

Supplementary material

This supplementary provides additional analyses into all evaluated datasets and settings.

- In App. A the achieved accuracies on OpticsBench (ImageNet) for the 70 different DNNs are visualized. The ranking compares all corruptions to the baseline (defocus blur) [10] together with Kendall’s τ rank correlation coefficient.
- App. B further quantifies with tables the benefit for OpticsAugment training on ImageNet-100 OpticsBench. Additionally, the accuracies for 2D common corruptions w/wo OpticsAugment training are listed. On top of that for all DNNs the comparison plots are shown on both benchmarks.
- Subsequently, App. C gives more insight into kernel generation and visualizes all OpticsBench and OpticsBenchRG kernels as used for the presented analysis.
- Image examples can be found in the supplementary material App. D
- Additional exemplary analysis on OpticsBenchRG with reddish and greenish kernels only is displayed in App. E. The benchmark is both evaluated on ImageNet and ImageNet-100 showing again the ranking for 70 DNNs on ImageNet with Kendall’s τ and on ImageNet-100 the averaged accuracies of w/wo OpticsAugment training.
- App. F concludes this supplementary with general implementation details, hyperparameter settings for training and computational resources. Additionally, a DNN trained on ImageNet using OpticsBench supplements existing analysis and an experiment with pipelining OpticsAugment and AugMix on ImageNet during training shows another possible use-case of the proposed OpticsAugment method as described in the main paper.

A. Ranking comparisons

The rank comparisons provided in Figure 9 and Figure 10 show the correlation between defocus blur [10] (baseline) ordering and the different corruptions. This additional analysis confirms that DNNs can handle the blur kernel types from OpticsBench differently well. Additionally to the visualization of the accuracies, the Kendall’s rank coefficient τ is evaluated [53]. A weak correlation is indicated by Kendall’s $\tau \ll 1.0$. The p -value denotes the result of a hypothesis test for $\tau = 0.0$, alternative $\tau \neq 0.0$. Most of the corruptions $\tau_{mean} = 0.276$ are weakly correlated with defocus blur $\tau \leq 0.3$. Robust ResNet50 models from the RobustBench leaderboard using DeepAugment

(*hendrycks2020many* in our plots) [23] or AugMix [22] are among the top 10 DNNs for different severities. Besides this, VisionTransformer DNNs are always among top 5 and also include augmentation during training. The EfficientNet architecture achieves also good results on OpticsBench.

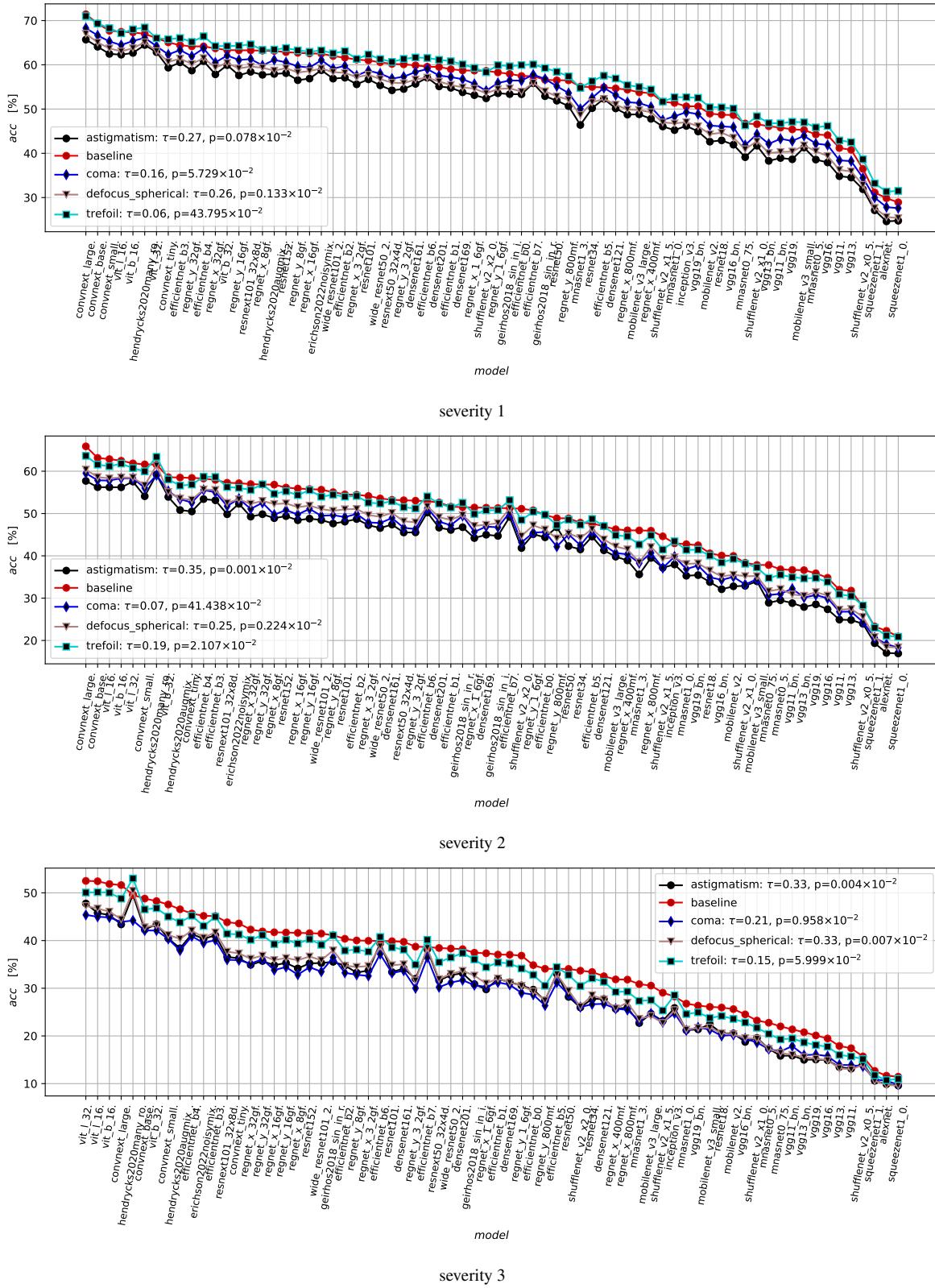
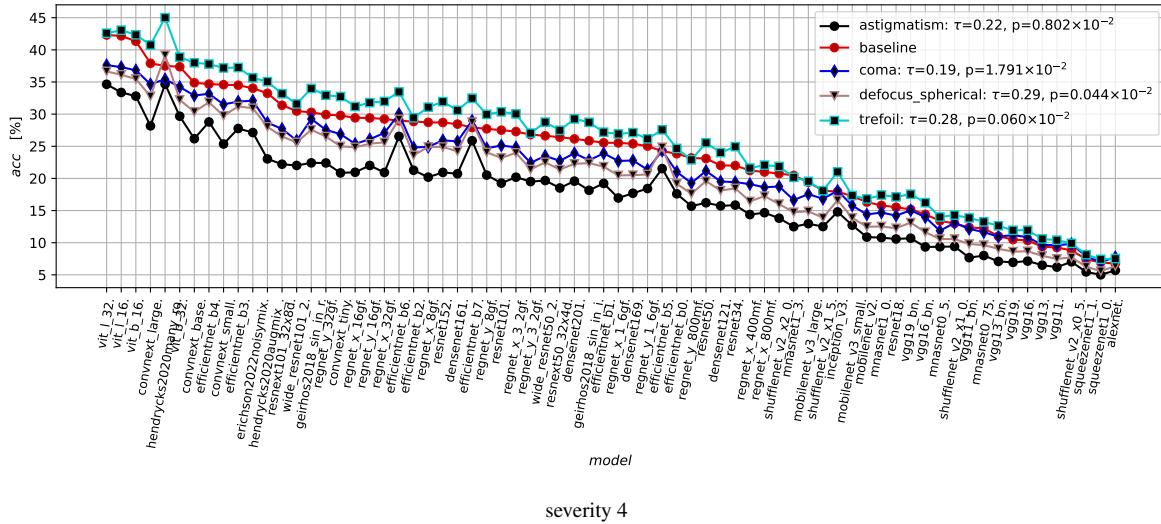
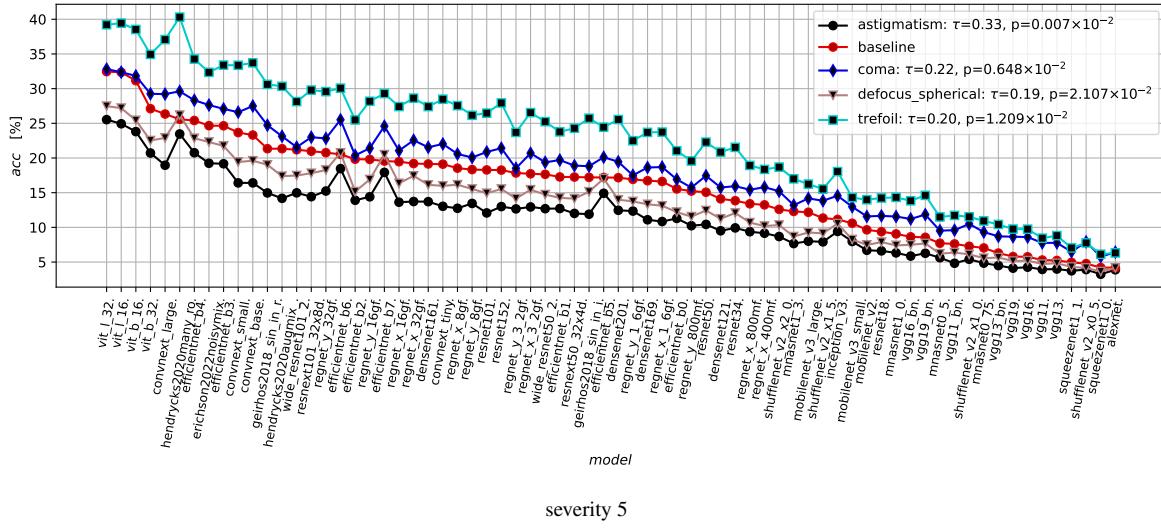


Figure 9: Ranking comparison of baseline and all corruptions for severities 1-3.



severity 4



severity 5

Figure 10: Ranking comparison of baseline and all corruptions for severities 4-5 .

B. OpticsAugment

This appendix displays additional tables for the ImageNet-100 OpticsBench and ImageNet-100-C analysis to quantify the benefit with OpticsAugment training. The different tables show for OpticsBench accuracies together with the improvement in accuracy Δ between our method and conventionally trained DNNs. We include the same tables for the evaluation on 2D common corruptions. All values are given in %. First, we report the accuracies on the ImageNet-100 validation dataset in Tab. 7.

Tab. 8 gives an overview for the achieved accuracies on OpticsBench ImageNet-100 and Tab. 14 for 2D common corruptions ImageNet-100-C. Although the validation accuracies are similar for w/wo OpticsAugment training, as the images are corrupted, the benefit with OpticsAugment

DNN	wo	w (ours)	DNN	wo	w (ours)
DenseNet	79.2	80.2	ResNet101	82.6	80.6
EfficientNet	78.0	78.2	ResNeXt50	77.4	75.6
MobileNet	76.2	76.6			

Table 7: Validation accuracies on ImageNet-100 for with (w) and without (wo) OpticsAugment trained DNNs. Both training schemes perform similarly well on the unmodified validation dataset.

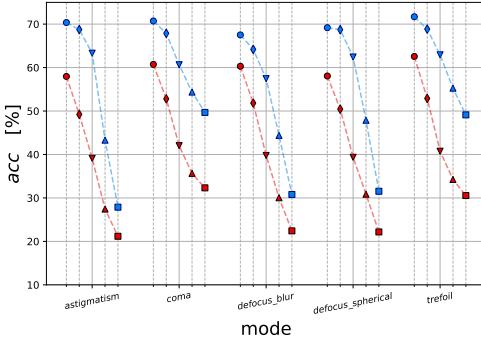
becomes clear. The analysis is then extended to OpticsBench corruptions in Tables 9-13. We also report the defocus blur corruption [10] for comparison. All DNNs benefit from the OpticsAugment training scheme. However, the performance gain is almost for all settings lowest for defocus blur, which had been out of domain during training.

This gives further proof that kernel types matter. The tables are visualized in Fig. 12 and 11. The visualization is also offered for DenseNet161 and ResNeXt50 to allow for another point of view compared to Fig. 7a and 7b.

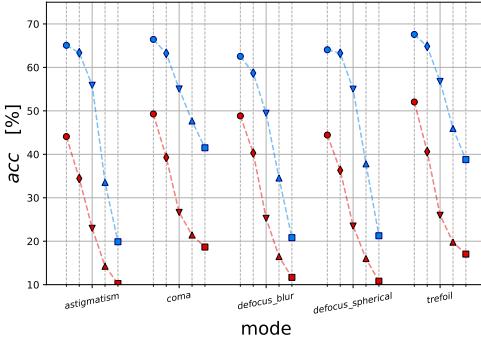
Tables 15-19 show for all 19 corruptions from [10] the particular accuracies and the difference in accuracy Δ .

Model	1	2	3	4	5
DenseNet (ours)	68.22	65.33	56.33	41.60	30.13
DenseNet	53.45	43.37	29.07	20.62	16.30
EfficientNet (ours)	61.00	55.34	42.14	30.27	23.35
EfficientNet	52.55	42.74	29.24	20.84	16.00
MobileNet (ours)	57.59	52.30	38.58	27.51	20.54
MobileNet	49.47	39.57	24.78	17.42	13.27
ResNet101 (ours)	69.90	67.68	61.36	49.04	37.80
ResNet101	59.92	51.44	40.21	31.65	25.73
ResNeXt50 (ours)	65.14	62.68	54.44	39.90	28.45
ResNeXt50	47.74	38.19	24.88	17.58	13.69

Table 8: Accuracies w/o OpticsAugment evaluated on ImageNet-100 OpticsBench. Average over all corruptions.

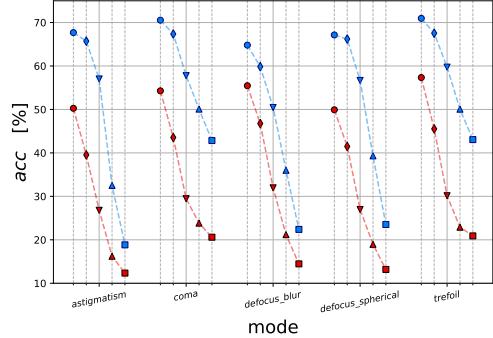


(a) ResNet101

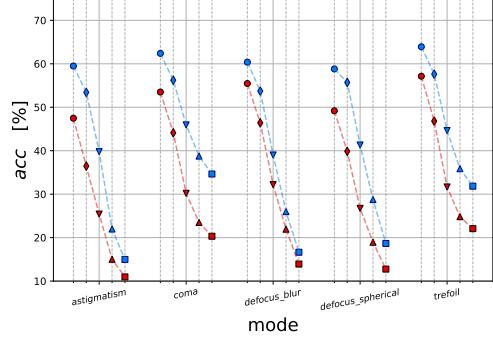


(b) ResNeXt50

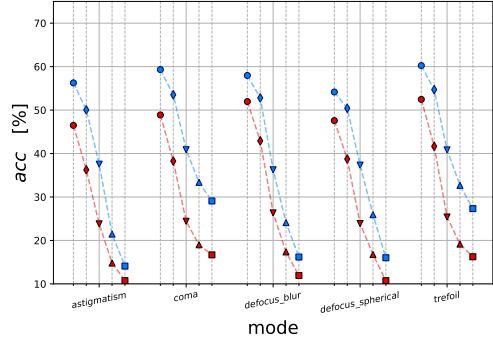
Figure 11: Accuracy evaluated on OpticsBench-ImageNet-100 for DNNs w/o OpticsAugment training and all severities 1-5 (circle, diamond, triangles and square markers) at each corruption. **OpticsAugment (blue) improves** accuracy compared to the conventionally trained DNN (red).



(a) DenseNet161



(b) EfficientNet



(c) MobileNet

Figure 12: Accuracy evaluated on OpticsBench-ImageNet-100 for DNNs w/o OpticsAugment training and all severities 1-5 (circle, diamond, triangles and square markers) at each corruption. **OpticsAugment (blue) improves** accuracy compared to the conventionally trained DNN (red): (a) DenseNet, (b) EfficientNet, (c) MobileNet.

	1			2			3			4			5		
Corruption	clean	ours	Δ												
astigmatism	50.26	67.68	17.42	39.54	65.72	26.18	26.80	57.02	30.22	16.22	32.52	16.30	12.34	18.84	6.50
coma	54.28	70.54	16.26	43.54	67.36	23.82	29.46	57.78	28.32	23.84	50.08	26.24	20.60	42.84	22.24
defocus.blur	55.46	64.80	9.34	46.76	59.84	13.08	31.96	50.44	18.48	21.18	36.00	14.82	14.46	22.40	7.94
defocus.spherical	49.92	67.14	17.22	41.48	66.20	24.72	26.98	56.68	29.70	18.96	39.32	20.36	13.18	23.52	10.34
trefoil	57.34	70.96	13.62	45.52	67.54	22.02	30.14	59.74	29.60	22.90	50.06	27.16	20.90	43.06	22.16
Σ	53.45	68.22	14.77	43.37	65.33	21.96	29.07	56.33	27.26	20.62	41.60	20.98	16.30	30.13	13.84

Table 9: Accuracies for DenseNet w/wo OpticsAugment evaluated on ImageNet-100 OpticsBench.

	1			2			3			4			5		
Corruption	clean	ours	Δ												
astigmatism	47.48	59.48	12.00	36.46	53.42	16.96	25.42	39.78	14.36	15.02	21.98	6.96	10.96	14.98	4.02
coma	53.50	62.40	8.90	44.12	56.22	12.10	30.20	45.94	15.74	23.48	38.76	15.28	20.32	34.64	14.32
defocus.blur	55.46	60.38	4.92	46.42	53.72	7.30	32.20	39.02	6.82	21.94	25.98	4.04	13.92	16.64	2.72
defocus.spherical	49.18	58.82	9.64	39.86	55.72	15.86	26.74	41.32	14.58	18.94	28.76	9.82	12.76	18.66	5.90
trefoil	57.14	63.92	6.78	46.82	57.62	10.80	31.66	44.64	12.98	24.82	35.86	11.04	22.06	31.84	9.78
Σ	52.55	61.00	8.45	42.74	55.34	12.60	29.24	42.14	12.90	20.84	30.27	9.43	16.00	23.35	7.35

Table 10: Accuracies for EfficientNet w/wo OpticsAugment evaluated on ImageNet-100 OpticsBench.

	1			2			3			4			5		
Corruption	clean	ours	Δ												
astigmatism	46.48	56.26	9.78	36.26	50.04	13.78	23.82	37.56	13.74	14.80	21.46	6.66	10.74	14.10	3.36
coma	48.88	59.32	10.44	38.26	53.52	15.26	24.42	40.88	16.46	19.00	33.38	14.38	16.68	29.08	12.40
defocus.blur	51.96	57.96	6.00	42.92	52.80	9.88	26.34	36.26	9.92	17.36	24.10	6.74	11.94	16.18	4.24
defocus.spherical	47.58	54.16	6.58	38.74	50.42	11.68	23.90	37.34	13.44	16.76	25.92	9.16	10.74	16.02	5.28
trefoil	52.46	60.24	7.78	41.66	54.70	13.04	25.40	40.84	15.44	19.16	32.68	13.52	16.24	27.32	11.08
Σ	49.47	57.59	8.12	39.57	52.30	12.73	24.78	38.58	13.80	17.42	27.51	10.09	13.27	20.54	7.27

Table 11: Accuracies for MobileNet w/wo OpticsAugment evaluated on ImageNet-100 OpticsBench.

	1			2			3			4			5		
Corruption	clean	ours	Δ												
astigmatism	57.96	70.36	12.40	49.22	68.74	19.52	39.12	63.32	24.20	27.44	43.30	15.86	21.18	27.88	6.70
coma	60.74	70.72	9.98	52.80	67.88	15.08	42.04	60.66	18.62	35.66	54.36	18.70	32.32	49.68	17.36
defocus.blur	60.30	67.52	7.22	51.82	64.18	12.36	39.78	57.46	17.68	30.04	44.38	14.34	22.42	30.80	8.38
defocus.spherical	58.06	69.18	11.12	50.44	68.72	18.28	39.36	62.44	23.08	30.86	47.88	17.02	22.18	31.54	9.36
trefoil	62.56	71.70	9.14	52.90	68.86	15.96	40.76	62.94	22.18	34.24	55.26	21.02	30.56	49.12	18.56
Σ	59.92	69.90	9.97	51.44	67.68	16.24	40.21	61.36	21.15	31.65	49.04	17.39	25.73	37.80	12.07

Table 12: Accuracies for ResNet101 w/wo OpticsAugment evaluated on ImageNet-100 OpticsBench.

	1			2			3			4			5		
Corruption	clean	ours	Δ												
astigmatism	44.08	65.08	21.00	34.44	63.36	28.92	22.98	55.90	32.92	14.24	33.54	19.30	10.26	19.88	9.62
coma	49.28	66.44	17.16	39.28	63.24	23.96	26.64	55.04	28.40	21.42	47.66	26.24	18.66	41.50	22.84
defocus.blur	48.84	62.54	13.70	40.30	58.68	18.38	25.28	49.46	24.18	16.46	34.54	18.08	11.68	20.82	9.14
defocus.spherical	44.44	64.06	19.62	36.30	63.26	26.96	23.50	55.00	31.50	16.00	37.80	21.80	10.80	21.26	10.46
trefoil	52.04	67.58	15.54	40.62	64.84	24.22	25.98	56.78	30.80	19.78	45.94	26.16	17.04	38.78	21.74
Σ	47.74	65.14	17.40	38.19	62.68	24.49	24.88	54.44	29.56	17.58	39.90	22.32	13.69	28.45	14.76

Table 13: Accuracies for ResNeXt50 w/wo OpticsAugment evaluated on ImageNet-100 OpticsBench.

Model	1	2	3	4	5
DenseNet (ours)	67.99	57.65	49.24	38.18	28.35
DenseNet	62.91	50.09	40.50	30.88	22.97
EfficientNet (ours)	63.89	53.36	45.14	34.66	26.02
EfficientNet	59.54	47.04	38.44	30.04	22.33
MobileNet (ours)	60.87	50.35	42.43	33.07	25.10
MobileNet	57.29	45.43	37.66	29.38	22.03
ResNet101 (ours)	69.13	60.15	52.93	42.70	33.05
ResNet101	67.89	57.07	48.38	37.80	28.95
ResNeXt50 (ours)	63.19	52.80	45.36	35.29	26.44
ResNeXt50	58.07	45.17	36.68	28.11	21.17

Table 14: Average Accuracies w/wo OpticsAugment evaluated on ImageNet-100-c 2D common corruptions [10]. Average over all corruptions.

Corruption	1			2			3			4			5		
	clean	ours	Δ												
brightness	76.04	78.24	2.20	72.78	75.34	2.56	67.86	70.52	2.66	59.72	63.08	3.36	48.06	52.70	4.64
contrast	57.78	65.40	7.62	44.76	54.46	9.70	25.98	34.52	8.54	8.08	11.80	3.72	3.00	4.88	1.88
defocus_blur	55.46	64.80	9.34	46.76	59.84	13.08	31.96	50.44	18.48	21.18	36.00	14.82	14.46	22.40	7.94
elastic_transform	71.84	74.28	2.44	60.66	63.94	3.28	71.94	74.20	2.26	67.54	71.34	3.80	53.24	60.34	7.10
fog	55.82	64.80	8.98	47.44	58.12	10.68	36.76	49.70	12.94	34.44	46.88	12.44	21.46	32.94	11.48
frost	64.48	65.92	1.44	46.40	50.12	3.72	33.50	37.72	4.22	31.62	37.02	5.40	24.70	29.38	4.68
gaussian_blur	67.14	72.62	5.48	51.02	62.86	11.84	36.62	54.76	18.14	25.40	44.08	18.68	12.96	17.42	4.46
gaussian_noise	59.12	64.76	5.64	34.46	47.50	13.04	10.22	25.00	14.78	2.34	10.26	7.92	1.02	3.84	2.82
glass_blur	61.28	67.40	6.12	51.34	57.62	6.28	36.56	40.58	4.02	30.02	35.02	5.00	22.16	27.18	5.02
impulse_noise	44.78	54.86	10.08	19.76	35.04	15.28	8.08	23.12	15.04	1.92	8.70	6.78	1.16	3.82	2.66
jpeg_compression	67.14	69.06	1.92	63.42	65.24	1.82	60.14	61.74	1.60	49.52	52.16	2.64	37.26	40.86	3.60
motion_blur	66.16	72.04	5.88	55.62	63.78	8.16	43.54	50.62	7.08	31.78	36.04	4.26	25.40	29.44	4.04
pixelate	73.16	76.48	3.32	72.08	76.66	4.58	65.16	72.28	7.12	56.00	65.38	9.38	51.14	60.14	9.00
saturate	62.00	63.80	1.80	48.16	49.34	1.18	69.68	72.90	3.22	43.26	47.48	4.22	26.76	30.56	3.80
shot_noise	57.84	64.02	6.18	31.70	44.94	13.24	11.72	26.50	14.78	2.60	10.42	7.82	1.58	5.32	3.74
snow	56.42	60.88	4.46	33.52	40.44	6.92	38.68	41.56	2.88	26.24	27.98	1.74	19.70	20.52	0.82
spatter	75.70	77.50	1.80	65.34	68.38	3.04	51.44	57.02	5.58	39.58	45.38	5.80	27.58	35.62	8.04
speckle_noise	62.88	68.10	5.22	51.86	60.58	8.72	21.74	35.46	13.72	11.66	23.98	12.32	6.26	14.52	8.26
zoom_blur	60.28	66.90	6.62	54.72	61.06	6.34	48.00	56.90	8.90	43.82	52.38	8.56	38.50	46.80	8.30
Σ	62.91	67.99	5.08	50.09	57.65	7.55	40.50	49.24	8.73	30.88	38.18	7.30	22.97	28.35	5.38

Table 15: Accuracies for DenseNet w/wo OpticsAugment evaluated on ImageNet-100-c 2D common corruptions [10].

	1			2			3			4			5		
Corruption	clean	ours	Δ	clean	ours	Δ	clean	ours	Δ	clean	ours	Δ	clean	ours	Δ
brightness	74.12	74.56	0.44	70.66	72.08	1.42	64.90	68.56	3.66	57.76	63.32	5.56	46.82	54.60	7.78
contrast	56.02	60.46	4.44	41.50	49.32	7.82	20.74	29.04	8.30	5.86	7.14	1.28	3.26	2.90	-0.36
defocus.blur	55.46	60.38	4.92	46.42	53.72	7.30	32.20	39.02	6.82	21.94	25.98	4.04	13.92	16.64	2.72
elastic_transform	69.78	69.94	0.16	59.82	57.96	-1.86	69.68	69.48	-0.20	66.26	67.14	0.88	56.10	56.50	0.40
fog	53.38	60.14	6.76	43.82	53.16	9.34	33.48	45.06	11.58	30.60	40.38	9.78	21.10	28.02	6.92
frost	59.98	64.04	4.06	42.96	47.40	4.44	32.08	36.56	4.48	30.80	35.72	4.92	25.16	28.08	2.92
gaussian.blur	66.44	68.24	1.80	50.66	56.92	6.26	36.06	43.50	7.44	24.90	29.60	4.70	12.30	13.32	1.02
gaussian.noise	52.06	61.34	9.28	28.36	45.36	17.00	9.32	24.46	15.14	3.72	9.34	5.62	1.60	3.56	1.96
glass.blur	58.52	61.02	2.50	49.28	51.16	1.88	33.32	35.32	2.00	27.58	29.56	1.98	21.28	21.04	-0.24
impulse.noise	40.72	54.50	13.78	19.78	38.22	18.44	10.22	24.56	14.34	3.22	8.90	5.68	1.50	3.46	1.96
jpeg.compression	63.62	65.04	1.42	58.86	62.00	3.14	55.20	58.68	3.48	44.22	49.98	5.76	32.70	39.30	6.60
motion.blur	66.20	67.96	1.76	56.70	61.18	4.48	44.10	50.54	6.44	32.56	36.22	3.66	24.86	27.84	2.98
pixelate	69.58	71.36	1.78	69.76	70.80	1.04	56.80	65.20	8.40	38.70	57.46	18.76	30.02	51.78	21.76
saturate	59.04	61.32	2.28	41.98	44.48	2.50	69.42	70.70	1.28	47.96	53.02	5.06	30.04	37.38	7.34
shot.noise	49.16	59.42	10.26	25.72	40.36	14.64	10.70	21.76	11.06	4.02	7.68	3.66	2.22	4.30	2.08
snow	55.42	60.36	4.94	36.30	40.02	3.72	39.88	42.92	3.04	30.60	29.66	-0.94	21.20	21.24	0.04
spatter	73.18	73.66	0.48	62.36	64.72	2.36	50.00	55.48	5.48	49.56	48.16	-1.40	39.02	37.28	-1.74
speckle.noise	53.24	62.96	9.72	41.66	54.84	13.18	18.88	30.00	11.12	12.04	17.80	5.76	7.06	9.60	2.54
zoom.blur	55.32	57.28	1.96	47.18	50.08	2.90	43.30	46.82	3.52	38.44	41.40	2.96	34.10	37.60	3.50
Σ	59.54	63.89	4.35	47.04	53.36	6.32	38.44	45.14	6.70	30.04	34.66	4.62	22.33	26.02	3.69

Table 16: Accuracies for EfficientNet w/wo OpticsAugment evaluated on ImageNet-100-c 2D common corruptions [10].

	1			2			3			4			5		
Corruption	clean	ours	Δ	clean	ours	Δ	clean	ours	Δ	clean	ours	Δ	clean	ours	Δ
brightness	71.08	72.62	1.54	67.70	70.96	3.26	63.58	67.18	3.60	58.14	61.22	3.08	49.98	52.98	3.00
contrast	48.70	58.90	10.20	32.92	47.06	14.14	14.88	27.10	12.22	3.78	7.10	3.32	1.84	3.10	1.26
defocus.blur	51.96	57.96	6.00	42.92	52.80	9.88	26.34	36.26	9.92	17.36	24.10	6.74	11.94	16.18	4.24
elastic.transform	66.50	67.52	1.02	54.58	54.68	0.10	65.56	67.52	1.96	61.90	65.52	3.62	51.68	56.60	4.92
fog	47.88	56.72	8.84	38.46	49.52	11.06	29.20	40.74	11.54	28.14	36.40	8.26	19.34	23.64	4.30
frost	56.04	58.88	2.84	39.88	41.00	1.12	27.54	28.80	1.26	26.80	27.32	0.52	20.18	21.48	1.30
gaussian.blur	62.74	64.66	1.92	46.44	54.92	8.48	30.66	39.44	8.78	20.00	25.70	5.70	10.62	12.42	1.80
gaussian.noise	53.80	55.92	2.12	35.02	39.78	4.76	17.20	21.26	4.06	6.76	9.42	2.66	2.56	3.84	1.28
glass.blur	57.68	60.14	2.46	49.16	50.70	1.54	35.46	35.54	0.08	28.58	31.26	2.68	19.68	24.00	4.32
impulse.noise	46.78	51.76	4.98	27.10	33.56	6.46	16.80	21.50	4.70	5.78	8.48	2.70	2.54	3.50	0.96
jpeg.compression	61.20	62.42	1.22	56.62	58.72	2.10	53.94	55.38	1.44	45.40	47.18	1.78	34.98	37.48	2.50
motion.blur	61.50	65.74	4.24	53.38	58.16	4.78	40.06	44.98	4.92	27.80	31.96	4.16	20.94	25.16	4.22
pixelate	69.04	69.12	0.08	67.76	68.40	0.64	61.80	63.96	2.16	51.62	58.12	6.50	44.00	53.60	9.60
saturate	55.58	57.64	2.06	40.18	41.92	1.74	67.94	68.48	0.54	48.46	48.46	0.00	33.88	33.56	-0.32
shot.noise	49.34	54.30	4.96	31.02	36.80	5.78	17.12	22.12	5.00	6.86	9.04	2.18	3.76	5.08	1.32
snow	52.78	57.84	5.06	31.14	37.48	6.34	35.48	39.78	4.30	24.74	29.14	4.40	16.48	20.14	3.66
spatter	71.16	71.58	0.42	60.28	62.98	2.70	49.54	53.06	3.52	45.52	48.18	2.66	33.70	35.50	1.80
speckle.noise	53.72	57.84	4.12	43.70	49.98	6.28	22.90	29.62	6.72	15.64	20.94	5.30	9.88	13.82	3.94
zoom.blur	50.98	54.98	4.00	44.88	47.18	2.30	39.48	43.54	4.06	34.86	38.76	3.90	30.56	34.76	4.20
Σ	57.29	60.87	3.58	45.43	50.35	4.92	37.66	42.43	4.78	29.38	33.07	3.69	22.03	25.10	3.07

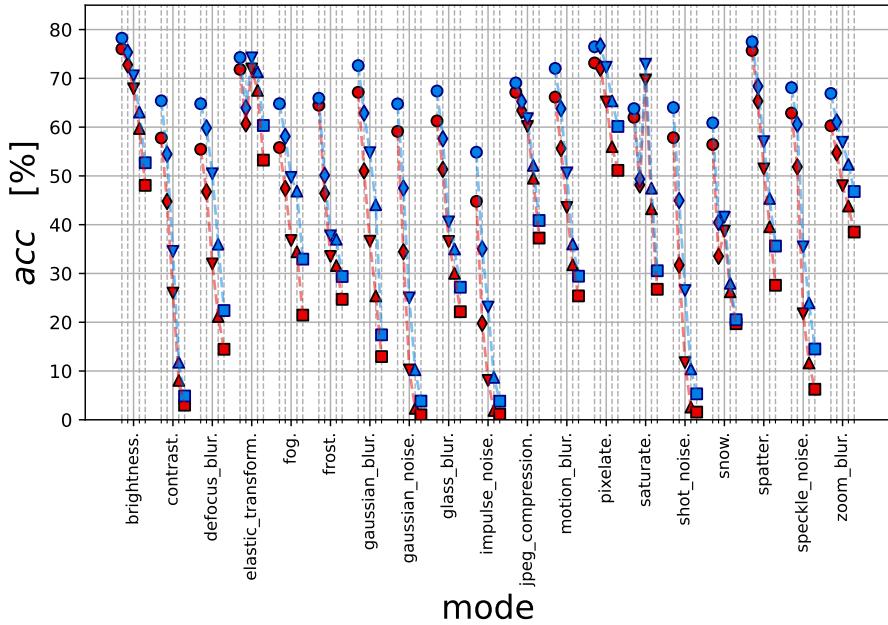
Table 17: Accuracies for MobileNet w/wo OpticsAugment evaluated on ImageNet-100-c 2D common corruptions [10].

Corruption	1			2			3			4			5		
	clean	ours	Δ												
brightness	80.00	78.96	-1.04	77.58	76.20	-1.38	74.30	71.74	-2.56	68.16	65.16	-3.00	58.74	55.76	-2.98
contrast	63.62	64.56	0.94	52.90	53.70	0.80	30.66	31.94	1.28	8.56	8.58	0.02	3.02	3.26	0.24
defocus.blur	60.30	67.52	7.22	51.82	64.18	12.36	39.78	57.46	17.68	30.04	44.38	14.34	22.42	30.80	8.38
elastic_transform	74.44	74.46	0.02	62.92	64.22	1.30	74.34	75.20	0.86	71.62	73.02	1.40	58.74	65.06	6.32
fog	63.14	62.56	-0.58	54.54	54.96	0.42	44.88	45.98	1.10	41.04	44.32	3.28	28.24	32.60	4.36
frost	68.52	67.66	-0.86	51.46	54.32	2.86	37.62	42.86	5.24	36.04	41.76	5.72	29.50	35.52	6.02
gaussian.blur	71.12	73.72	2.60	55.70	65.48	9.78	42.64	58.90	16.26	33.54	50.34	16.80	20.96	24.04	3.08
gaussian.noise	67.48	66.42	-1.06	51.34	51.88	0.54	29.38	31.02	1.64	12.72	13.90	1.18	4.20	5.36	1.16
glass.blur	64.54	67.68	3.14	54.66	60.58	5.92	40.18	47.34	7.16	33.90	41.76	7.86	26.98	34.60	7.62
impulse.noise	55.94	57.74	1.80	38.50	41.00	2.50	25.28	28.64	3.36	9.54	12.74	3.20	4.06	5.56	1.50
jpeg.compression	70.52	70.26	-0.26	66.12	66.98	0.86	62.76	64.62	1.86	50.34	56.14	5.80	37.76	45.18	7.42
motion.blur	69.78	73.82	4.04	60.54	69.84	9.30	48.90	61.24	12.34	36.26	47.78	11.52	29.52	37.44	7.92
pixelate	76.08	78.14	2.06	74.62	78.06	3.44	68.12	74.96	6.84	59.92	70.80	10.88	55.34	67.84	12.50
saturate	66.46	66.30	-0.16	53.22	52.04	-1.18	75.32	74.04	-1.28	57.16	53.92	-3.24	40.72	36.40	-4.32
shot_noise	64.52	65.10	0.58	49.62	49.52	-0.10	30.86	32.50	1.64	12.30	14.20	1.90	6.40	7.84	1.44
snow	64.30	65.32	1.02	43.38	47.36	3.98	46.30	47.28	0.98	32.76	34.08	1.32	25.06	27.30	2.24
spatter	79.26	78.28	-0.98	69.94	69.54	-0.40	59.40	61.02	1.62	51.30	55.94	4.64	40.66	45.38	4.72
speckle_noise	68.14	68.18	0.04	60.60	61.78	1.18	38.60	40.72	2.12	27.88	29.62	1.74	17.62	19.72	2.10
zoom.blur	61.66	66.86	5.20	54.94	61.14	6.20	49.94	58.18	8.24	45.12	52.92	7.80	40.08	48.34	8.26
Σ	67.89	69.13	1.25	57.07	60.15	3.07	48.38	52.93	4.55	37.80	42.70	4.90	28.95	33.05	4.10

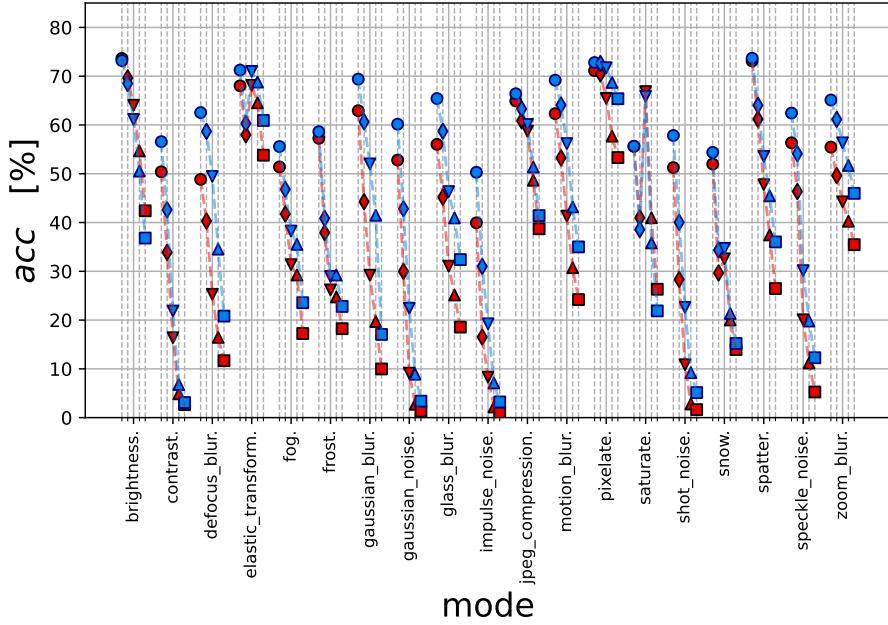
Table 18: Accuracies for ResNet101 w/wo OpticsAugment evaluated on ImageNet-100-c 2D common corruptions [10].

Corruption	1			2			3			4			5		
	clean	ours	Δ												
brightness	73.64	73.18	-0.46	69.64	68.50	-1.14	64.04	61.12	-2.92	54.68	50.54	-4.14	42.40	36.82	-5.58
contrast	50.40	56.58	6.18	33.88	42.60	8.72	16.38	21.86	5.48	4.88	6.78	1.90	2.66	3.10	0.44
defocus.blur	48.84	62.54	13.70	40.30	58.68	18.38	25.28	49.46	24.18	16.46	34.54	18.08	11.68	20.82	9.14
elastic.transform	68.02	71.26	3.24	57.98	60.30	2.32	68.12	70.98	2.86	64.54	68.80	4.26	53.80	60.92	7.12
fog	51.40	55.58	4.18	41.76	46.80	5.04	31.36	38.26	6.90	29.24	35.52	6.28	17.24	23.56	6.32
frost	57.26	58.62	1.36	37.92	40.86	2.94	26.18	28.94	2.76	24.74	29.24	4.50	18.24	22.80	4.56
gaussian.blur	62.92	69.40	6.48	44.28	60.64	16.36	29.20	52.02	22.82	19.70	41.48	21.78	9.98	17.06	7.08
gaussian.noise	52.80	60.16	7.36	29.98	42.82	12.84	9.12	22.44	13.32	2.74	8.90	6.16	1.34	3.38	2.04
glass.blur	56.02	65.42	9.40	45.18	58.72	13.54	31.06	46.34	15.28	25.14	40.94	15.80	18.56	32.40	13.84
impulse.noise	39.94	50.30	10.36	16.52	31.00	14.48	8.30	19.24	10.94	2.18	7.10	4.92	0.96	3.22	2.26
jpeg.compression	64.92	66.40	1.48	60.86	63.30	2.44	58.74	60.10	1.36	48.66	51.38	2.72	38.72	41.42	2.70
motion.blur	62.32	69.18	6.86	53.26	64.08	10.82	41.32	56.18	14.86	30.74	43.20	12.46	24.20	35.00	10.80
pixelate	71.12	72.80	1.68	70.48	72.60	2.12	65.46	71.74	6.28	57.70	68.72	11.02	53.32	65.38	12.06
saturate	55.62	55.64	0.02	41.00	38.56	-2.44	66.84	65.84	-1.00	40.98	35.82	-5.16	26.32	21.88	-4.44
shot_noise	51.26	57.84	6.58	28.32	40.04	11.72	10.84	22.60	11.76	2.80	9.22	6.42	1.64	5.14	3.50
snow	51.98	54.38	2.40	29.66	34.36	4.70	32.56	34.70	2.14	20.02	21.36	1.34	13.96	15.20	1.24
spatter	73.12	73.68	0.56	61.20	64.04	2.84	47.76	53.56	5.80	37.46	45.46	8.00	26.46	36.02	9.56
speckle.noise	56.34	62.44	6.10	46.36	54.10	7.74	20.06	30.14	10.08	11.20	19.80	8.60	5.26	12.28	7.02
zoom.blur	55.46	65.12	9.66	49.62	61.14	11.52	44.24	56.34	12.10	40.26	51.70	11.44	35.46	45.98	10.52
Σ	58.07	63.19	5.11	45.17	52.80	7.63	36.68	45.36	8.68	28.11	35.29	7.18	21.17	26.44	5.27

Table 19: Accuracies for ResNeXt50 w/wo OpticsAugment evaluated on ImageNet-100-c 2D common corruptions [10].

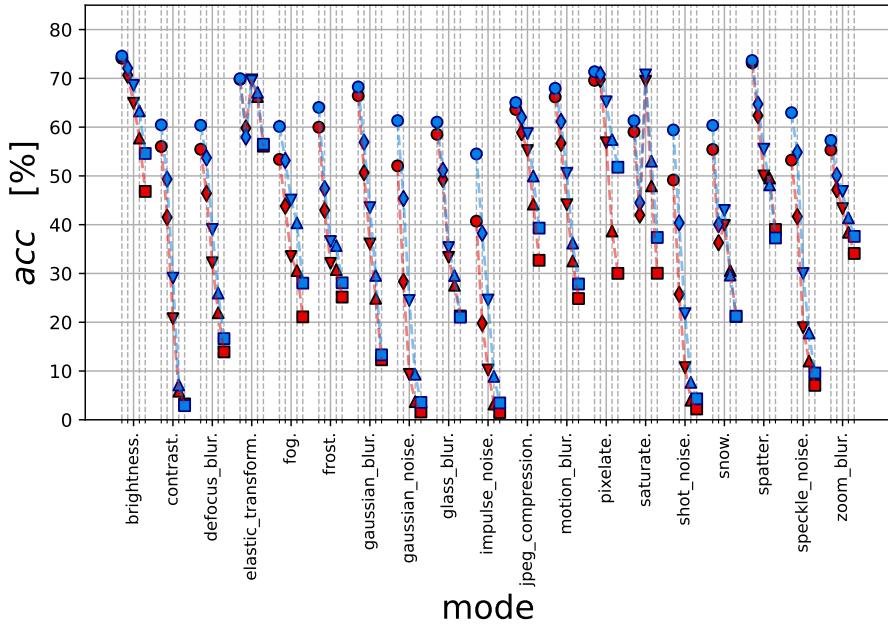


(a) DenseNet161

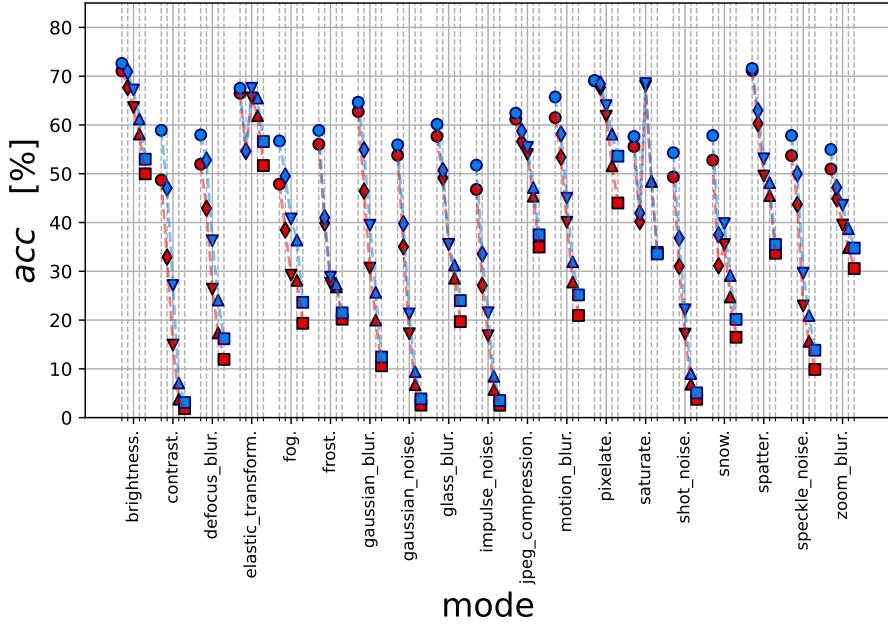


(b) ResNeXt50

Figure 13: Accuracy evaluated on ImageNet-100-C 2D common corruptions for DNNs w/wo OpticsAugment training and all severities 1-5 (circle, diamond, triangles and square markers) at each corruption. **OpticsAugment (blue)** accuracy compared to the conventionally trained DNN (red): (a) DenseNet, (b) ResNeXt50.

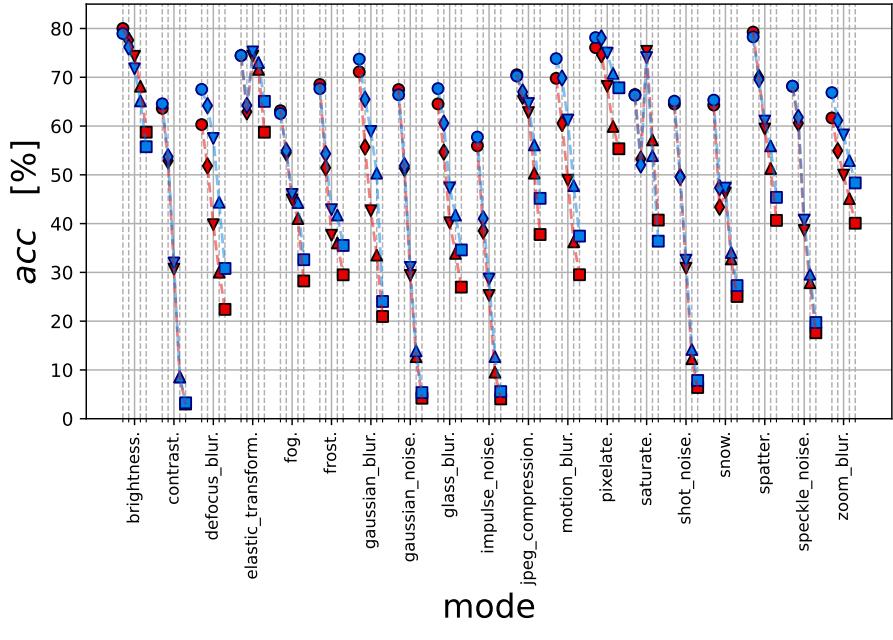


(a) EfficientNet



(b) MobileNet

Figure 14: Accuracy evaluated on ImageNet-100-C 2D common corruptions for DNNs w/wo OpticsAugment training and all severities 1-5 (circle, diamond, triangles and square markers) at each corruption. **OpticsAugment (blue)** accuracy compared to the conventionally trained DNN (red): (a) EfficientNet, (b) MobileNet.



(a) ResNet101

Figure 15: Accuracy evaluated on ImageNet-100-C 2D common corruptions for ResNet101 w/wo OpticsAugment training and all severities 1-5 (circle, diamond, triangles and square markers) at each corruption. **OpticsAugment (blue)** improves accuracy compared to the conventionally trained DNN (red).

C. Kernels

All kernels share the same baseline optical wavefront model, which is adapted from [41] and evaluated at the center, i.e. at field 0° with little aberrations, but non-zero. Although isolated Zernike modes are used to generate the different kernels, this ensures a more realistic PSF to avoid for instance a PSF depending solely on coma aberration. The baseline model consists of the wavefront description displayed in Tab. 20. The different kernels are then generated by adding the isolated Zernike modes from Tab. 1 to the baseline wavefront model with Eq. 2 and retrieving a PSF with Eq. 1. Although real lenses may consist of dozens of different balanced Zernike modes, the amplifying of a particular Zernike mode allows for categorization and benchmarking to particular aberrations. This creates the kernels from Fig. 17. In practice, a more balanced distribution of coefficients is observed.

Color	4	9	15	16
red	0.32671	0.088223	-0.061867	-4.7631E-06
green	0.11273	0.095923	-0.069497	-5.3967E-06
blue	-0.41772	0.10825	-0.085119	-6.7436E-06

Table 20: Wavefront baseline model used to produce the kernels (a,d,e) in Fig. 1 and Fig. 17. Other coefficients are zero, each value is in multiples of the wavelength λ for RGB color channels red, green and blue: $0.6563\text{ }\mu\text{m}$, $0.5876\text{ }\mu\text{m}$ and $0.4861\text{ }\mu\text{m}$. Zernike modes are in Fringe ordering, from left to right: defocus, spherical, secondary spherical and vertical quadrofoil as from [44].

We also include another experimental set of kernels sharing the baseline model from Tab. 20, but, to further increase chromatic aberrations, with red and blue channels merged. Thus, only the blue and green coefficient values are used and the red channel shares the same coefficients as the blue channel. Wavelength dependent scaling is turned off for the merged channels. The green channel is unchanged. This creates the reddish and greenish PSF kernels from Fig. 18 and the kernels (b,c,f) in Fig. 1, why we call the set of kernels RG or OpticsBenchRG.

The defocus blur kernels from [10] are reproduced in Fig. 16 for all severities to allow for comparison to disk-shaped kernels. As these kernels equally blur all color channels, they are grayscaled.



Figure 16: Defocus blur from [10] for severities 1-5 used for kernel matching and as *base blur type* for comparisons.

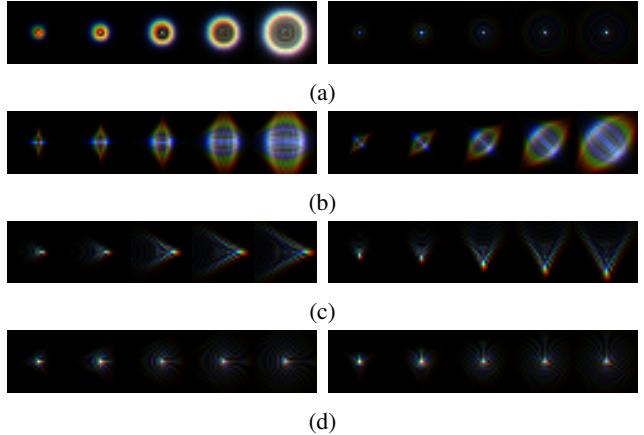


Figure 17: Kernels used to generate OpticsBench. Each row contains the different severities (1-5) for a single corruption using two Zernike modes. Larger kernel size leads to more severe blurring. (a) Defocus & Spherical, (b) Astigmatism, (c) Coma, (d) Trefoil. All kernels are l_1 -normalized and therefore have the same energy.

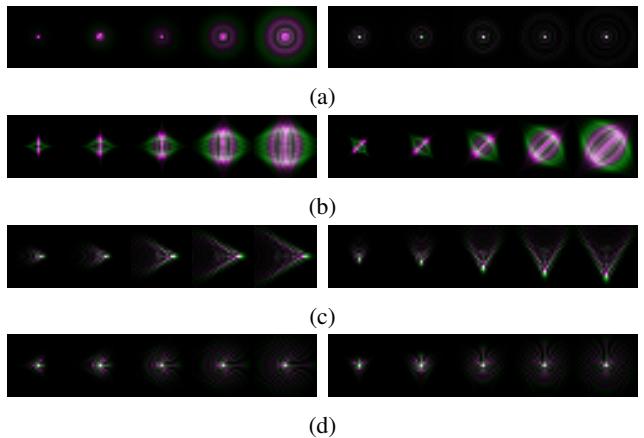


Figure 18: Kernels used to generate OpticsBenchRG. Each row contains the different severities (1-5) for a single corruption using two Zernike modes. Larger kernel size leads to more severe blurring. (a) Defocus & Spherical, (b) Astigmatism, (c) Coma, (d) Trefoil. All kernels are l_1 -normalized and therefore have the same energy.

D. Image examples

This section shows images from OpticsBench. Each row contains a single corruption and three image examples with increasing severities (from left to right). The corruptions are sorted as: astigmatism, defocus & spherical, coma, trefoil. The upper left image represents astigmatism at severity 1, the lower right image shows trefoil at severity 5.

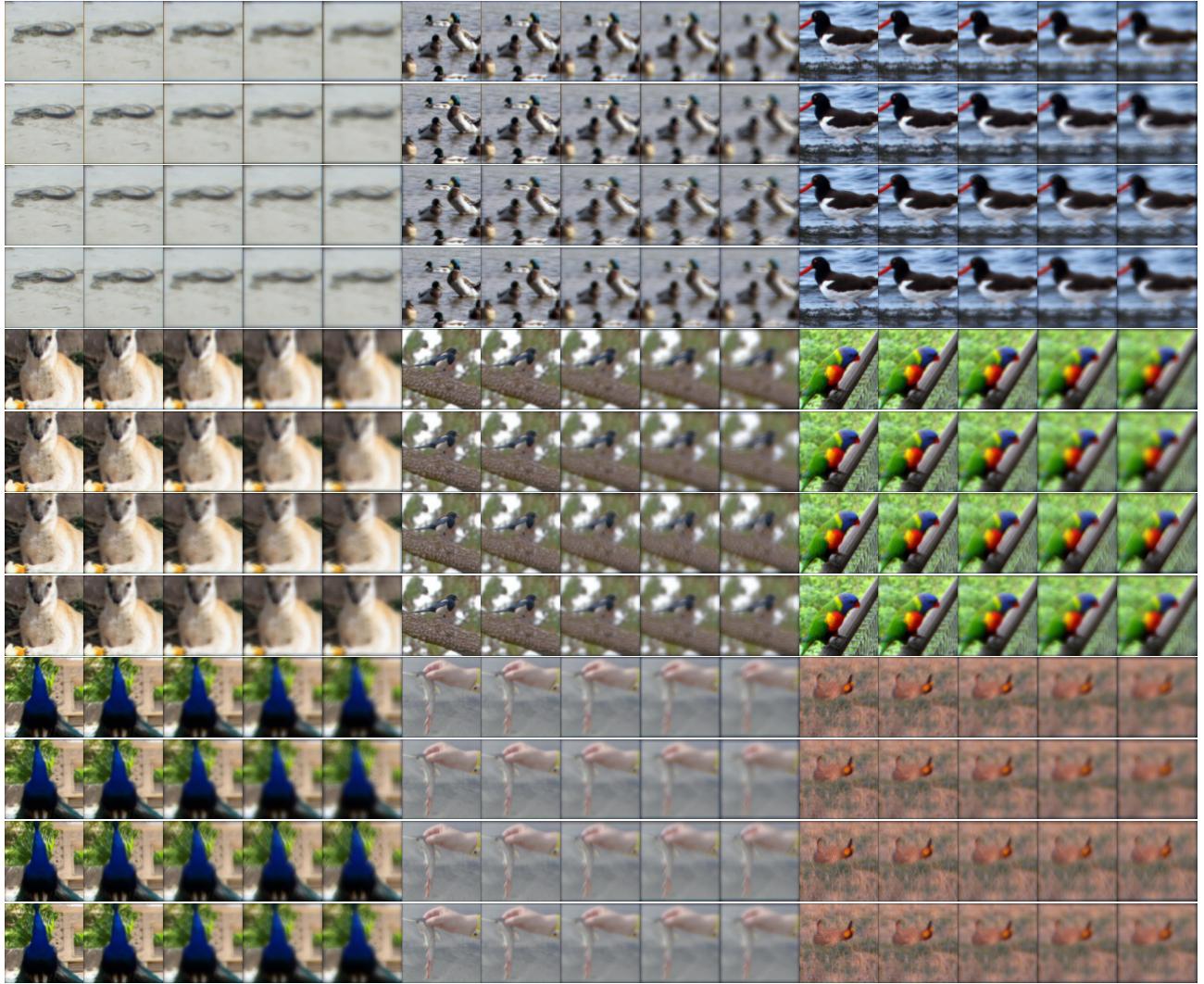


Figure 19: Image examples from ImageNet-1k OpticsBench.

E. OpticsBenchRG

This appendix includes exemplary evaluations on OpticsBenchRG on ImageNet and ImageNet-100. The benchmark consists of images blurred with the reddish and greenish optical kernels from Fig. 18 in App. C. Tab. 21 lists the average accuracies for all OpticsBenchRG corruptions. OpticsAugment (ours) achieves constantly better results. For selected DNNs Fig. 20 and Fig. 21 show the accuracies separately for each corruption and w/wo OpticsAugment (out of domain kernels compared to OpticsBenchRG) training.

Additionally, ranking comparisons on ImageNet and OpticsBenchRG for the 70 pretrained DNNs (5 from Robust-Bench leaderboard and 65 from PyTorch) are shown for selected severities in Fig. 22 for comparison with App. A.

Model	1	2	3	4	5
DenseNet (ours)	64.78	59.41	47.75	36.41	29.66
DenseNet	54.53	45.09	31.37	22.73	18.43
EfficientNet (ours)	60.55	54.23	42.50	32.41	26.13
EfficientNet	53.38	43.99	30.91	22.20	17.61
MobileNet (ours)	56.55	50.49	36.58	25.95	20.91
MobileNet	49.71	39.56	25.60	18.81	15.55
ResNet101 (ours)	67.95	63.90	54.34	43.11	34.75
ResNet101	60.42	52.44	41.21	33.31	27.85
ResNeXt50 (ours)	59.59	54.50	43.57	31.91	25.04
ResNeXt50	47.62	37.87	25.66	18.61	15.29

Table 21: Accuracies w/wo OpticsAugment evaluated on ImageNet-100 OpticsBenchRG. Average over all corruptions. Even when changing the optics corruption (*i.e.* in an out of domain setting), the proposed augmentation consistently leads to higher classification accuracies.

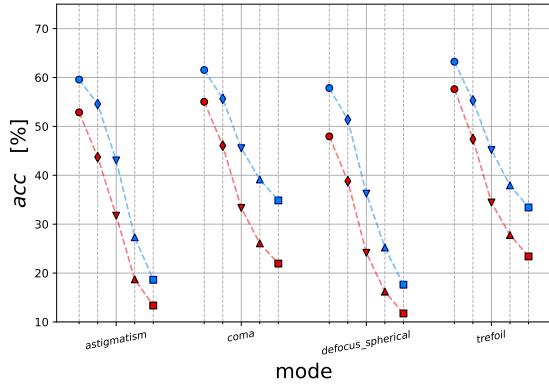
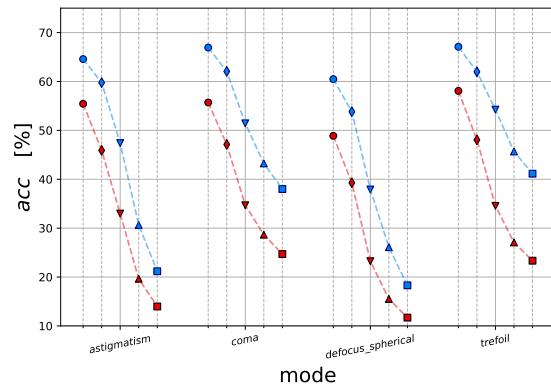
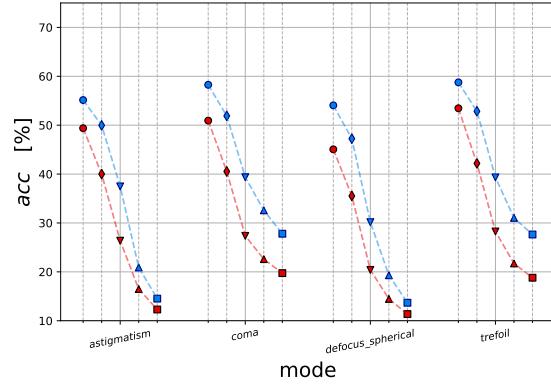


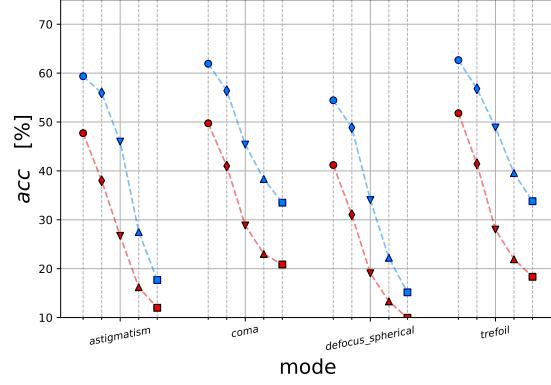
Figure 20: Accuracy evaluated on **OpticsBenchRG**-ImageNet-100 for EfficientNet w/wo OpticsAugment training and all severities 1-5 (circle to square markers) at each corruption. Although the exact kernels haven't been visible during training, still **OpticsAugment (blue)** improves accuracy compared to the conventionally trained DNN (red).



(a) DenseNet161

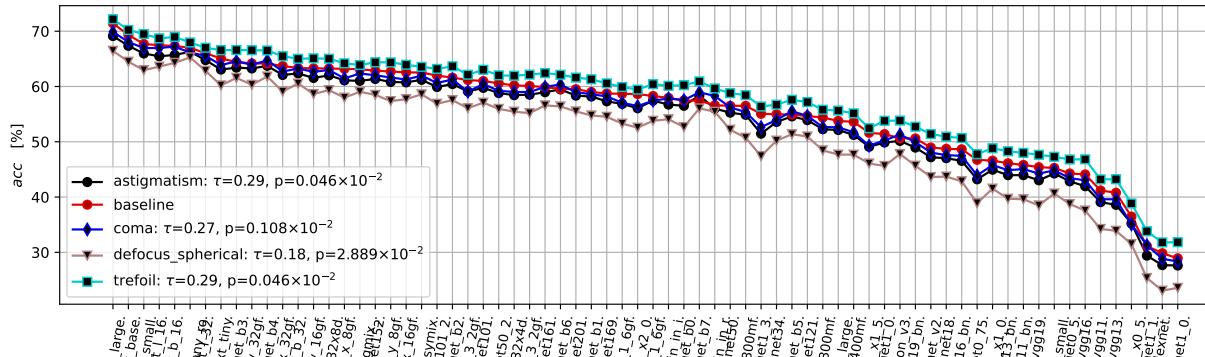


(b) MobileNet

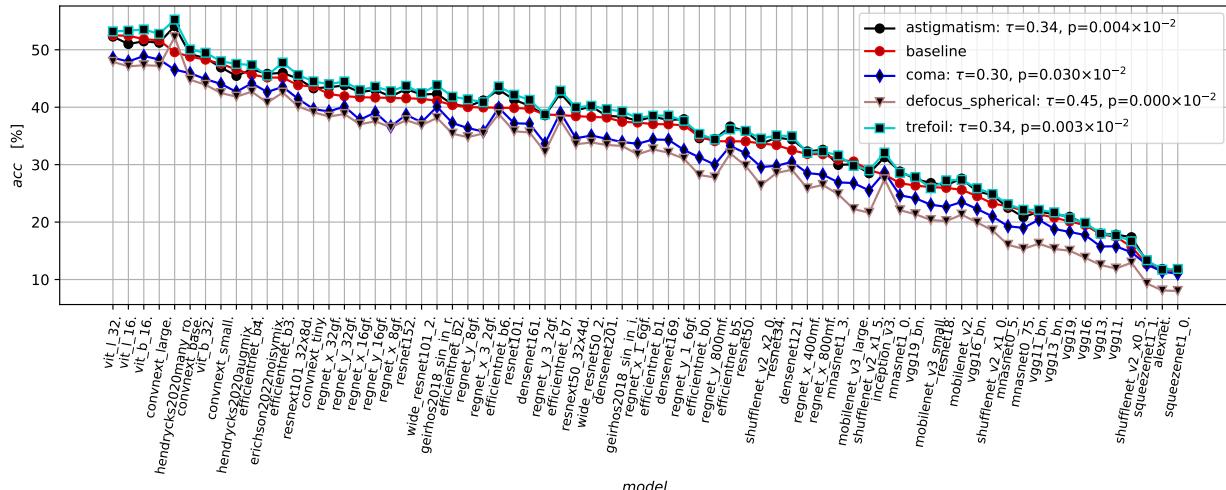


(c) ResNeXt50

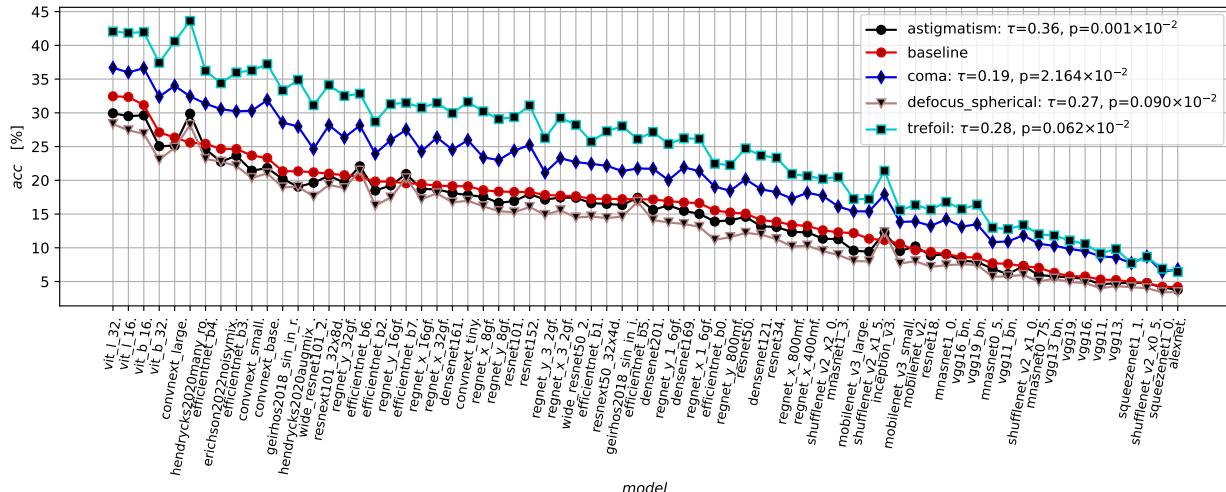
Figure 21: **OpticsBenchRG**-ImageNet-100 for DNNs w/wo OpticsAugment training and all severities 1-5 (circle to square markers). Although the exact kernels haven't been visible during training, **OpticsAugment (blue)** improves accuracy compared to the conventionally trained DNN (red): (a) DenseNet161, (b) MobileNet and (c) ResNeXt50.



(a)



(b)



(c)

Figure 22: Ranking comparison of baseline and all corruptions for severities 1,3 and 5 (a-c).

F. Implementation and additional analysis

Here, we include additional analysis on various datasets and give further implementation details.

F.1. Implementation details

We also provide code for a more detailed insight into the structure and run experiments. The code is organized into two main parts: Benchmark (OpticsBench and OpticsBenchRG) and training (OpticsAugment, variations and baseline training without additional augmentation). The whole code submission uses Python 3.6+ for downward compatibility for training on a high performance cluster (HPC) and Python ≥ 3.8 for the benchmark and pretrained variants. The latter allows to use a more recent pytorch and torchvision version to include VisionTransformer networks and other types.

Training is run on a HPC using slurm job scheduling and V100 GPUs. Training on ImageNet-100 required single V100 GPUs, but also multi GPU training had been utilized. The training for 90 epochs takes about one day for smaller DNNs such as EfficientNet and two days for larger DNNs such as ResNet101. The exact hyperparameter settings can be found in the code submission in recipes, however the particular batch size had been adjusted to increase the speed. For OpticsAugment training $\alpha = 1.0$ and $severity = 3$ is set. For training the ImageNet-100 train split is split again into a validation and train split to avoid any overlap with the original validation dataset, which is used as test dataset.

F.2. Additional analysis

First, an evaluation of adversarial robustness for different ImageNet-100 trained DNNs is presented in Tab. 22. Ours uses the OpticsAugment training scheme and is compared to a conventionally trained DNN on the same dataset. To allow for evaluation on ImageNet’s validation dataset, the train set is split into a validation and train split. To lower the computational resources needed for the computation, 1000 validation images are randomly selected and saved as test dataset for adversarial robustness. The attacks had been lowered to l_2 and $\epsilon = 4/255$ to avoid exclusively successful attacks. Still, with this setting no clear trend can be observed, the overall robustness to the attacks is low, but on average OpticsAugment does not lower adversarial robustness compared to a conventionally trained DNN. The evaluation for each DNN takes several hours on a NVIDIA GeForce 3080Ti 12GB VRAM GPU.

Additionally, in Tab. 24 and 23 the results for a pipelining of AugMix and OpticsAugment during ImageNet-100 training are listed for an evaluation on OpticsBenchRG. EfficientNet and MobileNet are either trained with only OpticsAugment (red) or with OpticsAugment and AugMix [22]. Fig. 23 visualizes the same DNNs on 2D common corrup-

DNN	Robust Acc	APGD-CE	APGD-DLR
DenseNet	5.2	13.9	5.7
DenseNet (ours)	6.4	14.5	6.4
EfficientNet	2.1	8.8	2.4
EfficientNet (ours)	1.7	8.4	1.9
MobileNet	1.2	6.2	1.6
MobileNet (ours)	1.8	7.6	2.2
ResNeXt50	1.2	11.3	1.6
ResNeXt50 (ours)	3.1	8.9	3.6

Table 22: Adversarial robustness in % to adversarial attacks using APGD-CE and APGD-DLR from AutoAttack [15], l_2 and $\epsilon = 4/255$, batch size 32 and 5 restarts on 1000 validation images of ImageNet-100.

tions. This shows another application scenario of OpticsAugment.

	1			2			3			4			5		
Corruption	ours & AugMix	ours	Δ												
astigmatism	59.52	59.58	0.06	53.00	54.58	1.58	38.82	43.04	4.22	23.38	27.32	3.94	16.06	18.62	2.56
coma	64.96	61.54	-3.42	57.74	55.66	-2.08	46.32	45.54	-0.78	37.70	39.14	1.44	32.50	34.86	2.36
defocus_spherical	58.00	57.84	-0.16	50.38	51.38	1.00	33.14	36.24	3.10	22.64	25.22	2.58	17.98	17.62	-0.36
trefoil	65.30	63.22	-2.08	57.42	55.30	-2.12	45.12	45.16	0.04	38.30	37.94	-0.36	34.82	33.42	-1.40
Σ	61.95	60.55	-1.40	54.64	54.23	-0.40	40.85	42.50	1.64	30.50	32.41	1.90	25.34	26.13	0.79

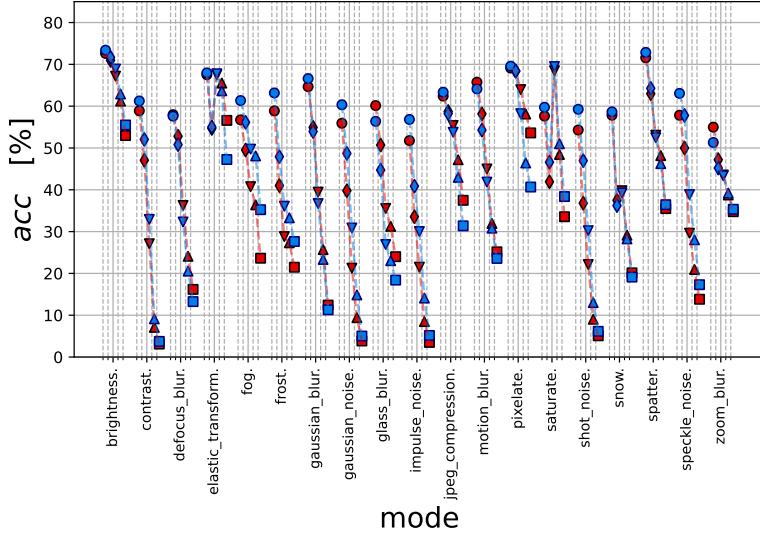
Table 23: Accuracies for EfficientNet & OpticsAugment w/wo AugMix. Evaluated on ImageNet-100 OpticsBenchRG.

	1			2			3			4			5		
Corruption	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ
astigmatism	56.14	55.14	-1.00	48.26	49.96	1.70	32.64	37.48	4.84	18.72	20.90	2.18	12.98	14.52	1.54
coma	60.12	58.26	-1.86	53.12	51.90	-1.22	39.46	39.36	-0.10	32.08	32.58	0.50	26.50	27.80	1.30
defocus_spherical	55.50	54.06	-1.44	47.14	47.24	0.10	29.12	30.16	1.04	20.70	19.30	-1.40	15.20	13.68	-1.52
trefoil	61.48	58.76	-2.72	53.54	52.84	-0.70	39.36	39.32	-0.04	32.40	31.04	-1.36	29.38	27.64	-1.74
Σ	58.31	56.55	-1.76	50.51	50.49	-0.03	35.14	36.58	1.44	25.98	25.95	-0.02	21.02	20.91	-0.10

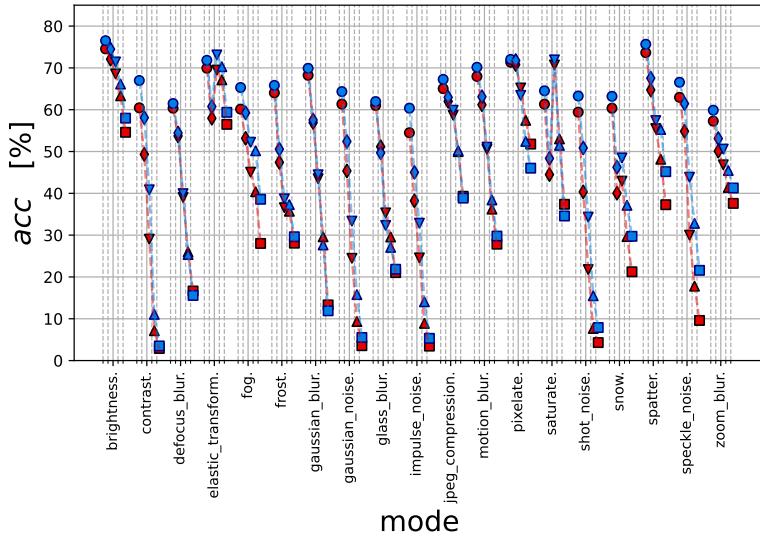
Table 24: Accuracies for MobileNet & OpticsAugment w/wo AugMix. Evaluated on ImageNet-100 OpticsBenchRG.

	1			2			3			4			5		
Corruption	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ	ours & AugMix	ours	Δ
brightness	76.52	74.56	-1.96	74.48	72.08	-2.40	71.42	68.56	-2.86	66.14	63.32	-2.82	57.98	54.60	-3.38
contrast	67.00	60.46	-6.54	58.10	49.32	-8.78	40.84	29.04	-11.80	11.06	7.14	-3.92	3.50	2.90	-0.60
defocus_blur	61.48	60.38	-1.10	54.42	53.72	-0.70	39.92	39.02	-0.90	25.38	25.98	0.60	15.58	16.64	1.06
elastic_transform	71.82	69.94	-1.88	60.76	57.96	-2.80	73.10	69.48	-3.62	70.28	67.14	-3.14	59.38	56.50	-2.88
fog	65.32	60.14	-5.18	59.26	53.16	-6.10	52.22	45.06	-7.16	50.18	40.38	-9.80	38.58	28.02	-10.56
frost	65.82	64.04	-1.78	50.56	47.40	-3.16	38.68	36.56	-2.12	37.30	35.72	-1.58	29.62	28.08	-1.54
gaussian_blur	69.90	68.24	-1.66	57.54	56.92	-0.62	44.44	43.50	-0.94	27.66	29.60	1.94	11.90	13.32	1.42
gaussian_noise	64.34	61.34	-3.00	52.40	45.36	-7.04	33.36	24.46	-8.90	15.78	9.34	-6.44	5.52	3.56	-1.96
glass_blur	61.94	61.02	-0.92	49.70	51.16	1.46	32.32	35.32	3.00	27.08	29.56	2.48	21.84	21.04	-0.80
impulse_noise	60.38	54.50	-5.88	45.02	38.22	-6.80	32.86	24.56	-8.30	14.06	8.90	-5.16	5.32	3.46	-1.86
jpeg_compression	67.26	65.04	-2.22	62.96	62.00	-0.96	59.88	58.68	-1.20	50.24	49.98	-0.26	38.86	39.30	0.44
motion_blur	70.16	67.96	-2.20	63.10	61.18	-1.92	51.04	50.54	-0.50	38.42	36.22	-2.20	29.78	27.84	-1.94
pixelate	72.04	71.36	-0.68	71.76	70.80	-0.96	63.44	65.20	1.76	52.42	57.46	5.04	46.02	51.78	5.76
saturate	64.52	61.32	-3.20	48.36	44.48	-3.88	71.92	70.70	-1.22	51.48	53.02	1.54	34.58	37.38	2.80
shot_noise	63.28	59.42	-3.86	50.86	40.36	-10.50	34.32	21.76	-12.56	15.50	7.68	-7.82	7.90	4.30	-3.60
snow	63.20	60.36	-2.84	46.24	40.02	-6.22	48.48	42.92	-5.56	37.14	29.66	-7.48	29.72	21.24	-8.48
spatter	75.66	73.66	-2.00	67.54	64.72	-2.82	57.40	55.48	-1.92	55.28	48.16	-7.12	45.18	37.28	-7.90
speckle_noise	66.56	62.96	-3.60	61.46	54.84	-6.62	43.86	30.00	-13.86	32.82	17.80	-15.02	21.58	9.60	-11.98
zoom_blur	59.88	57.28	-2.60	53.10	50.08	-3.02	50.58	46.82	-3.76	45.46	41.40	-4.06	41.28	37.60	-3.68
Σ	66.69	63.89	-2.79	57.24	53.36	-3.89	49.48	45.14	-4.34	38.09	34.66	-3.43	28.64	26.02	-2.61

Table 25: Accuracies for EfficientNet with pipelining of AugMix [22] & OpticsAugment and only OpticsAugment evaluated on ImageNet-100-c 2D common corruptions [10].



(a) MobileNet



(b) EfficientNet

Figure 23: Pipelining of AugMix [22] and OpticsAugment: Blue represents now a cascaded application of AugMix and OpticsAugment. Red represents the OpticsAugment trained version from Fig. 14b and 14a respectively. (a) MobileNet and (b) EfficientNet. Evaluated on 2D common corruptions on ImageNet-100-C [10].