A. Supplementary to Method

Here, we provide the proof for Proposition 1

Proposition 1.

(a) If $\min_i \|\widehat{\phi}(\mathbf{x}) - \widehat{\mathbf{z}}_i\|_2 \geq 2$*, then* $S(\mathbf{x}) \leq 0$.

(b) Suppose $\max_{i \leq k} \|\widehat{\phi}(\mathbf{x}) - \widehat{\mathbf{z}}_{(i)}\|_2 < \epsilon$*. If* $\min_{i \leq k} s_{(i)} > M$*, then*

$$S(\mathbf{x}) > M(S_{base}(\mathbf{x}) - \epsilon/2) \tag{5}$$

On the other hand, if $\max_{i \leq k} s_{(i)} \leq \delta$*, then*

$$S(\mathbf{x}) \leq \delta S_{base}(\mathbf{x}) \tag{6}$$

Proof. (a) Note that

$$\|\widehat{\phi}(\mathbf{x}) - \widehat{\mathbf{z}}_i\|_2 = 2 - 2\,\mathrm{sim}(\mathbf{z}_i, \mathbf{z}). \tag{7}$$

Hence, if $\min_i \|\widehat{\phi}(\mathbf{x}) - \widehat{\mathbf{z}}_i\|_2 > 2$, then $\max_i \mathrm{sim}(\mathbf{z}_i, \mathbf{z}) \leq 0$. Therefore,

$$S(\mathbf{x}) = S_{base}(\mathbf{x}) \cdot \frac{1}{k} \sum_{i=1}^{k} s_{(i)}\,\mathrm{sim}(\mathbf{z}_{(i)}, \mathbf{z}) \leq S_{base}(\mathbf{x}) \cdot 0. \tag{8}$$

(b) Assume $\max_{i \leq k} \|\widehat{\phi}(\mathbf{x}) - \widehat{\mathbf{z}}_{(i)}\|_2 < \epsilon$. Then, $\mathrm{sim}(\mathbf{z}_{(i)}, \mathbf{z}) \geq 1 - \epsilon/2$ due to (7). Therefore, if $\min_{i \leq k} s_{(i)} > M$

$$\begin{aligned} S(\mathbf{x}) &= S_{base}(\mathbf{x}) \frac{1}{k} \sum_{i=1}^{k} s_{(i)}\,\mathrm{sim}(\mathbf{z}_{(i)}, \mathbf{z}) && (9) \\ &\geq S_{base}(\mathbf{x})(1 - \epsilon/2) \frac{1}{k} \sum_{i=1}^{k} s_{(i)} && (10) \\ &> S_{base}(\mathbf{x})(1 - \epsilon/2) \frac{1}{k} kM && (11) \\ &= M S_{base}(\mathbf{x})(1 - \epsilon/2). && (12) \\ & && (13) \end{aligned}$$

On the other hand, if $\max_{i \leq k} s_{(i)} \leq \delta$, then

$$S(\mathbf{x}) = S_{base}(\mathbf{x}) \frac{1}{k} \sum_{i=1}^{k} s_{(i)}\,\mathrm{sim}(\mathbf{z}_{(i)}, \mathbf{z}) \leq S_{base}(\mathbf{x}) \frac{1}{k} k\delta \cdot 1 = \delta S_{base}(\mathbf{x}) \tag{14}$$

as $\mathrm{sim}(\mathbf{z}_{(i)}, \mathbf{z}) \leq 1$. This completes the proof. □

Corollary 2. *Consider* $\mathbf{x}_h$ *and* $\mathbf{x}_l$ *such that*

$$s_{(1)_h}\,\mathrm{sim}(\mathbf{z}_{(1)_h}, \mathbf{z}_h) \geq \cdots \geq s_{(n)_h}\,\mathrm{sim}(\mathbf{z}_{(n)_h}, \mathbf{z}_h). \tag{15}$$

and

$$s_{(1)_l}\,\mathrm{sim}(\mathbf{z}_{(1)_l}, \mathbf{z}_l) \geq \cdots \geq s_{(n)_l}\,\mathrm{sim}(\mathbf{z}_{(n)_l}, \mathbf{z}_l). \tag{16}$$

where $\mathbf{z}_h = \phi(\mathbf{x}_h)$ *and* $\mathbf{z}_l = \phi(\mathbf{x}_l)$*. Suppose* $\max_{i \leq k} \|\widehat{\phi}(\mathbf{x}_h) - \widehat{\mathbf{z}}_{(i)_h}\|_2 < \epsilon$ *and* $\max_{i \leq k} \|\widehat{\phi}(\mathbf{x}_l) - \widehat{\mathbf{z}}_{(i)_l}\|_2 < \epsilon$*. Suppose* $\min_{i \leq k} s_{(i)_h}(\mathbf{x}_h) > M$ *and* $\max_{i \leq k} s_{(i)_l}(\mathbf{x}_h) \leq \delta$*. Then,*

$$\frac{S(\mathbf{x}_h)}{S_{base}(\mathbf{x}_h)} > \frac{S(\mathbf{x}_l)}{S_{base}(\mathbf{x}_l)} \tag{17}$$

if

$$M - \delta > \frac{\epsilon}{2 S_{base}(\mathbf{x}_h)} \tag{18}$$

Method	OOD Model	iNaturalist FPR	iNaturalist AUROC	iNaturalist AUPR	SUN FPR	SUN AUROC	SUN AUPR	Places FPR	Places AUROC	Places AUPR	Textures FPR	Textures AUROC	Textures AUPR	OpenImage-O FPR	OpenImage-O AUROC	OpenImage-O AUPR	Average FPR	Average AUROC	Average AUPR
MSP	ResNet-50	29.74	93.78	98.59	59.54	84.56	95.69	60.94	84.28	95.92	50.02	84.90	97.45	47.44	89.68	95.90	49.54	87.44	96.71
MaxLogit	ResNet-50	22.06	95.99	99.15	50.90	88.43	96.99	53.78	87.37	96.79	42.25	88.42	97.90	41.63	92.23	97.04	42.12	90.49	97.57
KL	ResNet-50	20.98	96.17	99.19	47.06	88.91	97.08	51.15	87.70	96.85	39.31	88.90	97.96	41.57	92.32	97.06	40.01	90.80	97.63
ViM	ResNet-50	16.68	96.87	99.35	39.34	90.86	97.56	49.21	88.48	97.03	15.87	94.21	98.77	28.18	94.59	97.94	29.86	**93.00**	**98.13**
Mahalanobis	ResNet-50	35.04	94.79	98.94	64.99	86.55	96.73	70.31	83.92	96.00	15.02	95.52	99.29	37.52	93.89	97.84	44.58	90.93	97.76
SSD	ResNet-50	33.76	94.64	98.89	56.04	88.35	97.14	65.12	84.52	96.06	11.81	96.54	99.45	37.97	93.29	97.56	40.94	91.47	97.82
Gradnorm	ResNet-50	13.70	97.24	99.41	28.75	93.34	98.34	37.73	91.04	97.71	28.69	91.88	98.55	35.75	91.50	96.46	28.92	93.00	98.09
KNN	ResNet-50	37.53	93.86	98.67	54.57	86.98	96.71	63.34	83.54	95.68	17.45	94.13	99.00	40.77	92.46	97.15	42.73	90.19	97.44
Energy	ResNet-50	20.98	96.17	99.19	47.05	88.91	97.08	51.15	87.70	96.85	39.31	88.90	97.96	41.56	92.32	97.06	40.01	90.80	97.63
NNGuide	ResNet-50	12.02	97.47	99.43	31.62	91.66	97.63	38.88	90.12	97.34	24.93	91.52	98.27	31.60	93.66	97.47	**27.81**	92.89	98.03
MSP	MobileNet	72.65	84.01	96.27	81.78	76.49	93.90	81.39	76.23	93.83	73.90	78.51	96.43	75.47	82.04	92.83	77.04	79.46	94.65
MaxLogit	MobileNet	76.24	81.80	95.62	83.00	74.88	93.31	82.48	74.72	93.28	73.55	77.66	96.21	75.03	80.90	92.06	78.06	77.99	94.10
KL	MobileNet	91.93	67.88	91.98	94.36	65.80	91.02	93.16	66.26	91.10	80.28	71.55	95.19	83.78	72.78	88.50	88.70	68.85	91.56
ViM	MobileNet	86.86	69.57	92.14	88.67	66.37	90.80	92.16	62.43	89.56	40.71	89.59	98.34	72.95	80.01	91.79	76.27	73.59	92.53
Mahalanobis	MobileNet	66.86	82.62	95.80	80.01	72.49	92.61	86.51	67.54	91.02	31.95	92.54	98.85	59.00	86.26	94.53	**64.87**	80.29	94.56
SSD	MobileNet	86.34	64.32	89.37	88.42	61.87	88.52	93.24	53.99	85.57	41.68	90.45	98.67	79.21	74.42	88.79	77.78	69.01	90.18
Gradnorm	MobileNet	94.24	62.85	90.08	93.66	63.23	89.80	95.24	60.18	88.83	78.56	73.61	95.79	87.69	66.52	84.91	89.88	65.28	89.88
KNN	MobileNet	81.76	75.73	94.17	91.17	66.04	90.96	92.62	62.02	89.56	35.80	90.87	98.50	69.87	81.43	92.54	74.24	75.22	93.14
Energy	MobileNet	91.92	67.88	91.98	94.36	65.80	91.02	93.16	66.26	91.10	80.28	71.55	95.19	83.78	72.78	88.50	88.70	68.85	91.56
NNGuide	MobileNet	68.24	82.07	95.69	79.57	76.10	93.86	81.87	74.23	93.19	38.78	89.32	98.18	61.16	84.58	93.77	65.92	**81.26**	**94.94**
MSP	ViT	27.58	93.96	98.63	57.43	85.18	96.36	61.13	84.34	96.12	53.21	84.96	97.61	44.32	89.89	95.95	48.74	87.67	96.94
MaxLogit	ViT	13.19	97.19	99.37	47.45	86.80	96.43	54.36	83.13	95.20	44.70	86.11	97.52	28.41	93.23	97.02	37.62	89.29	97.11
KL	ViT	12.64	97.34	99.40	48.05	86.47	96.33	56.41	82.22	94.93	46.79	85.72	97.47	28.33	93.31	97.04	38.44	89.01	97.03
ViM	ViT	3.42	99.20	99.82	49.66	88.05	96.86	59.69	83.68	95.58	42.55	88.46	98.11	20.50	95.79	98.29	35.16	91.04	97.73
Mahalanobis	ViT	4.94	98.85	99.74	58.77	88.15	97.07	65.62	85.46	96.45	43.49	90.30	98.60	23.87	95.92	98.53	39.34	91.73	98.08
SSD	ViT	11.19	97.50	99.43	84.91	70.87	92.07	88.23	65.10	90.29	69.38	79.81	96.69	45.01	88.62	95.24	59.74	80.38	94.74
Gradnorm	ViT	14.06	96.62	99.14	46.68	86.60	96.09	56.70	82.84	94.95	43.37	87.73	97.89	29.41	92.63	96.50	38.04	89.28	96.91
KNN	ViT	29.46	94.07	98.64	72.15	83.88	95.76	74.17	81.47	95.36	51.21	87.18	98.06	45.25	91.49	96.81	54.45	87.62	96.93
Energy	ViT	12.64	97.34	99.40	48.05	86.47	96.33	56.41	82.22	94.93	46.79	85.72	97.47	28.33	93.31	97.04	38.44	89.01	97.03
NNGuide	ViT	9.17	97.96	99.55	45.64	90.03	97.48	53.82	87.25	96.75	39.26	90.01	98.42	23.11	95.47	98.28	**34.20**	**92.14**	**98.10**
MSP	RegNet	23.62	94.64	98.75	52.53	86.58	96.70	56.83	85.13	96.32	49.22	86.47	97.97	34.65	91.94	96.75	43.37	88.95	97.30
MaxLogit	RegNet	7.79	98.03	99.52	31.68	91.55	97.79	41.05	88.08	96.78	32.73	91.19	98.64	16.76	95.68	98.06	26.00	92.91	98.16
KL	RegNet	6.58	98.29	99.58	29.46	91.85	97.84	40.71	87.89	96.70	30.87	91.51	98.68	16.10	95.83	98.10	24.74	93.07	98.18
ViM	RegNet	1.97	99.52	99.90	28.19	93.15	98.30	42.72	89.05	97.26	20.53	95.58	99.40	13.55	97.15	98.87	21.39	94.89	98.74
Mahalanobis	RegNet	2.22	99.36	99.87	49.30	89.85	97.54	61.84	85.77	96.54	27.91	93.90	99.15	19.50	96.48	98.71	32.15	93.07	98.36
SSD	RegNet	5.09	98.82	99.76	60.33	85.88	96.55	70.87	80.27	95.08	38.14	92.58	99.01	28.75	93.54	97.43	40.64	90.22	97.57
Gradnorm	RegNet	87.58	57.01	87.08	82.97	65.84	90.21	91.01	56.04	86.70	74.81	75.63	96.20	77.95	60.39	78.62	82.86	62.98	87.76
KNN	RegNet	4.30	98.76	99.73	46.12	88.45	96.69	56.28	85.15	96.11	28.33	91.93	98.72	21.26	95.51	98.28	31.26	91.96	97.91
Energy	RegNet	6.68	98.28	99.57	29.41	91.88	97.85	40.51	87.97	96.72	30.85	91.48	98.68	16.19	95.81	98.09	24.73	93.08	98.18
NNGuide	RegNet	1.83	99.57	99.90	21.58	94.43	98.58	31.47	91.87	97.92	17.00	95.82	99.42	10.79	97.73	99.09	**16.53**	**95.89**	**98.98**

Table 6. Results on ImageNet-1k (ID) across five different OODs (*i.e*. iNaturalist, SUN, Places, Textures, OpenImage-O).

Proof. Note that we have (5) and (6). Thus, we have

$$\frac{S(\mathbf{x}_h)}{S_{base}(\mathbf{x}_h)} > \frac{M(S_{base}(\mathbf{x}_h) - \epsilon/2)}{S_{base}(\mathbf{x}_h)} \geq \frac{\delta S_{base}(\mathbf{x}_l)}{S_{base}(\mathbf{x}_l)} \geq \frac{S(\mathbf{x}_l)}{S_{base}(\mathbf{x}_l)} \tag{19}$$

if and only if

$$M - \delta - \frac{\epsilon}{2S_{base}(\mathbf{x}_h)} > 0 \tag{20}$$

which is equivalent to $M - \delta > \frac{\epsilon}{2S_{base}(\mathbf{x}_h)}$. This completes the proof. $\square$

Corollary 2 states the following: Consider $\mathbf{x}_h$ in a high confidence region, and $\mathbf{x}_l$ in a relatively lower confidence region. Assume both $\mathbf{x}_h$ and $\mathbf{x}_l$ are near to the train ID data (*i.e*. bank set). Then, the incremental factor is higher on $\mathbf{x}_h$ than $\mathbf{x}_l$ if $\mathbf{x}_h$ if the nearest neighbors to $\mathbf{x}_h$ have sufficiently high confidence.

B. Supplementary to Experiments

B.1. Evaluation on ImageNet-1k

Backbone models We evaluate detection scores on four different model architectures ResNet-50 [12], MobileNet [30], ViT [9], and RegNet [27].

- We use ResNet-50 trained on ImageNet-1k from scratch. The model can be downloaded from `https://github.com/deeplearning-wisc/knn-ood` in 'Pre-trained model'.
- We use MobileNet-v2 trained on ImageNet-1k from scratch. The model can be downloaded from `https://pytorch.org/vision/stable/models/generated/torchvision.models.mobilenet_v2.html#torchvision.models.MobileNet_V2_Weights`.

	iNaturalist			SUN			Places			Textures			OpenImage-O			Average on first four			Average on all		
Detection method	FPR95	AUROC	AUPR	FPR95	AUROC	AUPR	FPR95	AUROC	AUPR	FPR95	AUROC	AUPR	FPR95	AUROC	AUPR	FPR95	AUROC	AUPR	FPR95	AUROC	AUPR
ODIN*	47.66	89.66	-	60.15	84.59	-	67.89	81.78	-	50.23	85.62	-	-	-	-	56.48	85.41	-	-	-	-
GODIN*	61.91	85.40	-	60.83	85.60	-	63.70	83.81	-	77.85	73.27	-	-	-	-	66.07	82.02	-	-	-	-
DICE*	25.63	94.49	-	35.15	90.83	-	46.49	87.48	-	31.72	90.30	-	-	-	-	34.75	90.78	-	-	-	-
RankFeat*	41.31	91.91	-	29.27	94.07	-	39.34	90.93	-	37.29	91.70	-	-	-	-	36.80	92.15	-	-	-	-
BATS*	12.57	97.67	-	22.62	95.33	-	34.34	91.83	-	38.90	92.27	-	-	-	-	27.11	94.28	-	-	-	-
ASH*	14.21	97.32	-	22.08	95.10	-	33.45	92.31	-	21.17	95.50	-	-	-	-	22.73	95.06	-	-	-	-
ReAct* (+ Energy)	20.38	96.22	-	24.20	94.20	-	33.85	91.58	-	47.30	89.80	-	-	-	-	31.43	92.95	-	-	-	-
ReAct + MSP	44.36	91.62	98.17	58.46	86.43	96.65	63.83	84.51	96.18	56.24	86.51	98.01	57.04	88.40	95.64	55.72	87.27	97.25	55.99	87.49	96.93
ReAct + MaxLogit	26.47	95.29	99.00	39.83	91.74	98.04	48.18	89.44	97.42	45.41	90.75	98.72	44.82	91.54	96.88	39.97	91.80	98.29	40.94	91.75	98.01
ReAct + KL	19.99	96.31	99.21	29.67	93.40	98.38	39.70	90.95	97.71	41.42	91.62	98.84	41.54	91.85	96.93	32.69	93.07	98.54	34.46	92.82	98.21
ReAct + ViM	18.87	96.69	99.32	32.39	93.82	98.60	45.45	90.38	97.67	7.55	98.45	99.81	38.72	92.34	97.15	26.06	94.83	98.85	28.60	94.33	98.51
ReAct + Mahalanobis	44.96	91.44	98.14	62.50	84.64	96.37	73.04	79.23	94.80	11.10	97.78	99.72	55.98	85.90	94.33	47.90	88.27	97.26	49.52	87.80	96.67
ReAct + SSD	56.83	86.00	96.65	71.06	79.56	94.79	80.38	73.08	92.67	16.40	96.45	99.53	65.70	78.79	90.01	56.17	83.77	95.91	58.07	82.78	94.73
ReAct + GradNorm	14.88	97.01	99.33	25.54	94.19	98.57	36.49	91.12	97.74	23.60	94.57	99.23	39.46	89.67	95.46	25.13	94.22	98.72	27.99	93.31	98.07
ReAct + KNN	37.05	93.03	98.49	55.73	86.11	96.58	67.99	80.70	95.04	8.92	98.01	99.74	53.02	88.26	95.43	42.42	89.46	97.46	44.54	89.22	97.06
ReAct + Energy	19.99	96.31	99.21	29.67	93.40	98.38	39.70	90.95	97.71	41.42	91.62	98.84	41.54	91.85	96.93	32.69	93.07	98.54	34.46	92.82	98.21
ReAct + NNGuide	11.12	97.70	99.50	20.51	95.26	98.83	29.99	92.70	98.13	17.27	96.11	99.46	35.10	92.49	97.09	**19.72**	**95.45**	**98.98**	**22.80**	**94.85**	**98.60**

Table 7. Results on ImageNet-1k with the network truncators.

- We use ViT-B/16 pretrained on ImageNet-21k and then fine-tuned on ImageNet-1k with the full weight update. The model can be downloaded from `https://pytorch.org/vision/stable/models/generated/torchvision.models.vit_b_16.html#torchvision.models.ViT_B_16_Weights`.
- We use RegNet-Y-16GF pretrained on ImageNet-21k and then fine-tuned on ImageNet-1k with the full weight update. The model can be downloaded from `https://pytorch.org/vision/stable/models/generated/torchvision.models.regnet_y_16gf.html#torchvision.models.RegNet_Y_16GF_Weights`.

B.1.1 Comparison of detection scores

Results The result on the ImageNet-1k OOD benchmark is given in Tab. 6.

B.1.2 Compatibility with network truncator

B.2. Evaluation against natural distribution shift (ImageNet-1k-V2)

Dataset ImageNet-1k-V2 [36, 28] contains samples of the same semantic classes as those of original ImageNet-1k. Due to the different data collecting schemes applied on ImageNet-1k-V2, the data experiences natural distribution shift. The dataset involves three different data folds. Their differing characteristics are determined by how they are collected. We evaluate the performance by combining the different folds.

Backbone models We use the same backbone models used in the ImageNet-1k benchmark.

Setup The model is trained on the train fold of original ImageNet-1k. Then, during testing, the test set ID is the combined ImageNet-1k-V2 folds, and the test OOD is either of five different OODs (*i.e.*, iNaturalist, SUN, Places, Textures, and OpenImage-O).

Results The results on the ImageNet-1k-V2 are given in Tab. 8.

B.3. Evaluation on the CIFAR-100 benchmark

Backbone model A standard ResNet-18 model with the default PyTorch configuration is trained on the train fold of CIFAR-100 from scratch for 200 epochs with the SGD optimizer. We select the best model by the validation set accuracy.

Results The results on the CIFAR-100 OOD benchmark is given in Tab. 9.

B.4. Ablation

B.4.1 Compatibility to other classifier-based confidence scores

Note Note that the all confidence scores we use have their range in $[0, \infty)$. Particularly, the MaxLogit and Energy confidence scores satisfy this range as long as the maximum unit of the logit is greater than or equal to 0.

Method	OOD Model	iNaturalist FPR	iNaturalist AUROC	iNaturalist AUPR	SUN FPR	SUN AUROC	SUN AUPR	Places FPR	Places AUROC	Places AUPR	Textures FPR	Textures AUROC	Textures AUPR	OpenImage-O FPR	OpenImage-O AUROC	OpenImage-O AUPR	Average FPR	Average AUROC	Average AUPR
MSP	ResNet-50	36.31	92.39	92.64	65.44	82.07	80.12	66.23	81.69	81.13	55.35	82.73	87.05	54.39	87.64	81.91	55.54	85.30	84.57
MaxLogit	ResNet-50	28.51	94.85	95.41	56.70	86.13	85.10	59.06	84.89	84.27	47.15	86.49	89.03	48.43	90.35	86.24	47.97	88.54	88.01
KL	ResNet-50	26.39	95.11	95.62	51.87	86.78	85.45	55.50	85.34	84.49	42.84	87.12	89.30	46.78	90.51	86.34	44.67	88.97	88.24
ViM	ResNet-50	20.34	96.24	96.61	43.10	89.39	87.86	52.86	86.61	85.54	17.18	93.58	93.48	32.06	93.55	90.25	33.11	**91.88**	**90.75**
Mahalanobis	ResNet-50	39.90	93.76	94.89	68.36	84.35	84.93	73.32	81.46	81.94	16.05	94.96	96.11	41.63	92.73	90.40	47.85	89.45	89.65
SSD	ResNet-50	36.68	93.81	94.74	58.82	86.86	86.82	67.51	82.67	82.44	12.38	96.19	97.02	40.66	92.30	89.44	43.21	90.36	90.09
GradNorm	ResNet-50	16.75	96.61	96.83	32.99	92.21	91.51	41.85	89.63	88.59	31.87	90.78	92.31	39.83	90.12	83.85	32.66	91.87	90.62
KNN	ResNet-50	39.81	93.07	93.77	56.63	85.71	85.29	65.30	82.05	81.33	17.91	93.69	94.82	43.20	91.56	87.98	44.57	89.22	88.64
Energy	ResNet-50	26.38	95.11	95.62	51.88	86.78	85.45	55.50	85.34	84.49	42.85	87.12	89.30	46.78	90.51	86.34	44.68	88.97	88.24
NNGuide	ResNet-50	14.27	96.89	96.80	34.56	90.32	87.95	42.23	88.48	86.68	27.38	90.44	91.04	35.44	92.35	87.91	**30.78**	91.70	90.08
MSP	MobileNet	75.68	81.49	83.19	83.66	73.43	73.93	83.46	73.15	73.75	76.32	75.80	82.79	77.91	79.35	72.03	79.40	76.64	77.14
MaxLogit	MobileNet	78.71	79.15	80.55	84.84	71.81	71.85	84.48	71.64	71.80	75.50	75.00	81.86	77.43	78.23	69.24	80.19	75.17	75.06
KL	MobileNet	92.70	64.99	69.21	95.02	62.87	65.74	93.86	63.39	66.00	81.31	69.24	78.25	84.95	70.36	60.39	89.57	66.17	67.92
ViM	MobileNet	87.49	68.06	70.28	89.03	64.78	65.70	92.47	60.69	62.33	41.55	89.07	91.93	73.97	78.99	70.57	76.90	72.32	72.16
Mahalanobis	MobileNet	67.52	81.74	82.69	80.25	71.24	71.39	86.72	66.12	66.61	32.29	92.21	94.38	59.56	85.56	79.29	**65.27**	79.37	78.87
SSD	MobileNet	85.87	64.66	63.62	88.03	62.20	61.47	93.03	54.31	54.69	40.74	90.66	94.19	78.53	74.76	64.32	77.24	69.32	67.66
GradNorm	MobileNet	94.32	62.01	65.30	93.74	62.41	63.90	95.28	59.31	61.44	78.67	73.00	82.00	87.87	65.77	53.72	89.98	64.50	65.27
KNN	MobileNet	83.08	74.75	77.98	92.08	64.94	67.67	93.23	60.90	63.73	37.51	90.44	92.79	71.57	80.62	73.82	75.49	74.33	75.20
Energy	MobileNet	92.69	64.99	69.21	95.02	62.87	65.74	93.86	63.39	66.00	81.31	69.24	78.25	84.95	70.36	60.39	89.57	66.17	67.92
NNGuide	MobileNet	70.18	80.16	81.41	81.27	73.81	74.61	83.59	71.86	72.26	40.65	88.28	90.77	63.31	82.89	75.60	67.80	**79.40**	**78.93**
MSP	ViT	33.17	92.32	92.40	63.43	81.97	82.01	66.79	80.97	81.06	58.90	81.96	87.14	50.76	87.43	81.09	54.61	84.93	84.74
MaxLogit	ViT	19.72	95.88	95.86	56.13	83.15	81.28	62.67	79.01	76.22	53.64	82.71	86.32	37.69	90.84	84.06	45.97	86.32	84.75
KL	ViT	19.33	95.99	95.98	57.33	82.69	80.81	64.98	77.90	75.17	55.74	82.12	86.03	37.79	90.83	84.08	47.03	85.91	84.41
ViM	ViT	4.34	98.96	98.91	55.11	85.81	84.50	64.44	80.93	79.21	47.21	86.47	89.91	24.53	94.77	91.17	**39.13**	89.39	88.74
Mahalanobis	ViT	6.30	98.58	98.48	62.70	86.11	86.09	69.17	83.13	83.65	48.42	88.66	92.61	28.34	94.97	92.95	42.99	**90.29**	**90.76**
SSD	ViT	10.31	97.66	97.61	83.16	72.06	72.34	87.18	66.35	67.51	67.40	80.75	86.47	43.36	89.25	83.03	58.28	81.21	81.39
GradNorm	ViT	21.85	95.06	94.45	56.94	82.79	79.68	66.08	78.35	75.14	53.30	84.18	87.96	39.91	89.97	81.55	47.62	86.07	83.75
KNN	ViT	33.94	93.34	93.60	75.12	82.53	81.79	76.53	80.05	80.60	54.72	86.11	90.64	49.59	90.54	87.04	57.98	86.52	86.73
Energy	ViT	19.33	95.99	95.98	57.33	82.69	80.81	64.98	77.90	75.17	55.74	82.12	86.03	37.79	90.83	84.08	47.03	85.91	84.41
NNGuide	ViT	13.96	97.18	97.25	54.73	87.42	86.80	61.47	84.18	83.57	46.86	87.68	91.11	31.65	93.92	91.00	41.73	90.08	89.95
MSP	RegNet	28.48	93.13	92.83	58.44	83.54	83.03	62.95	81.83	81.41	54.71	83.54	88.58	40.37	89.88	83.82	48.99	86.38	85.93
MaxLogit	RegNet	12.18	96.84	96.28	41.26	87.68	85.59	51.19	83.14	80.32	42.35	87.25	90.56	23.88	93.47	87.12	34.17	89.67	87.97
KL	RegNet	10.59	97.19	96.59	38.75	87.91	85.54	50.02	82.62	79.54	41.26	87.40	90.63	22.81	93.56	87.03	32.69	89.74	87.87
ViM	RegNet	3.38	99.22	99.19	37.13	90.39	89.18	52.27	85.02	83.67	28.39	93.58	95.77	18.93	95.78	92.62	28.02	92.80	92.09
Mahalanobis	RegNet	3.08	99.14	99.26	55.81	87.90	87.75	67.00	83.27	83.56	33.83	92.67	95.25	23.19	95.64	93.55	36.58	91.72	91.87
SSD	RegNet	6.45	98.52	98.70	65.12	83.77	83.83	74.48	77.58	78.13	43.07	91.30	94.74	31.84	92.45	87.86	44.19	88.73	88.65
GradNorm	RegNet	88.78	54.91	55.98	84.73	63.85	63.64	92.11	53.86	54.84	77.46	73.88	82.86	79.28	58.61	40.45	84.47	61.02	59.56
KNN	RegNet	4.82	98.67	98.67	49.88	87.55	84.99	59.94	84.05	83.05	30.42	91.36	93.64	23.63	95.08	92.34	33.74	91.34	90.54
Energy	RegNet	10.80	97.16	96.57	38.82	87.95	85.61	50.09	82.73	79.70	41.57	87.37	90.61	23.01	93.54	86.98	32.86	89.75	87.89
NNGuide	RegNet	2.95	99.32	99.22	28.56	92.20	90.88	39.10	88.81	87.30	23.85	93.96	95.91	15.38	96.56	93.87	**21.97**	**94.17**	**93.44**

Table 8. Results on ImageNet-1k-V2 (ID) across five different OODs (*i.e*. iNaturalist, SUN, Places, Textures, OpenImage-O).

	CIFAR-100 FPR95	CIFAR-100 AUROC	CIFAR-100 AUPR	SVHN FPR95	SVHN AUROC	SVHN AUPR	LSUN FPR95	LSUN AUROC	LSUN AUPR	iSUN FPR95	iSUN AUROC	iSUN AUPR	ImageNet FPR95	ImageNet AUROC	ImageNet AUPR	Average FPR95	Average AUROC	Average AUPR
MSP	82.25	77.28	79.96	64.72	86.24	78.30	71.45	83.21	85.75	71.31	83.01	86.69	72.95	81.98	84.53	72.53	82.34	83.05
MaxLogit	82.06	77.95	80.07	59.83	88.87	82.24	64.53	86.84	88.79	65.87	86.62	89.51	67.30	85.42	87.42	67.92	85.14	85.61
KL	82.57	77.75	79.95	59.39	89.10	82.53	61.86	87.41	89.15	62.41	87.19	89.83	65.14	85.91	87.71	66.27	85.47	85.84
ViM	87.57	71.04	73.85	74.78	81.65	72.62	81.01	78.13	81.55	77.84	79.21	83.58	79.18	78.45	81.53	80.07	77.70	78.63
Mahalanobis	87.61	70.50	71.40	75.90	81.69	72.97	75.29	81.53	84.44	73.86	80.90	84.63	75.05	79.80	82.47	77.54	78.88	79.18
SSD	90.85	60.32	59.83	83.19	70.20	49.35	82.50	71.80	73.08	80.29	71.33	73.74	79.21	71.59	71.59	83.21	69.05	65.52
GradNorm	83.16	68.15	66.22	51.85	86.12	71.58	65.78	76.58	73.68	64.69	78.20	77.90	69.01	74.50	71.30	66.90	76.71	72.14
KNN	82.79	76.24	75.43	65.48	87.21	80.51	65.96	86.62	88.94	67.15	85.44	88.45	68.99	85.35	87.82	70.07	84.17	84.23
Energy	82.57	77.75	79.95	59.39	89.10	82.53	61.86	87.41	89.15	62.41	87.19	89.83	65.14	85.91	87.71	66.27	85.47	85.84
NNGuide	81.74	78.34	80.46	52.04	90.93	85.25	61.30	88.02	89.78	62.08	87.84	90.50	65.61	86.82	88.82	**64.56**	**86.39**	**86.96**

Table 9. Results on CIFAR-100.

Results The result is given in Fig. 7.

B.4.2 Ablation on the components of NNGuide

Descriptions We describe in detail the detection methods used in the ablation study of NNGuide components (*i.e*. Tab. 5). Let f be a neural network that outputs the classification logit, and ϕ the feature extractor inside the network. Let S_{base} be the score function that computes the base confidence (*i.e*. negative Energy) score given an input. Let $\{\mathbf{x}_1, \ldots, \mathbf{x}_n\}$ be the ID bank set, and $\{\mathbf{z}_1, \ldots, \mathbf{z}_n\}$ the corresponding features (*i.e*. $\mathbf{z}_i = \phi(\mathbf{x}_i)$) with $s_i = S_{base}(\mathbf{x}_i)$. Let $\mathbf{x}$ be a test input and $\mathbf{z}$ its extracted feature.

- **KNN**: The KNN score is computed by

$$S_{KNN}(\mathbf{x}) = \mathrm{sim}(\mathbf{z}_{(k)}, \mathbf{z}) \tag{21}$$

where the ordered indices (i) satisfy

$$\mathrm{sim}(\mathbf{z}_{(1)}, \mathbf{z}) \geq \cdots \geq \mathrm{sim}(\mathbf{z}_{(n)}, \mathbf{z}). \tag{22}$$

Components	OOD Model	iNaturalist FPR	iNaturalist AUROC	iNaturalist AUPR	SUN FPR	SUN AUROC	SUN AUPR	Places FPR	Places AUROC	Places AUPR	Textures FPR	Textures AUROC	Textures AUPR	OpenImage-O FPR	OpenImage-O AUROC	OpenImage-O AUPR	Average FPR	Average AUROC	Average AUPR
KNN	ResNet-50	37.53	93.86	98.67	54.57	86.98	96.71	63.34	83.54	95.68	17.45	94.13	99.00	40.77	92.46	97.15	42.73	90.19	97.44
KNN with average similarity	ResNet-50	40.80	93.82	98.71	54.65	87.84	96.91	62.34	85.13	96.14	19.84	93.91	98.99	42.16	92.87	97.42	43.96	90.71	97.64
Energy	ResNet-50	20.98	96.17	99.19	47.05	88.91	97.08	51.15	87.70	96.85	39.31	88.90	97.96	41.56	92.32	97.06	40.01	90.80	97.63
Product fusion	ResNet-50	18.16	96.64	99.29	43.62	89.86	97.27	50.33	88.07	96.91	23.58	92.26	98.42	31.98	94.02	97.73	33.53	92.17	97.92
Sum fusion	ResNet-50	21.51	96.38	99.24	44.61	89.87	97.30	52.44	87.78	96.85	20.14	93.05	98.55	31.43	94.26	97.83	34.03	92.27	97.96
Max fusion	ResNet-50	37.53	93.87	98.67	54.55	86.98	96.71	63.33	83.54	95.69	17.45	94.13	98.97	40.76	92.46	97.15	42.72	90.19	97.44
Min fusion	ResNet-50	20.98	96.17	99.19	47.05	88.91	97.08	51.15	87.70	96.85	39.31	88.90	97.96	41.56	92.32	97.06	40.01	90.80	97.63
Mahalanobis guidance	ResNet-50	21.35	96.33	99.25	53.52	88.72	97.15	59.53	86.76	96.69	19.04	93.84	98.81	32.49	94.36	97.93	37.19	92.00	97.97
Guidance term only	ResNet-50	18.22	95.83	98.97	30.46	91.16	97.37	39.11	88.86	96.82	23.23	92.34	98.39	40.54	89.71	95.55	30.31	91.58	97.42
W/O confidence scaling	ResNet-50	22.12	96.22	99.21	46.09	89.47	97.22	51.63	87.82	96.88	25.39	91.86	98.40	35.91	93.66	97.62	36.23	91.81	97.87
NNGuide	ResNet-50	12.02	97.47	99.43	31.62	91.66	97.63	38.88	90.12	97.34	24.93	91.52	98.27	31.60	93.66	97.47	**27.81**	**92.89**	**98.03**
KNN	RegNet	4.30	98.76	99.73	46.12	88.45	96.69	56.28	85.15	96.11	28.33	91.93	98.72	21.26	95.51	98.28	31.26	91.96	97.91
KNN with average similarity	RegNet	3.24	99.28	99.83	37.68	90.59	97.32	46.79	87.91	96.84	24.45	93.00	98.87	14.79	97.06	98.85	25.39	93.57	98.34
Energy	RegNet	6.68	98.28	99.57	29.41	91.88	97.85	40.51	87.97	96.72	30.85	91.48	98.68	16.19	95.81	98.09	24.73	93.08	98.18
Product fusion	RegNet	2.51	99.44	99.87	25.98	93.43	98.21	36.91	90.50	97.54	20.25	95.07	99.26	10.49	97.97	99.21	19.23	95.28	98.82
Sum fusion	RegNet	3.55	99.20	99.81	24.74	93.69	98.39	35.67	90.54	97.53	23.16	94.44	99.20	10.99	97.55	98.97	19.62	95.08	98.78
Max fusion	RegNet	4.30	98.76	99.73	46.09	88.46	96.69	56.26	85.17	96.11	28.32	91.94	98.73	21.25	95.52	98.28	31.24	91.97	97.91
Min fusion	RegNet	6.68	98.28	99.57	29.41	91.88	97.85	40.51	87.97	96.72	30.85	91.48	98.68	16.19	95.81	98.09	24.73	93.08	98.18
Mahalanobis guidance	RegNet	1.24	99.61	99.92	34.07	92.65	98.23	47.87	88.98	97.31	19.77	95.37	99.36	12.45	97.70	99.16	23.08	94.86	98.80
Guidance term only	RegNet	2.27	99.43	99.86	30.68	91.71	97.66	40.14	89.34	97.20	19.59	94.21	99.11	18.82	95.78	98.27	22.30	94.09	98.42
W/O confidence scaling	RegNet	2.35	99.50	99.89	23.99	94.09	98.46	34.06	91.50	97.83	19.84	95.23	99.31	8.68	98.30	99.35	17.78	95.72	98.97
NNGuide	RegNet	1.83	99.57	99.90	21.58	94.43	98.58	31.47	91.87	97.92	17.00	95.82	99.42	10.79	97.73	99.09	**16.53**	**95.89**	**98.98**

Table 10. Ablation study on the components of NNGuide. The ID is ImageNet-1k.

Components	OOD Model	iNaturalist FPR	iNaturalist AUROC	iNaturalist AUPR	SUN FPR	SUN AUROC	SUN AUPR	Places FPR	Places AUROC	Places AUPR	Textures FPR	Textures AUROC	Textures AUPR	OpenImage-O FPR	OpenImage-O AUROC	OpenImage-O AUPR	Average FPR	Average AUROC	Average AUPR
KNN	ResNet-50	39.81	93.07	93.77	56.63	85.71	85.29	65.30	82.05	81.33	17.91	93.69	94.82	43.20	91.56	87.98	44.57	89.22	88.64
KNN with average similarity	ResNet-50	44.61	92.66	93.80	58.47	86.10	85.70	65.82	83.14	82.60	21.11	93.24	94.67	46.01	91.61	88.80	47.20	89.35	89.11
Energy	ResNet-50	26.38	95.11	95.62	51.88	86.78	85.45	55.50	85.34	84.49	42.85	87.12	89.30	46.78	90.51	86.34	44.68	88.97	88.24
Product fusion	ResNet-50	23.45	95.79	96.20	48.01	88.03	86.44	54.37	85.93	84.91	25.31	91.25	91.69	37.77	92.68	89.23	37.78	90.74	89.69
Sum fusion	ResNet-50	26.44	95.55	96.05	48.58	88.14	86.72	56.06	85.72	84.84	21.55	92.24	92.38	36.49	93.06	89.81	37.82	90.94	89.96
Max fusion	ResNet-50	39.81	93.07	93.77	56.63	85.71	85.30	65.30	82.05	81.33	17.91	93.69	94.69	43.20	91.56	87.98	44.57	89.22	88.61
Min fusion	ResNet-50	26.38	95.11	95.62	51.88	86.78	85.45	55.50	85.34	84.49	42.85	87.12	89.30	46.78	90.51	86.34	44.68	88.97	88.24
Mahalanobis guidance	ResNet-50	26.57	95.46	96.15	57.85	86.62	86.15	63.44	84.35	84.14	20.16	93.03	93.60	37.02	93.10	90.29	41.01	90.51	90.07
Guidance term only	ResNet-50	20.15	95.41	94.93	32.50	90.55	87.73	41.43	88.10	85.54	24.97	91.89	92.10	42.83	88.93	81.63	32.37	90.98	88.38
W/O confidence scaling	ResNet-50	28.12	95.23	95.85	50.65	87.52	86.23	56.27	85.58	84.78	27.54	90.73	91.52	41.89	92.18	88.82	40.89	90.25	89.44
NNGuide	ResNet-50	14.27	96.89	96.80	34.56	90.32	87.95	42.23	88.48	86.68	27.38	90.44	91.04	35.44	92.35	87.91	**30.78**	**91.70**	**90.08**
KNN	RegNet	4.82	98.67	98.67	49.88	87.55	84.99	59.94	84.05	83.05	30.42	91.36	93.64	23.63	95.08	92.34	33.74	91.34	90.54
KNN with average similarity	RegNet	3.99	99.14	99.05	42.51	89.34	87.03	51.81	86.42	85.28	27.44	92.17	94.04	17.45	96.51	94.25	28.64	92.72	91.93
Energy	RegNet	10.80	97.16	96.57	38.82	87.95	85.61	50.09	82.73	79.70	41.57	87.37	90.61	23.01	93.54	86.98	32.86	89.75	87.89
Product fusion	RegNet	3.79	99.15	99.05	33.50	91.18	89.16	45.05	87.41	85.87	27.73	93.23	95.15	15.07	96.95	94.86	25.03	93.58	92.82
Sum fusion	RegNet	5.62	98.63	98.44	33.27	90.62	89.04	45.00	86.35	84.20	32.06	91.58	94.12	16.77	96.04	92.60	26.55	92.64	91.68
Max fusion	RegNet	4.82	98.67	98.67	49.88	87.55	85.00	59.94	84.06	83.06	30.42	91.37	93.64	23.63	95.08	92.35	33.74	91.35	90.54
Min fusion	RegNet	10.80	97.16	96.57	38.82	87.95	85.61	50.09	82.73	79.70	41.57	87.37	90.61	23.01	93.54	86.98	32.86	89.75	87.89
Mahalanobis guidance	RegNet	1.96	99.39	99.44	43.34	90.25	89.77	56.84	85.71	85.30	26.83	93.78	95.92	17.22	96.73	94.99	29.24	93.17	93.09
Guidance term only	RegNet	2.74	99.32	99.21	34.15	90.65	88.41	43.91	88.01	86.62	22.29	93.48	95.26	21.10	95.13	91.53	24.84	93.32	92.21
W/O confidence scaling	RegNet	3.79	99.19	99.11	32.71	91.72	90.27	43.47	88.32	86.95	27.65	93.23	95.27	13.81	97.29	95.50	24.29	93.95	93.42
NNGuide	RegNet	2.95	99.32	99.22	28.56	92.20	90.88	39.10	88.81	87.30	23.85	93.96	95.91	15.38	96.56	93.87	**21.97**	**94.17**	**93.44**

Table 11. Ablation study on the components of NNGuide. The ID is ImageNet-1k-V2, where test ID samples undergo natural distribution shift.

- **KNN with average similarity**: The score of KNN with the average similarity slightly modifies the original KNN by

$$S_{KNN-avg}(\mathbf{x}) = \frac{1}{k}\sum_{i=1}^{k} \mathrm{sim}(\mathbf{z}_{(i)}, \mathbf{z}). \tag{23}$$

- **Energy**: The (negative) Energy score is computed by

$$S_{base}(\mathbf{x}) = \log \sum_{c=1}^{K} \exp f_c(\mathbf{x}) \tag{24}$$

- **Naive fusion**: The basic fusion of KNN and the base confidence is performed by either of $S_{KNN}(x) \cdot S_{base}(x)$, $c_{sum}S_{KNN}(x) + S_{base}(x)$, $c_{\max}S_{KNN}(x) + S_{base}(x)$, and $c_{\min}S_{KNN}(x) + S_{base}(x)$. Note that the coefficients c_{sum}, $c_{\max}$, and $c_{\min}$ are the coefficients to min-max normalize the scores to manually balance the importance of the two scores. Note that min-max normalization is done based on the bank set.

- **Mahalanobis guidance**: In this case, the guidance term $G(x)$ is given as the Mahalanobis score

$$G(\mathbf{x}) = \exp(-\min_{c=1}^{K}(\mathbf{x}-\boldsymbol{\mu}_c)^T\Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu}_c)/(2\cdot d)) \tag{25}$$

where $\boldsymbol{\mu}_c$ is the mean of c-th class features, Σ is the shared covariance matirx, and d is the dimension of feature. (Without the

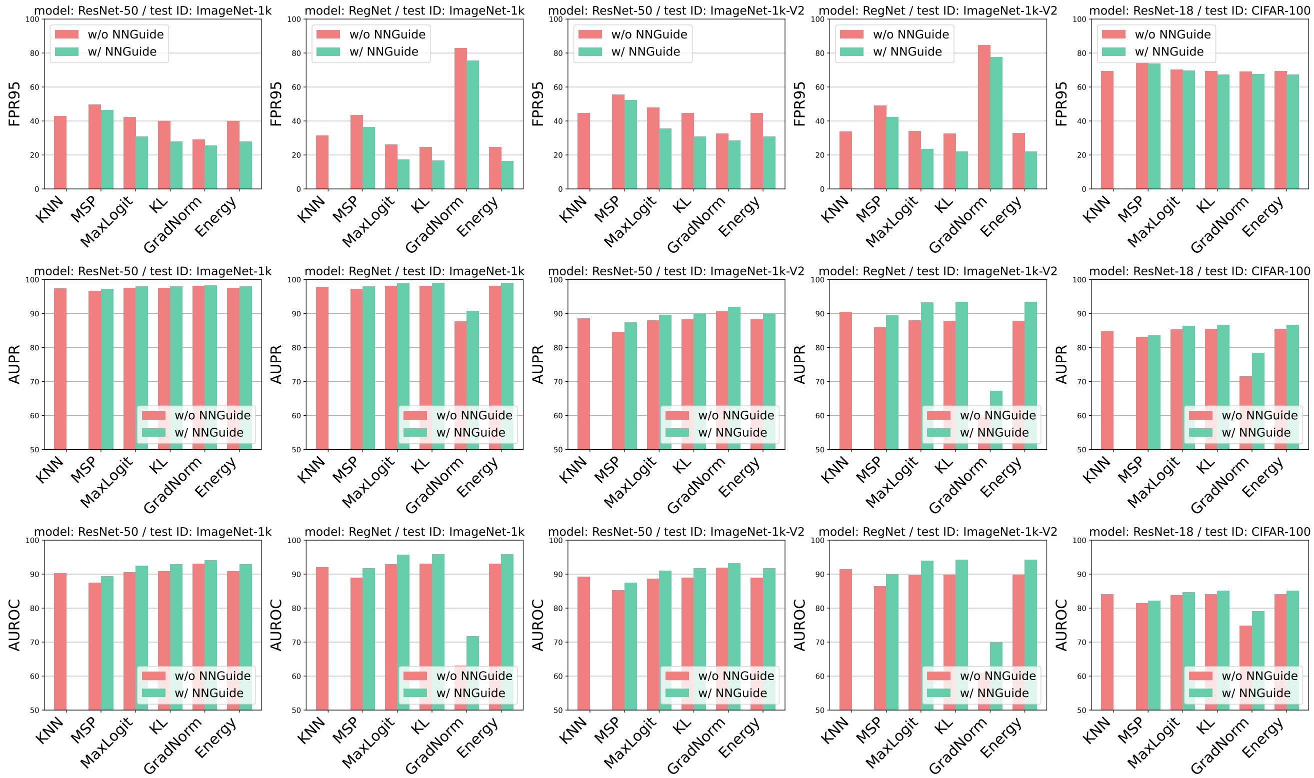

Figure 7. The compatibility to other classifier-based scores. The average performance across five different OODs is reported.

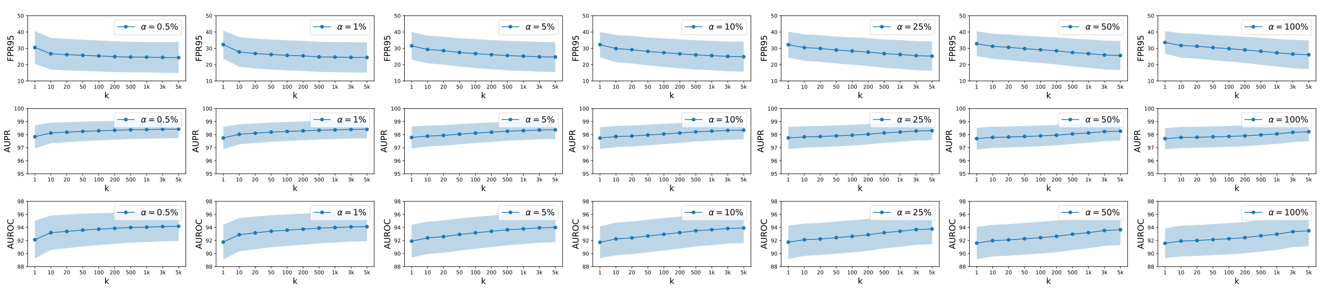

Figure 8. The performance of NNGuide across the number k of nearest neighbors and the sampling ratio α.

- **Guidance-term only**: In this case, the score function in utilization is

$$S_{guide-only}(\mathbf{x}) = G(\mathbf{x}) \tag{26}$$

  where $G(\mathbf{x})$ is the nearest-neighbor guidance term given in (3).

- **Without confidence scaling**: In this case, the detection score function is computed by without the scaling term in the nearest neighbor similarities. Namely,

$$S_{w/o-scale}(\mathbf{x}) = S_{base}(\mathbf{x}) \cdot G_{w/o-scale}(\mathbf{x}) \tag{27}$$

  where $G_{w/o-scale}(\mathbf{x}) = S_{KNN-avg}(\mathbf{x})$ as given in (23).

Results We perform ablation study on the NNGuide components on both ImageNet-1k and ImageNet-1k-V2 across ResNet-18 and RegNet. The results are given in Tab. 10 and 11.

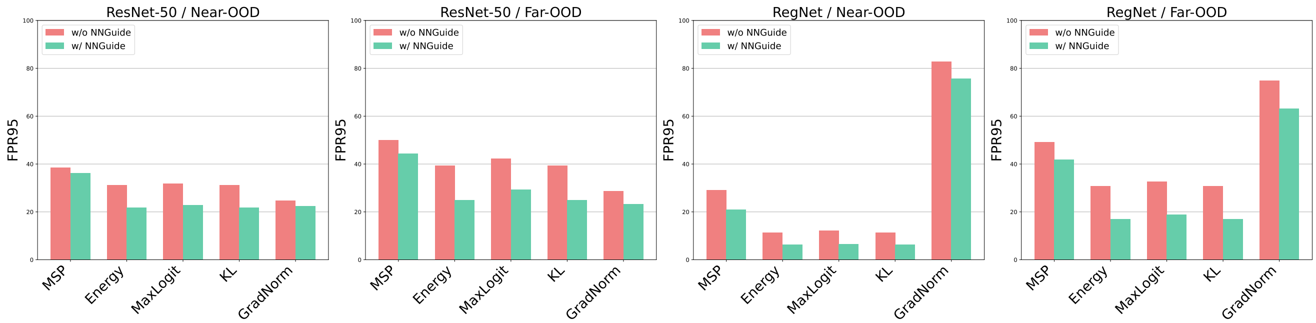

Figure 9. The improvement by our proposed nearest neighbor guidance against far-OOD data (Textures) and near-OOD data (iNaturalist and OpenImage-O). The ID data is ImageNet-1k and the model is ResNet-50.

	SVHN		Places365		iSUN		Texture		LSUN		AVG	
	FPR95	AUROC	FPR95	AUROC	FPR95	AUROC	FPR95	AUROC	FPR95	AUROC	FPR95	AUROC
CIDER	21.42	94.87	82.16	67.32	63.75	82.25	32.96	92.49	9.38	98.13	41.93	87.01
CIDER-NNGuide	21.52	94.97	81.95	67.40	58.71	84.65	30.18	93.24	9.75	98.00	**40.42**	**87.65**

Table 12. The results of NNGuide with CIDER on CIFAR-100 (ID).

OOD data	KNN	Energy	ViM	NNGuide-Energy	NNGuide-ViM
ImageNet-O	51.90 / 89.16	41.30 / 90.46	36.75 / 92.55	41.65 / 91.04	**33.10 / 92.96**

Table 13. The result of NNGuide with ViM on ImageNet-O in (FPR95↓ / AUROC↑). Here, ID is the ImageNet-1k.

B.4.3 Analysis of the hyperparameters

Fig. 8 indicates the full analysis of the nearest neighbor hyperparameters α and k.

B.4.4 Dataset analysis: near-OOD vs far-OOD

Fig. 9 indicates that the nearest neighbor guidance improves the base confidence score against both far-OOD data (*i.e.* Textures) and near-OOD data (*i.e.* iNaturalist and OpenImage-O). Notably, the improvement is more significant against the far-OOD data. This is expected by Theorem 1. Overall, NNGuide achieves balanced robustness against both far-OOD and near-OOD.

C. Additional Experiments

C.1. Experiments with CIDER

To analyze the compatibility of NNGuide with the state-of-the-art trainig method CIDER [25] that is particularly effective for the KNN score, we implemented NNGuide based on the official Github repository of CIDER[1] using the provided model weights therefrom. Tab. 12 shows the performance of NNGuide with CIDER on CIFAR-100, indicating that NNGuide is compatible to CIDER. We note that, to compute base energy score for NNGuide, we defined the classifier weights by the class-wise means, and used $k = 100$ with $\alpha = 1\%$.

C.2. Experiments on ImageNet-O with ViM

To evaluate on ImageNet-O [16], we applied NNGuide on ViM utilizing the implementation from the official Github repository of ViM[2]. We used the ViT-B-P16-384 backbone from `mmcls` as it achieves the SOTA with ViM. Using the same provided ImageNet-1k train feature bankset with k=100 and the sampling ratio $\alpha = 10\%$, we obtained the result in Tab. 13, where 'NNGuide-Energy' indicates the application of NNGuide with the base score being the negative energy (*i.e.* $S_{base}(\mathbf{x}) = -\text{Energy}(\mathbf{x})$), while 'NNGuide-ViM' denotes NNGuide with the base score being ViM (*i.e.* $S_{base}(\mathbf{x}) = -\text{ViM}(\mathbf{x})$). As the ImageNet-O is specifically designed to weaken the classifier-based confidence, both the vanilla Energy and our NNGuide-Energy perform poorly for OOD detection. For the ImageNet-O dataset, the integration of ViM with the ViT architecture proves to be exceptionally effective. The adversarial nature of ImageNet-O primarily targets classifier

[1] https://github.com/deeplearning-wisc/cider
[2] https://github.com/vim/vim

Method	near-OOD CIFAR-100	TIN	Average (near-OOD)	far-OOD MNIST	SVHN	Texture	Places365	Average (far-OOD)
Energy	51.46 / 86.15	45.02 / 88.58	48.24 / 87.36	44.50 / 90.59	44.94 / 88.39	48.32 / 86.85	41.88 / 89.60	44.91 / 88.86
KNN	52.49 / 89.55	46.66 / 91.41	49.58 / 90.48	50.08 / 91.63	33.32 / 95.13	46.01 / 92.77	43.78 / 91.82	43.30 / 92.83
NNGuide	51.54 / 86.64	43.99 / 89.07	47.77 / 87.86	47.43 / 89.82	43.64 / 89.62	46.91 / 88.44	40.62 / 90.39	44.65 / 89.57

Table 14. The result of NNGuide on CIFAR-10 (ID) in (FPR95↓ / AUROC↑)

confidence and convolutional networks. This makes the combination of ViT and ViM especially robust against ImageNet-O as ViT is non-convolutional and ViM does not rely solely on raw confidence. Accordingly, the result in Tab. 13 indicates that NNGuide's effectiveness is significantly enhanced when used in conjunction with ViM.

C.3. Experiments on CIFAR-10

NNGuide is particularly effective for large-scale data. For a small-scale data with few classes such as CIFAR-10, ID features are already well separated class-wise. Hence KNN can already well detect near-OOD in a fine-grained manner without NNGuide, indicated by its performance similar to Energy. The result shown in Tab. 14 (attained by using the official OpenOOD Github repository[3]) verifies our claim. Note that the above result is obtained with $\alpha = 10\%$ and $k = 10$.

[3] https://github.com/Jingkang50/OpenOOD