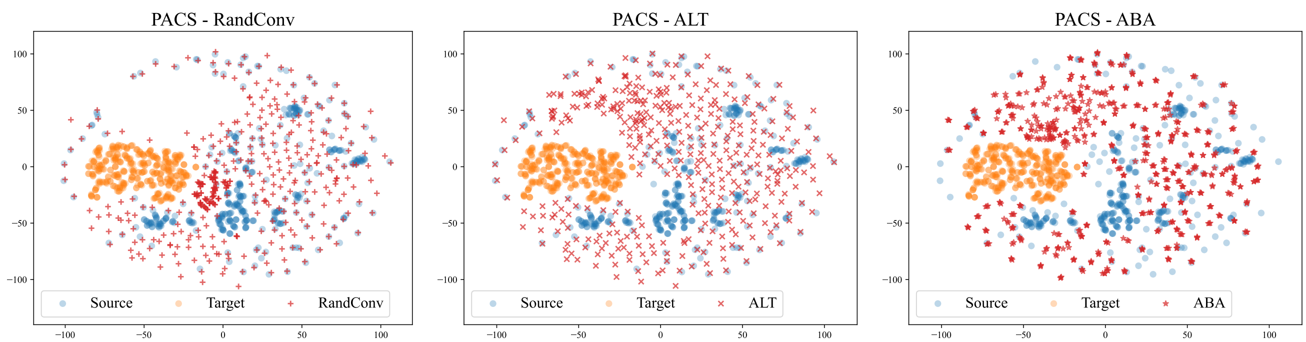

Figure 8: TSNE plot for source domain, target domain and augmented image distribution by RandConv, ALT, ABA.

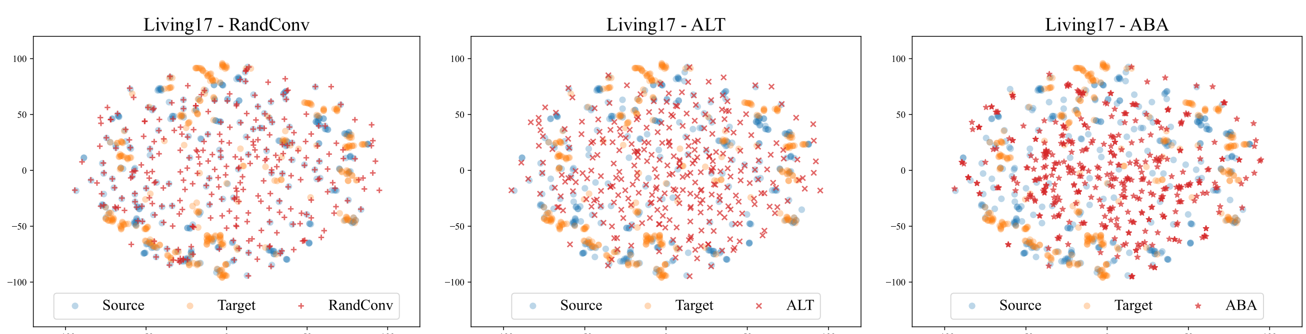

Figure 9: TSNE plot for source domain, target domain and augmented image distribution by RandConv, ALT, ABA.

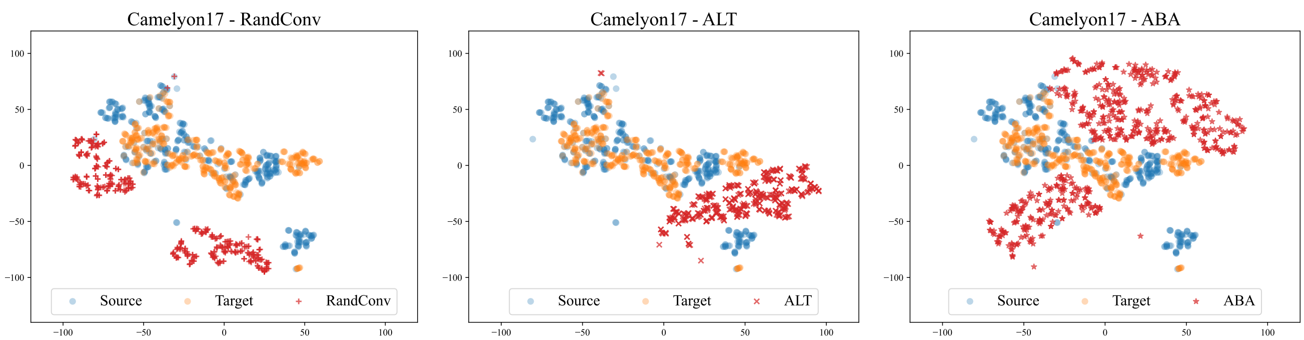

Figure 10: TSNE plot for source domain, target domain and augmented image distribution by RandConv, ALT, ABA.