Supplementary Materials

A. More Results

Full Comparison on ImageNet Benchmark. Full comparisons with more competitors on the ImageNet benchmark are illustrated in Tab. 3, including the results of traditional methods [5, 8, 10, 13, 14, 21, 23] by fine-tuning CLIP visual encoder with labeled training samples following [11]. Compared with other traditional OOD detection methods that require fine-tuning, our ANTS is training-free and achieves better OOD detection performance on ImageNet-1k.

Results on OpenOOD Benchmark. The OpenOOD benchmark results are presented in Tab. 1, including the results of other methods requiring manually labeled training samples. Compared with other methods [9, 15, 19] that require manually labeled training samples, our ANTS surpasses other CLIP-based zero-shot OOD detection methods on both far-OOD and near-OOD tasks in the OpenOOD benchmark.

Table 1. Full results on OpenOOD Benchmark, where ImageNet is adopted as the ID dataset.

Methods	FPR95 ↓		AUROC ↑	
	Near-OOD	Far-OOD	Near-OOD	Far-OOD
Requires Manually Labeled Training Samples				
GEN [15]	–	–	78.97	90.98
AugMix [9] + ReAct [20]	–	–	79.94	93.70
RMDS [19]	–	–	80.09	92.60
AugMix [9] + ASH [4]	–	–	82.16	96.05
Zero Shot (No Training Required)				
MCM [16]	79.02	68.54	60.11	84.77
NegLabel [11]	68.18	27.34	76.92	93.30
EOE [2]	82.93	46.73	66.94	89.14
AdaNeg [27]	67.51	17.31	76.70	96.43
ANTS	60.98	15.38	82.15	96.50

Detailed OOD Detection Results of ANTS on OpenOOD Benchmark. The detailed OOD detection results of ANTS on the OpenOOD benchmark are shown in Tab. 2. We see that ANTS achieves good results in both Far-OOD and Near-OOD scenarios, demonstrating its strong adaptability to different OOD situations.

Near-OOD Detection. We alternate the use of ImageNet-10 and ImageNet-20 as ID and OOD datasets. The results are shown in Tab. 4. We see that ANTS significantly outperforms EOE and AdaNeg under the two experimental settings, demonstrating the advantage of our constructed adaptive negative text space.

Other Instantiations of Adaptive Weighted Score. As shown in Tab. 5, we consider various instantiations of the adaptive weighted score function. Specifically, we examine functions that employ only the ENS score, only the VSNL score, as well as logarithmic, exponential, and fractional functions. The results indicate that using the fractional function in conjunction with the ENS score and VSNL score yields the best results.

Table 2. Detailed OOD detection results of ANTS on the OpenOOD benchmark, where ImageNet is adopted as the ID dataset.

Near-/Far-OOD	Datasets	FPR95 ↓	AUROC ↑
Near-OOD	SSB-hard	62.73	81.97
	NINCO	59.23	82.32
	Mean	60.98	82.15
Far-OOD	iNaturalist	0.76	99.60
	Textures	16.50	96.78
	OpenImage-O	28.89	93.13
	Mean	15.38	96.50

Robustness to Domain Shift. To verify the robustness of ANTS to domain shift, we test several variants of ImageNet with different domain shifts. As shown in Tab. 6, ANTS outperforms MCM and NegLabels on the four different ID datasets, highlighting the remarkable robustness of our ANTS to domain shifts.

OOD Detection Results with Various ID Datasets. We compare the zero-shot OOD detection performance of ANTS and other methods on several ID datasets. As illustrated in Tab. 7, ANTS outperforms the other three methods across different ID datasets.

Robustness of ANTS to Noisy Negative Images. We investigate the impact of different rates of ID noise in negative images on the model OOD detection performance, as shown in Fig. 1. When the ID ratio of negative images is relatively low (less than 0.5), our ANTS achieves excellent OOD detection performance across different ID ratios. This demonstrates the robustness of ANTS against ID noise.

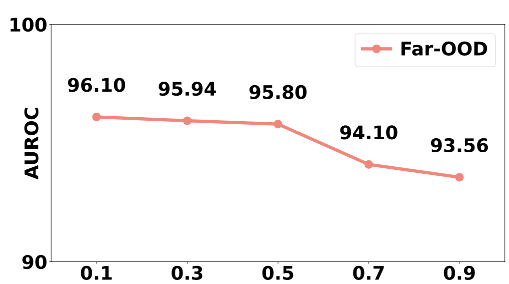


Figure 1. Robustness of ANTS to Noisy Negative Images

B. Case Study

We visualize the adaptive negative text space with some ID and OOD images for a case study, as shown in Fig. 2. We see that images from the ID dataset exhibit high similarity to the ID classes. For Far-OOD, as shown in Fig. 3, the images from the OOD dataset demonstrate high similarity to the ENS space. For Near-OOD, as shown in Fig. 4, the images from the OOD dataset show a high similarity to the VSNL space.

Table 3. OOD detection results by using ImageNet-1k as the ID dataset. ViTB/16 is used as the encoder.

Methods	INaturalist		SUN		Places		Textures		Average	
	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓
Training-required (or with Fine-tuning)										
MSP [8]	87.44	58.36	79.73	73.72	79.67	74.41	79.69	71.93	81.63	69.61
ODIN [13]	94.65	30.22	87.17	54.04	85.54	55.06	87.85	51.67	88.80	47.75
Energy [14]	95.33	26.12	92.66	35.97	91.41	39.87	86.76	57.61	91.54	39.89
GradNorm [10]	72.56	81.50	72.86	82.00	73.70	80.41	70.26	79.36	72.35	80.82
ViM [23]	93.16	32.19	87.19	54.01	83.75	60.67	87.18	53.94	87.82	50.20
KNN [21]	94.52	29.17	92.67	35.62	91.02	39.61	85.67	64.35	90.97	42.19
VOS [5]	94.62	28.99	92.57	36.88	91.23	38.39	86.33	61.02	91.19	41.32
NPOS [22]	96.19	16.58	90.44	43.77	89.44	45.27	88.80	46.12	91.22	37.93
ZOC [6]	86.09	87.30	81.20	81.51	83.39	73.06	76.46	98.90	81.79	85.19
CLIPN [24]	95.27	23.94	93.93	26.17	92.28	33.45	90.93	40.83	93.10	31.10
LSN [18]	95.83	21.56	94.35	26.32	91.25	34.48	90.42	38.54	92.26	30.22
LoCoOp [17]	93.93	29.45	90.32	41.13	90.54	44.15	93.24	33.06	92.01	36.95
ID-Like [1]	98.19	8.98	91.64	42.03	90.57	44.00	94.32	25.27	93.68	30.07
NegPrompt [12]	90.49	37.79	92.25	32.11	91.16	35.52	88.38	43.93	90.57	37.34
CoVer [26]	95.98	22.55	93.42	32.85	90.27	40.71	90.14	43.39	92.45	34.88
SCT [12]	95.86	13.94	95.33	20.55	92.24	29.86	89.06	41.51	93.27	26.47
LAPT [29]	99.63	1.16	96.01	19.12	92.01	33.01	91.06	40.32	94.68	23.40
Zero Shot (No Training Required)										
MCM [16]	94.59	32.20	92.25	38.80	90.31	46.20	86.12	58.50	90.82	43.93
EOE [2]	97.52	12.29	95.73	20.40	92.95	30.16	85.64	57.63	92.96	30.09
NegLabel [11]	99.49	1.91	95.49	20.53	91.64	35.59	90.22	43.56	94.21	25.40
OODD [25]	99.36	2.22	95.01	21.49	87.10	44.76	93.27	30.69	93.69	24.79
CLIPScope [7]	99.61	1.29	96.77	15.56	93.54	28.45	91.41	38.37	95.30	20.88
AdaNeg [28]	99.71	0.59	97.44	9.50	94.55	34.34	94.93	31.27	96.66	18.92
CSP [3]	99.60	1.54	96.66	13.66	92.90	29.32	93.86	25.52	95.76	17.51
ANTS	**99.75**	**0.54**	**98.77**	**5.43**	96.10	20.21	**96.38**	**18.52**	**97.75**	**11.20**

Table 4. Near OOD detection results.

Method	ImageNet-10 (ID) ImageNet-20 (OOD)		ImageNet-20 (ID) ImageNet-10 (OOD)	
	AUROC ↑	FPR95 ↓	AUROC ↑	FPR95 ↓
MCM [16]	98.71	5.00	97.87	17.40
NegLabel [11]	96.86	5.10	96.46	14.60
EOE [2]	99.09	4.20	98.10	13.93
AdaNeg [28]	99.17	3.00	97.25	14.40
ANTS (Ours)	**99.56**	**2.00**	**98.31**	**8.90**

Table 5. OOD detection results of other instantiations of Adaptive Weighted Score.

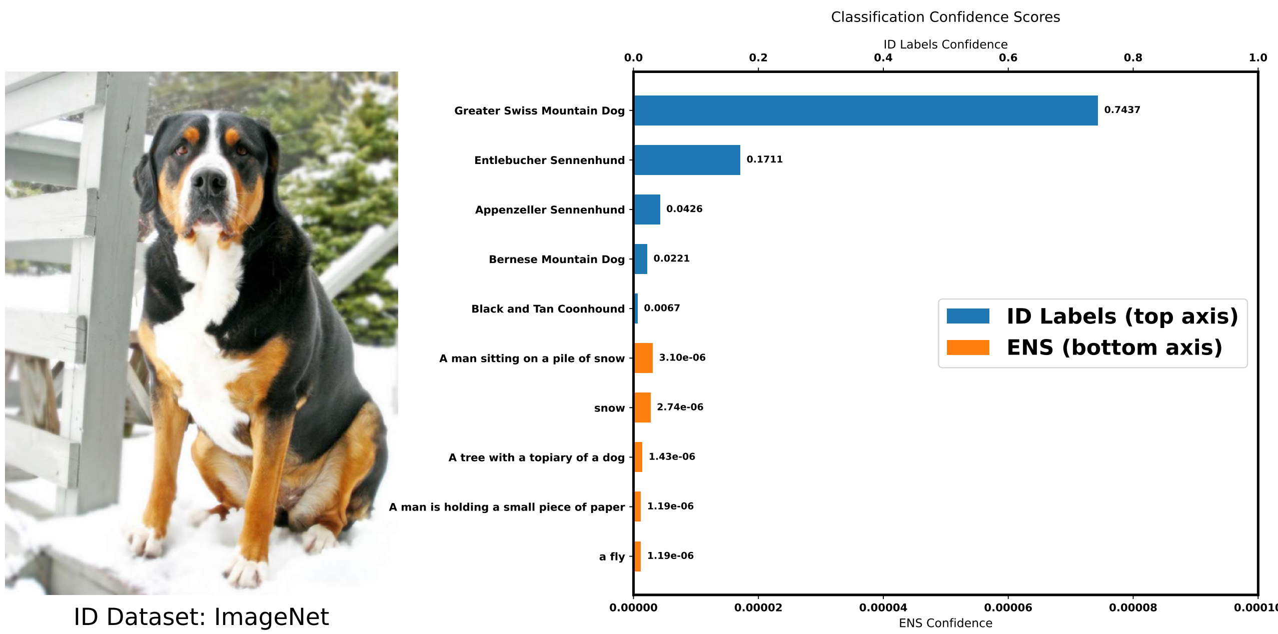
Methods	FPR95 ↓		AUROC ↑	
	Near-OOD	Far-OOD	Near-OOD	Far-OOD
Only ENS	66.23	21.70	77.58	95.81
Only VSNL	62.36	31.15	79.10	92.46
Logarithmic	61.58	21.04	79.60	95.83
Exponential	62.08	22.80	78.98	95.68
Fractional	**59.23**	**19.96**	**82.32**	**96.40**

Table 6. The robustness of zero-shot OOD detection to domain shift. The VITB/16 CLIP encoder is used.

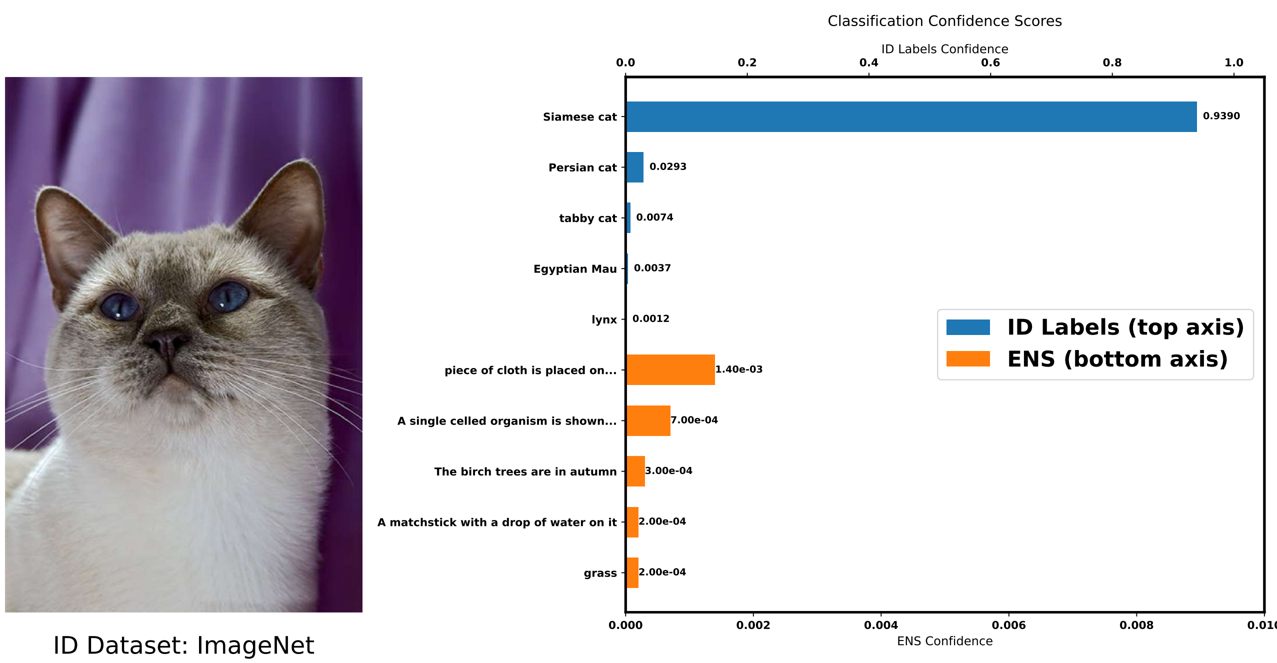
ID Dataset	Methods	OOD datasets INaturalist		SUN		Places		Textures		Average	
		AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓
ImageNet-S	MCM	87.74	63.06	85.35	67.24	81.19	70.64	74.77	79.59	82.26	70.13
	NegLabel [11]	99.34	2.24	94.93	22.73	90.78	38.62	89.29	46.10	93.59	27.42
	ANTS (Ours)	99.75	0.80	98.62	6.24	94.17	20.95	93.39	26.08	96.48	13.52
ImageNet-A	MCM [16]	79.50	76.85	76.19	79.78	70.95	80.51	61.98	86.37	72.16	80.88
	NegLabel [11]	98.80	4.09	89.83	44.38	82.88	60.10	80.25	64.34	87.94	43.23
	ANTS (Ours)	98.70	3.55	96.06	21.36	89.38	32.61	93.12	25.55	94.31	20.77
ImageNet-R	MCM [16]	83.22	71.51	80.31	74.98	75.53	76.67	67.66	83.72	76.68	76.72
	NegLabel [11]	99.58	1.60	96.03	15.77	91.97	29.48	90.60	35.67	94.54	20.63
	ANTS (Ours)	99.32	1.31	98.17	10.80	93.80	20.54	94.40	22.84	96.42	13.88
ImageNet-V2	MCM [16]	91.79	45.90	89.88	50.73	86.52	56.25	81.51	69.57	87.43	55.61
	NegLabel [11]	99.40	2.47	94.46	25.69	90.00	42.03	88.46	48.90	93.08	29.77
	ANTS (Ours)	99.50	1.32	98.45	7.98	94.28	22.01	95.93	19.75	97.04	12.77

Table 7. Zero-shot OOD detection performance with different ID datasets. The VITB/16 CLIP encoder is used.

ID Dataset	Methods	OOD datasets INaturalist		SUN		Places		Textures		Average	
		AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓	AUROC↑	FPR95↓
CUB-200-2011	MCM [16]	98.24	9.83	99.10	4.93	98.57	6.65	98.75	6.97	98.66	7.09
	EOE [2]	99.98	0.07	100.00	0.01	99.92	0.28	100.00	0.00	99.98	0.09
	NegLabel [11]	99.96	0.18	99.99	0.02	99.90	0.33	99.99	0.01	99.96	0.13
	ANTS (Ours)	99.96	0.03	99.99	0.00	99.83	0.02	100.00	0.00	99.95	0.01
STANFORD-CARS	MCM [16]	99.77	0.05	99.95	0.02	99.89	0.24	99.96	0.02	99.89	0.08
	EOE [2]	99.99	0.00	99.99	0.01	99.97	0.11	100.00	0.00	99.99	0.03
	NegLabel [11]	99.99	0.01	99.99	0.01	99.99	0.03	99.99	0.01	99.99	0.01
	ANTS (Ours)	100.00	0.00	100.00	0.00	99.97	0.00	100.00	0.00	99.99	0.00
Food-101	MCM [16]	99.78	0.64	99.75	0.90	99.58	1.86	98.62	4.04	99.43	1.86
	EOE [2]	99.98	0.06	100.00	0.00	99.97	0.14	99.01	2.61	99.74	0.70
	NegLabel [11]	99.99	0.01	99.99	0.01	99.99	0.01	99.60	1.61	99.90	0.40
	ANTS (Ours)	99.99	0.01	100.00	0.00	99.98	0.05	99.72	0.13	99.92	0.05
Oxford-IIIT Pet	MCM [16]	99.38	2.85	99.73	1.06	99.56	2.11	99.81	0.80	99.62	1.70
	EOE [2]	100.00	0.00	99.99	0.01	99.97	0.14	99.97	0.11	99.98	0.07
	NegLabel [11]	99.38	2.85	99.73	1.06	99.56	2.11	99.81	0.80	99.62	1.70
	ANTS (Ours)	100.00	0.00	100.00	0.03	99.97	0.03	99.97	0.00	99.99	0.02

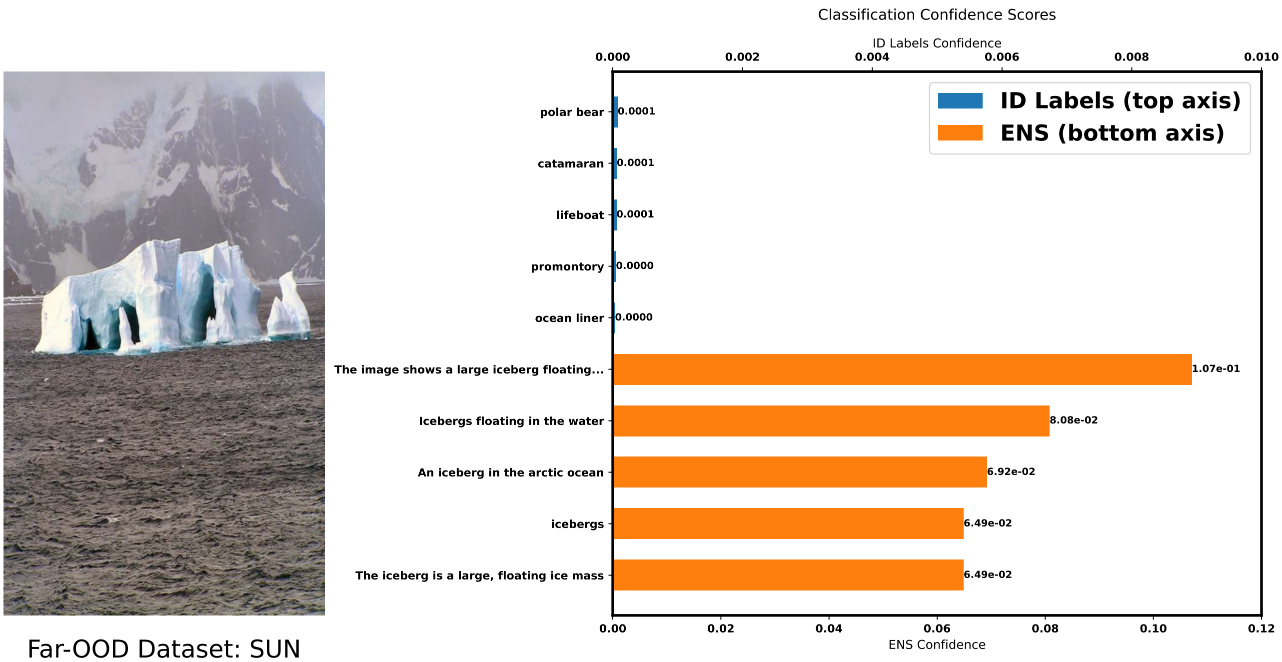


(a)

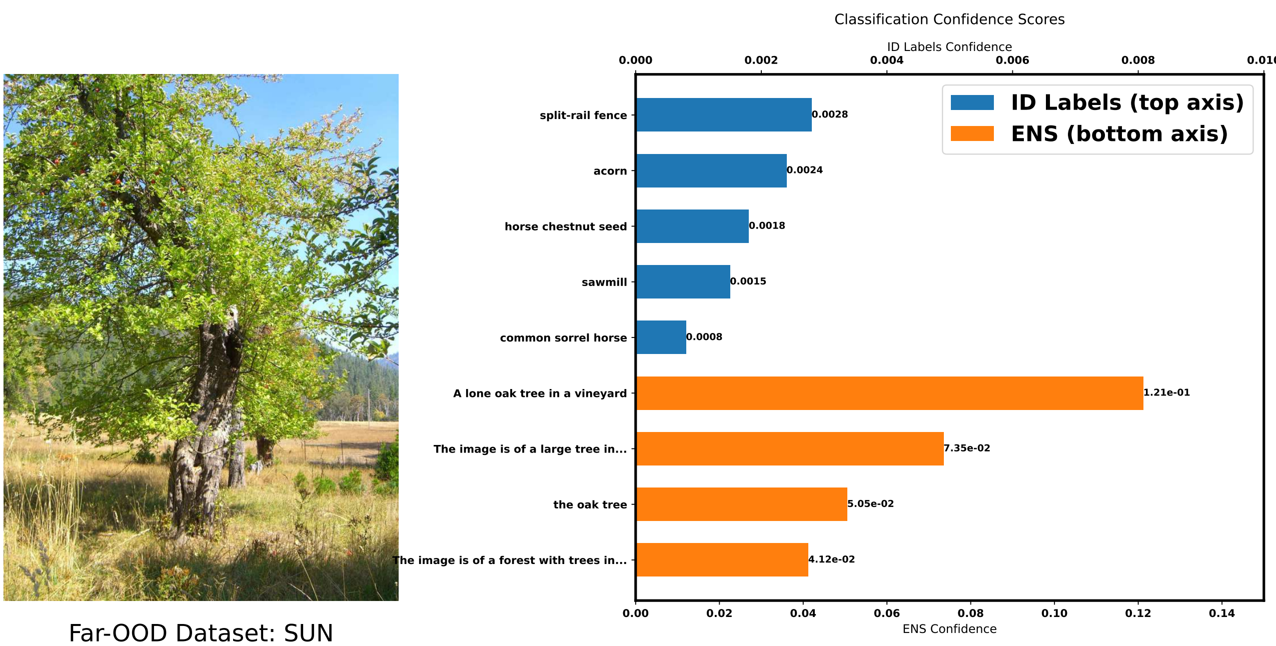


(b)

Figure 2. Example cases of classification confidence scores on ImageNet ID samples.

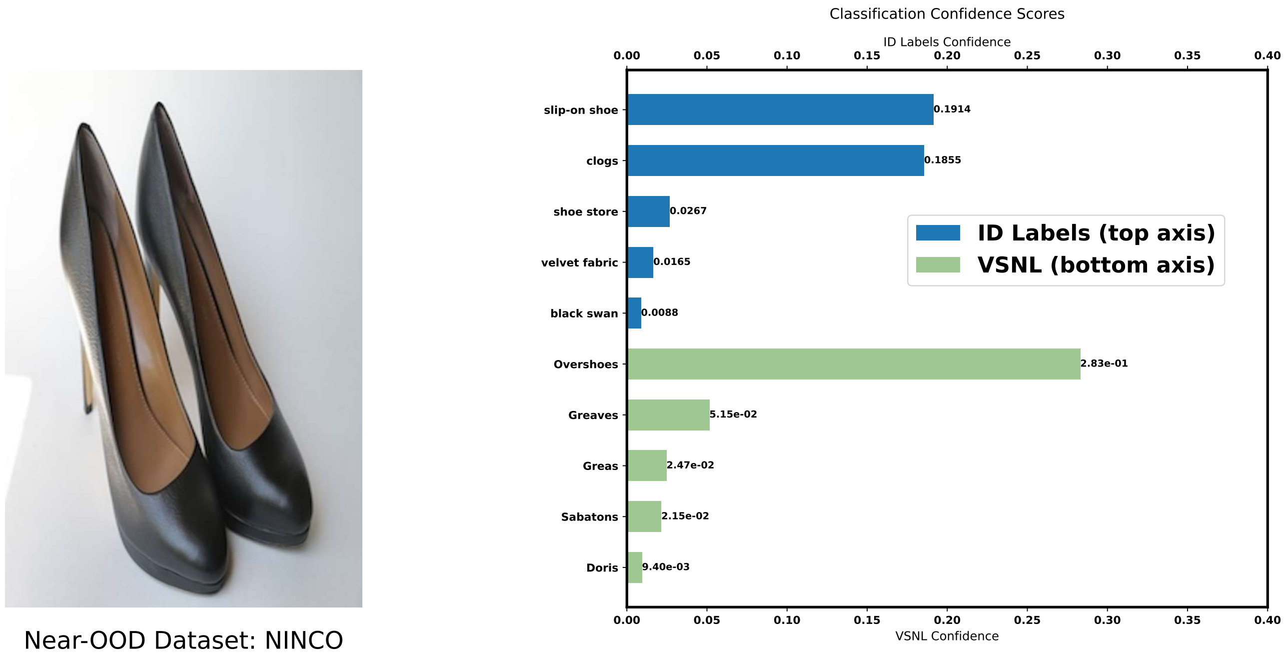


(a)

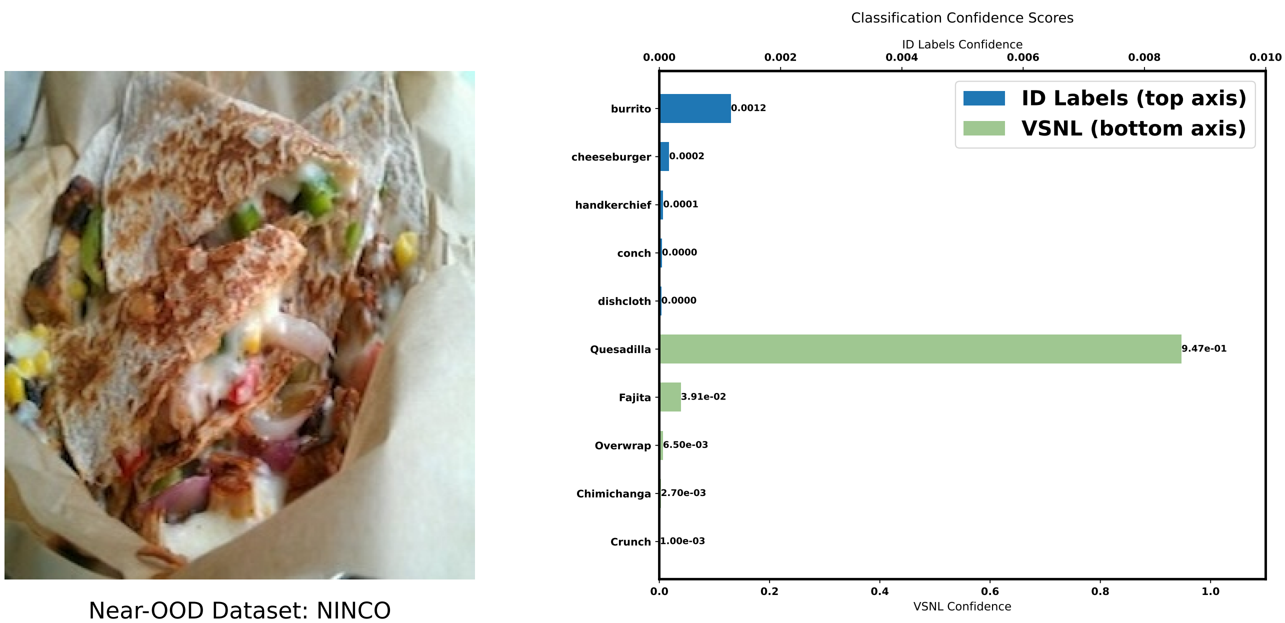


(b)

Figure 3. Example cases of classification confidence scores on Far-OOD samples of the SUN dataset.



(a)



(b)

Figure 4. Example cases of classification confidence scores on Near-OOD samples of the NINCO dataset.

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