
RainPGD: Investigating Rain-Robust Adversarial Patches

Alaqsa Akbar

s202281480@kfupm.edu.sa

Dr. Abduljabbar Siddiqui

abduljabbar.siddiqui@kfupm.edu.sa

KFUPM-SDAIA Joint Research Center

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Abstract

Adversarial patches pose a significant threat to object detection models by targeting localized image regions to mislead predictions. However, their effectiveness under adverse weather conditions, such as rain, remains underexplored. This paper introduces RainPGD, a novel adversarial patch generation method designed to maintain robustness in rainy conditions. To achieve this, we augment training images with various rain intensities, enabling RainPGD to learn perturbations that remain effective in adverse weather. We also present RainyCOCO, a modified version of the COCO dataset, containing images augmented with simulated rain, to support model training and evaluation under inclement conditions. Experimental results indicate that RainPGD shows a slight improvement in degrading object detection performance under rain, achieving a 0.86% decrease in model recall compared to a standard PGD patch. Although RainPGD incurs some performance trade-offs in clear conditions, it demonstrates potential for weather-resilient adversarial attacks, making it a valuable step toward robust adversarial training for real-world applications. The code and RainyCOCO dataset are publicly available for research use.

1 Introduction

With the increase in popularity of Artificial Intelligence, there has been a corresponding surge in object detection applications [1]. However, this surge also increases the demand for secure models. Adversarial patch attacks are a form of malicious attack that targets object detectors and image classifiers, in general. These attacks work by distorting a region of an image in a way that causes the object detector to misidentify objects. For example, adversarial patches have been shown to cause models to misclassify stop signs [2]. To defend against such attacks, it is crucial to develop a strong understanding of how these attacks are generated. By creating more robust adversarial attacks, object detection models can, in turn, become more resilient to them.

Currently, there appear to be no studies that investigate the effects of weather conditions on adversarial patches. Moreover, no efforts have been made to strengthen adversarial patch generation under rainy conditions. The field has primarily focused on de-raining images to improve object detection performance [3]–[5]. Therefore, exploring methods to train adversarial patches against rain and other adverse weather conditions could potentially yield better results and warrant further investigation.

In this paper, we introduce an adversarial patch attack generation method that we call RainPGD designed to be robust to adverse weather conditions, particularly rain. Preliminary testing revealed that adversarial patches performed similarly under both adverse and non-adverse weather. Under normal conditions, the patches had an mAP of 0.054, while under rainy conditions, the patches had an mAP of 0.055. We hypothesize that patches can be generated that could further degrade the performance of object detection models even under heavy weather conditions. This is because rain droplets obscure several pixels behind them, which may be crucial to the effectiveness of the patch. RainPGD augments the training data in real-time during the training process, allowing the adversarial algorithm to adapt to adverse weather conditions.

Alongside our investigations, we introduce the code used to augment any image by adding rain, implemented in the `add_rain()` function found in `RainPGD/utils.py`. This function simulates rain with three different intensities: **weak**, **heavy**, and **torrential**. Additionally, we present a modified version of the COCO dataset [6], called RainyCOCO, which consists entirely of COCO images augmented using the `add_rain()` function. RainyCOCO is designed to facilitate object detector training in adverse weather conditions. However, we recommend augmenting the training images in real time during the training process to introduce randomness into the dataset.

The code for this paper can be found at: <https://github.com/alaqsa-akbar/RainPGD>.

The RainyCOCO dataset can be found at: <https://huggingface.co/datasets/alaqsa-akbar/RainyCOCO>

2 Related Work

2.1 Object Detection

In this paper, Faster R-CNN [7] was used for the training and evaluation. However, in theory, this should still be effective against single stage detection (SSD) models.

2.2 Adversarial Training

In this paper, we focus on improving the untargeted image-specific and location-specific patches. These are the stronger form of adversarial patches. We will apply the patches on an input image x that is of shape $[0, 1]^{H \times W \times 3}$ where H and W are the height and width respectively. Adversarial patches are generated using a projected gradient descent algorithm [8]. The algorithm aims to maximize

the loss of the targeted model by solving the equation [9]:

$$\hat{P}(x, l) = \arg \max_{P \in \{P' : \|P'\|_\infty \leq \epsilon\}} \mathcal{L}(h(A(x, l, P)); y)$$

where $\mathcal{L}$ is the loss $\mathcal{L}^{\text{Faster R-CNN}}$ that compares h (the Faster R-CNN algorithm) with y (the ground truth labels). A is a function that applies a patch P onto image x at location l , $\|\cdot\|_\infty$ is the l_∞ norm, and ϵ is the attack budget. Solving this equation would be difficult, as such, a projected gradient descent algorithm is utilized [8], [9]:

$$P^{t+1} = \prod_{\mathbb{P}} (P^t + \alpha \text{sign}(\nabla_{P^t} \mathcal{L}(h(A(x, l, P^t)); y)))$$

where t is the iteration count, α is the step size, $\prod$ is the projection function that will project onto $\mathbb{P} = \{P \in \{P' : \|P'\|_\infty \leq \epsilon\} \text{ and } A(x, l, P) \in [0, 1]^{H \times W \times 3}\}$. In the case of patch attacks, we will use $\epsilon = 1$ to allow maximum freedom of pixel manipulation in the localized area.

3 Proposed Methodology

In order to improve robustness to rainy conditions, the rain patch must be trained against a target image representing the ideal scenario. To do so, we must figure add rain onto target images and then train the patch against them.

3.1 Training Against Rain

During the training process, rain conditions are randomly augmented onto the image. This happens before calculating the loss from the target estimator model. This is done to allow the PGD algorithm to learn the rain streaks and try to find the optimal perturbations to use with the rain. The proposed methodology will look like figure 1. Assume R is the function that applies rain conditions to an image with the patch applied $A(x, l, P^t)$ with a probability of p . The projected gradient descent algorithm becomes:

$$P^{t+1} = \prod_{\mathbb{P}} (P^t + \alpha \text{sign}(\nabla_{P^t} \mathcal{L}(h(R(A(x, l, P^t)), p); y)))$$

By adding a random probability p , the patch is trained to also be effective under non-rainy conditions. As a result, p would be a hyper-parameter needed to be tuned where a higher p would train a patch for areas with more frequent rain while a lower p would train for areas with less frequent rain.

3.2 Augmenting Images

The function R works by implementing a modified methodology utilized in Photoshop [10] by us-

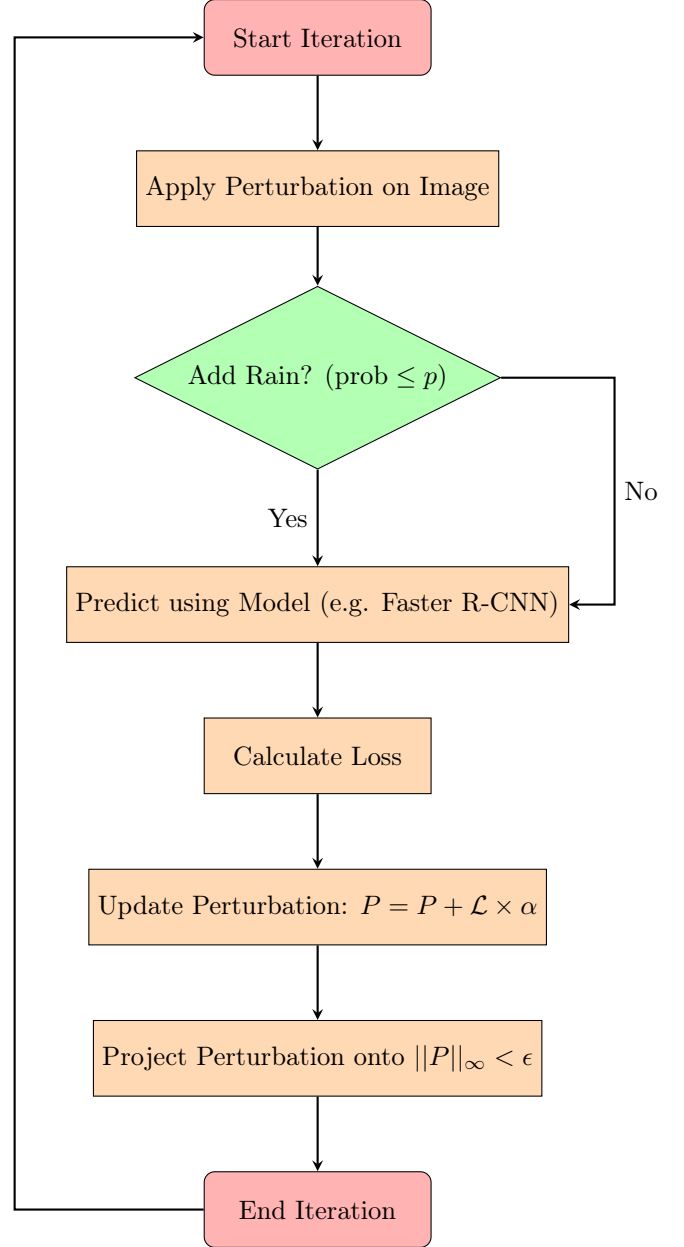


Figure 1: Flowchart of the proposed methodology

ing OpenCV [11]. The method found in Photoshop was used by previous papers that worked on state-of-the-art rain removal [3]. The algorithm works by creating a mask image m and applying it over the target image x where m is initially $m = [0]^{H \times W \times 3}$. Some points are then randomly selected from x through a discrete uniform distribution. The number of points selected is also a sampled from a uniform distribution using the equation:

$$s \sim U(0.8 \times HWr, HWr)$$

where s and r is a value chosen based on the rain strength chosen. Through experimentation, the values chosen for r were:

- 'weak': 0.002
- 'heavy': 0.004
- 'torrential': 0.006

These points are then converted into white rain streaks. The length of the one streak is calculated similarly using:

$$l \sim U(0.8 \times \frac{H}{15}, \frac{H}{15})$$

where l is the streak length and 15 is a number chosen through experimentation. Similarly the angle of the rain streaks, θ , is also sampled from a uniform distribution between $\frac{\pi}{4}$ and $\frac{3\pi}{4}$. Finally a line with values of 1 is drawn from $q_t + \delta$ to $q_t - \delta$ creating the matrix $\begin{pmatrix} q_t + \delta \\ q_t - \delta \end{pmatrix}$ where q_t is one of the chosen points and δ can be calculated using:

$$\delta = \frac{l}{2} \times \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}$$

A Gaussian blur, $G(m)$, is then applied to the mask using a kernel size of (9, 9). The brightness is reduced by a factor 0.7; this was chosen through experimentation. The mask is then applied using the screen blend algorithm found in Photoshop [12]:

$$S(x, m) = 1 - (1 - x) \odot (1 - m)$$

Finally, this would make the equation for $R(x, p)$ to be:

$$R(x, p) = \begin{cases} x & U(0, 1) > p \\ S(x, G(x + \sum_t \begin{pmatrix} q_t + \delta \\ q_t - \delta \end{pmatrix})) & U(0, 1) \leq p \end{cases}$$

4 Experimental Setup

For the testing of RainPGD, a Windows 10 computer was used with an RTX 3080 GPU and an Intel i9-12900k CPU. 6 different tests were run on the first 1000 images from the validation split of the 2017 COCO dataset. The 6 tests were the following:

- No patch applied on a normal image
- PGD patch applied on a normal image
- RainPGD patch applied on a normal image
- No patch on a an image with rain added
- PGD patch on an image with rain added
- RainPGD patch on an image with rain added

Each patch was trained for 200 iterations. When training RainPGD and testing under rainy conditions, the rain probability was set to 0.7. The patches were trained to be applied randomly onto images. The patch size was 100x100 square patches. The patches were trained against PyTorch's `fasterrcnn_resnet50_fpn` [13], trained on the 2017 COCO dataset, wrapped with Adversarial Robustness Toolbox (ART)'s `PyTorchFasterRCNN` class. Much of the implementation relied on ART's [14] `ProjectedGradientDescent` class and SegmentAndComplete's [9] `PGDPatch` class. The tests can be resimulated using `generate_adv_data.py` to generate the patches for each test case followed by using `eval_attack.py`.

To evaluate the results, the `pycocotools` library was used and generated results of the following categories:

Average Precision (AP):

• IoU=0.50:0.95	area=all	maxDets=100
• IoU=0.50	area=all	maxDets=100
• IoU=0.75	area=all	maxDets=100
• IoU=0.50:0.95	area=small	maxDets=100
• IoU=0.50:0.95	area=large	maxDets=100

Average Recall (AR):

• IoU=0.50:0.95	area=all	maxDets=1
• IoU=0.50:0.95	area=all	maxDets=10
• IoU=0.50:0.95	area=all	maxDets=100
• IoU=0.50:0.95	area=small	maxDets=100
• IoU=0.50:0.95	area=mid	maxDets=100
• IoU=0.50:0.95	area=large	maxDets=100

Average precision describes the model's precision or the ratio of correct predictions to total predictions. It can be calculated using:

$$\frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Average recall describes the model's ability to recall classes from a given image or the ratio of correct predictions to the total number of ground truths. It can be calculated using:

$$\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

A lower AP and AR score suggests a better performing adversarial patch as it causes the object-detection model to perform worse. In the case of non-targeting adversarial patch, AR is more important as the purpose of the non-targeting patches is to reduce the model's ability to detect objects. The main metric to observe would be $AR@[IoU=0.50:0.95, \text{maxDets}=100]$ as this allows for the most detections which is more representative of the real world.

To generate the RainyCOCO dataset, the `add_rain` function was applied to all 55000 images

in the train split of the 2017 COCO dataset. 3 different images were generated from each COCO image, one corresponding to each rain intensity. Similarly, this was done to the 5000 images in the validation split of the 2017 COCO dataset.

5 Results and Discussions

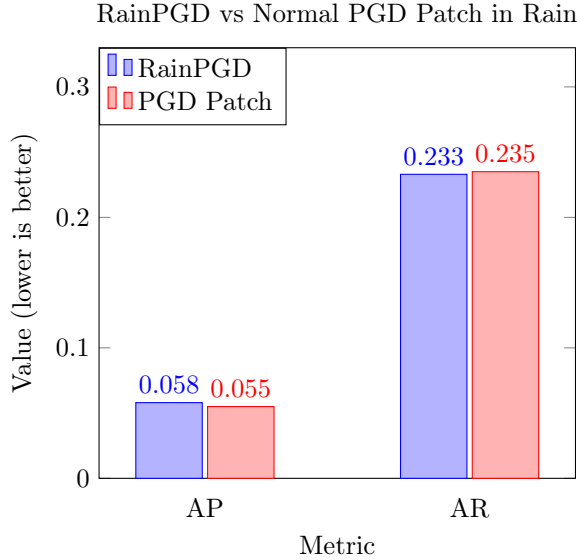


Figure 2: Comparison of AR and AP values for RainPGD and PGD Patch under rainy weather conditions (lower is better)

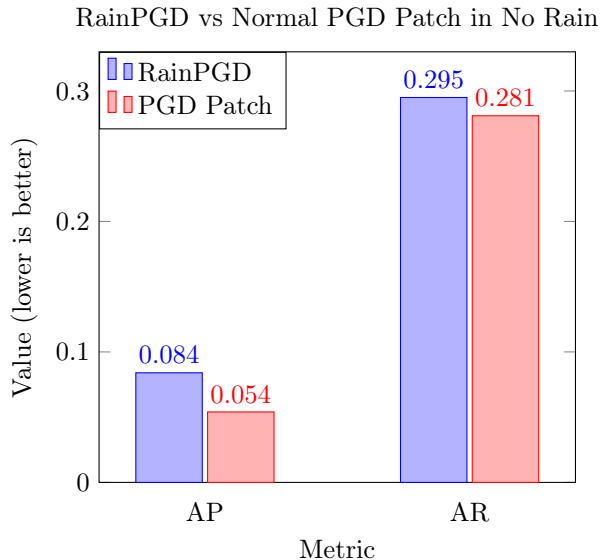


Figure 3: Comparison of AR and AP values for RainPGD and PGD Patch in clear weather conditions (lower is better)

The full table of results is available in the appendix in tables 3 to 8, while the summarized outcomes are shown in Figure figs. 2 and 3 and tables 1

Table 1: Evaluation Results for Rainy Conditions

Metric	No Patch	PGD Patch	RainPGD Patch
AP@[IoU=0.5:0.95]	0.219	0.055	0.058
AP@[IoU=0.5]	0.357	0.100	0.106
AP@[IoU=0.75]	0.232	0.053	0.056
AP@[small]	0.057	0.006	0.010
AP@[medium]	0.273	0.083	0.080
AP@[large]	0.353	0.138	0.132
AR@[IoU=0.5:0.95]@[IoU=0.50:0.95, maxDets=1]	0.208	0.147	0.147
AR@[IoU=0.5:0.95]@[IoU=0.50:0.95, maxDets=10]	0.306	0.227	0.226
AR@[IoU=0.5:0.95]@[IoU=0.50:0.95, maxDets=100]	0.314	0.235	0.233
AR@[small]	0.072	0.057	0.055
AR@[medium]	0.373	0.292	0.289
AR@[large]	0.530	0.380	0.378

Table 2: Evaluation Results for Normal Conditions

Metric	No Patch	PGD Patch	RainPGD Patch
AP@[IoU=0.5:0.95]	0.293	0.054	0.084
AP@[IoU=0.5]	0.460	0.098	0.147
AP@[IoU=0.75]	0.318	0.052	0.085
AP@[small]	0.077	0.004	0.013
AP@[medium]	0.352	0.085	0.112
AP@[large]	0.478	0.165	0.193
AR@[IoU=0.5:0.95]@[IoU=0.50:0.95, maxDets=1]	0.260	0.174	0.187
AR@[IoU=0.5:0.95]@[IoU=0.50:0.95, maxDets=10]	0.383	0.272	0.287
AR@[IoU=0.5:0.95]@[IoU=0.50:0.95, maxDets=100]	0.392	0.281	0.295
AR@[small]	0.097	0.067	0.071
AR@[medium]	0.466	0.348	0.366
AR@[large]	0.646	0.455	0.471

and 2. The findings indicate that RainPGD enhances patch performance under rainy conditions, reducing model recall from 0.235 with a standard PGD patch to 0.233 with RainPGD under rainy conditions. This corresponds to a 0.86% decrease in model performance relative to standard PGD, signifying a 0.86% improvement in patch robustness in rain. However, under clear conditions, RainPGD performs worse, showing a 4.75% decrease in performance, likely due to its training with a rain probability of 0.7. A lower rain probability might yield a more balanced performance across conditions but further experimentation is needed.

In terms of model precision, the mean average precision (mAP) metric revealed that RainPGD performed 5.17% worse than the standard PGD patch under rainy conditions. Despite this, the recall metric remains more relevant as it directly supports the goal of creating a non-targeting patch.

These results suggest that the RainPGD patch is indeed adapting to rain patterns, enabling it to perform marginally better under rainy conditions. However, this improvement may not justify the performance loss in clear conditions. One potential reason for this trade-off could be the noisy and inconsistent rain patterns during training, which may harm the patch’s learning as it needs to learn from several different pattern rain patterns. This can be seen in the loss curves for each of the training of patches using RainPGD 4 in comparison to the loss curve of in the training of normal PGD 5. Extending training over more iterations could help mitigate this, but further experimentation is needed.

Another notable finding is the minimal difference in model performance with and without rainy conditions when no patch or a standard PGD

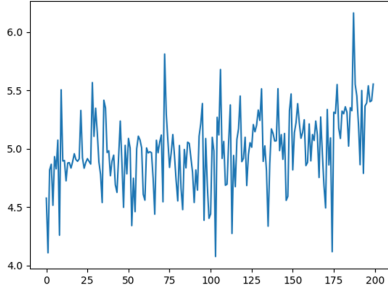


Figure 4: RainPGD Loss Curve (Loss vs Epoch)

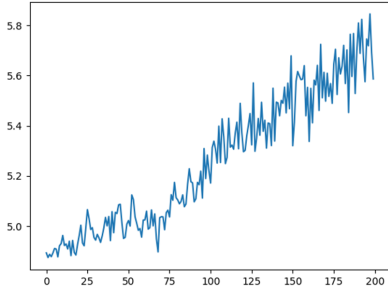


Figure 5: Normal PGD Loss Curve (Loss vs Epoch)

patch is used. This stability implies that accommodating rainy conditions may not be essential. Yet, the RainPGD patch’s improvement over the standard PGD patch under rain suggests there is potential value in this approach.

One interesting metric appears when comparing RainPGD with and without rain and current methods with and without rain. Current methods see an improvement in adversarial attack of around 16.4% while RainPGD sees an improvement of around 21.0% highlighting that RainPGD is in fact learning the patterns of rain. It is possible that methodologies like RainPGD could perform better in conditions that are more damaging to the current PGD implementations as opposed to what we saw with rain where rain helped current methods in their adversarial targets. Similarly, this could prove interesting in targeted attacks as opposed to purely non-targeting.

6 Conclusion and Future Work

In this paper, we introduced RainPGD, a novel adversarial patch generation algorithm designed to be resilient under adverse weather conditions, specifically rain. Our experiments showed a 0.86% improvement in recall compared to traditional methods, indicating RainPGD’s potential for en-

hancing robustness in challenging conditions. The approach underlying RainPGD can likely be extended to other environments, such as snow or dust, and even to more complex applications where adaptive patches are needed.

However, for now we advise to utilize the already existing PGD methods which offer a more balanced result.

Further exploration is essential to optimize RainPGD and fully understand its potential. Future work could focus on refining the rain simulation method, exploring varied hyper-parameters, and testing RainPGD with targeted adversarial patches to broaden its applicability. The paper highlighted that RainPGD does in fact learn to adapt to the adverse-weather conditions, and as such, we believe that there are applications where this methodology could be useful if experimented with more.

Additionally, we introduced the RainyCOCO dataset, intended to support ongoing research by providing a standardized dataset for evaluating performance in rainy weather. We hope RainyCOCO will facilitate further advancements in weather-robust AI systems.

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A Evaluation Results

Table 3: Evaluation results for non-adversarial images under normal conditions

Class	AP_all	AP_50	AP_75	AP_small	AP_medium	AP_large	AR_all_1	AR_all_10	AR_all_100	AR_small	AR_medium	AR_large
person	0.405	0.632	0.440	0.134	0.536	0.674	0.171	0.433	0.466	0.170	0.602	0.748
bicycle	0.218	0.407	0.218	0.057	0.306	0.537	0.193	0.291	0.302	0.081	0.425	0.628
car	0.218	0.353	0.230	0.071	0.431	0.565	0.126	0.282	0.288	0.104	0.551	0.718
motorcycle	0.344	0.613	0.357	0.094	0.330	0.553	0.239	0.413	0.436	0.108	0.448	0.645
airplane	0.499	0.763	0.561	0.251	0.553	0.609	0.454	0.573	0.578	0.277	0.602	0.693
bus	0.550	0.729	0.648	0.130	0.346	0.741	0.463	0.605	0.608	0.142	0.432	0.798
train	0.550	0.800	0.617	0.000	0.152	0.600	0.572	0.646	0.646	0.000	0.383	0.690
truck	0.274	0.468	0.281	0.080	0.299	0.436	0.282	0.430	0.434	0.117	0.479	0.657
boat	0.167	0.332	0.140	0.055	0.247	0.429	0.121	0.246	0.266	0.091	0.390	0.602
traffic light	0.089	0.196	0.073	0.038	0.299	0.429	0.074	0.134	0.134	0.061	0.428	0.589
fire hydrant	0.477	0.643	0.560	0.029	0.540	0.715	0.439	0.507	0.507	0.044	0.560	0.755
stop sign	0.501	0.565	0.556	0.036	0.606	0.878	0.485	0.527	0.527	0.033	0.662	0.915
parking meter	0.385	0.575	0.437	0.104	0.365	0.613	0.292	0.422	0.422	0.119	0.376	0.674
bench	0.158	0.266	0.170	0.044	0.168	0.325	0.194	0.262	0.266	0.060	0.285	0.530
bird	0.216	0.341	0.225	0.088	0.453	0.655	0.145	0.251	0.259	0.103	0.531	0.731
cat	0.564	0.882	0.599	0.000	0.572	0.579	0.608	0.673	0.673	0.000	0.646	0.696
dog	0.512	0.732	0.574	0.098	0.528	0.574	0.508	0.619	0.619	0.095	0.571	0.715
horse	0.495	0.725	0.560	0.157	0.514	0.680	0.348	0.565	0.566	0.180	0.591	0.743
sheep	0.397	0.625	0.437	0.152	0.503	0.555	0.119	0.438	0.489	0.203	0.582	0.675
cow	0.338	0.489	0.401	0.055	0.493	0.627	0.158	0.402	0.411	0.086	0.585	0.728
elephant	0.525	0.780	0.601	0.234	0.460	0.635	0.261	0.607	0.629	0.241	0.524	0.749
bear	0.627	0.826	0.721	0.000	0.725	0.669	0.511	0.677	0.677	0.000	0.769	0.719
zebra	0.551	0.807	0.612	0.273	0.570	0.697	0.257	0.605	0.616	0.285	0.620	0.756
giraffe	0.610	0.868	0.691	0.197	0.669	0.684	0.343	0.657	0.662	0.200	0.688	0.750
backpack	0.070	0.147	0.052	0.042	0.125	0.140	0.117	0.183	0.185	0.080	0.301	0.458
umbrella	0.303	0.516	0.315	0.088	0.380	0.522	0.213	0.407	0.431	0.140	0.508	0.682
handbag	0.070	0.149	0.053	0.040	0.149	0.071	0.104	0.174	0.174	0.066	0.312	0.455
tie	0.187	0.310	0.209	0.064	0.384	0.459	0.198	0.247	0.248	0.079	0.484	0.619
suitcase	0.249	0.429	0.254	0.056	0.266	0.499	0.167	0.335	0.359	0.070	0.401	0.666
frisbee	0.384	0.487	0.471	0.205	0.619	0.823	0.337	0.419	0.419	0.209	0.682	0.863
skis	0.139	0.297	0.122	0.122	0.342	0.084	0.177	0.228	0.236	0.140	0.514	0.425
snowboard	0.245	0.407	0.293	0.118	0.503	0.371	0.301	0.339	0.339	0.128	0.633	0.620
sports ball	0.096	0.122	0.120	0.063	0.239	0.628	0.096	0.108	0.108	0.066	0.322	0.629
kite	0.175	0.279	0.182	0.117	0.406	0.267	0.150	0.241	0.254	0.129	0.517	0.559
baseball bat	0.190	0.400	0.175	0.173	0.306	0.001	0.227	0.271	0.271	0.178	0.400	0.150
baseball glove	0.148	0.274	0.134	0.056	0.303	0.528	0.157	0.185	0.185	0.063	0.379	0.600
skateboard	0.360	0.563	0.380	0.180	0.534	0.434	0.387	0.424	0.424	0.186	0.607	0.612
surfboard	0.258	0.447	0.280	0.083	0.393	0.430	0.236	0.338	0.344	0.103	0.470	0.641
tennis racket	0.330	0.579	0.310	0.138	0.479	0.343	0.353	0.395	0.395	0.153	0.525	0.568
bottle	0.217	0.337	0.250	0.076	0.416	0.613	0.145	0.275	0.290	0.116	0.531	0.798
wine glass	0.200	0.338	0.205	0.025	0.344	0.683	0.119	0.255	0.256	0.054	0.421	0.803
cup	0.239	0.346	0.268	0.061	0.371	0.576	0.192	0.334	0.336	0.099	0.505	0.762
fork	0.231	0.409	0.222	0.095	0.402	0.350	0.266	0.333	0.333	0.123	0.511	0.577
knife	0.111	0.199	0.102	0.063	0.253	0.253	0.147	0.199	0.199	0.092	0.415	0.392
spoon	0.099	0.198	0.091	0.071	0.215	0.195	0.137	0.216	0.221	0.107	0.441	0.507
bowl	0.308	0.458	0.334	0.087	0.328	0.537	0.260	0.451	0.460	0.142	0.503	0.740
banana	0.167	0.344	0.133	0.061	0.193	0.354	0.105	0.249	0.324	0.105	0.369	0.580
apple	0.128	0.199	0.136	0.028	0.182	0.354	0.109	0.245	0.277	0.054	0.368	0.672
sandwich	0.305	0.505	0.350	0.021	0.171	0.440	0.276	0.490	0.490	0.044	0.327	0.673
orange	0.229	0.318	0.255	0.028	0.334	0.424	0.129	0.360	0.416	0.087	0.533	0.734
broccoli	0.169	0.352	0.151	0.015	0.209	0.226	0.083	0.298	0.364	0.051	0.396	0.528
carrot	0.143	0.276	0.122	0.062	0.246	0.205	0.090	0.244	0.282	0.110	0.437	0.447
hot dog	0.251	0.442	0.208	0.061	0.333	0.407	0.212	0.332	0.352	0.073	0.442	0.560
pizza	0.442	0.648	0.495	0.046	0.348	0.631	0.370	0.544	0.547	0.048	0.481	0.752
donut	0.308	0.430	0.337	0.116	0.392	0.704	0.119	0.366	0.407	0.138	0.551	0.843
cake	0.265	0.454	0.281	0.088	0.307	0.417	0.234	0.387	0.411	0.116	0.437	0.650
chair	0.190	0.350	0.185	0.073	0.263	0.336	0.137	0.304	0.319	0.124	0.399	0.606
couch	0.349	0.596	0.364	0.000	0.254	0.405	0.369	0.545	0.546	0.000	0.383	0.620
potted plant	0.189	0.361	0.180	0.072	0.256	0.270	0.208	0.334	0.341	0.108	0.402	0.547
bed	0.354	0.639	0.359	0.000	0.116	0.382	0.455	0.533	0.534	0.000	0.157	0.573
dining table	0.238	0.398	0.235	0.047	0.110	0.356	0.346	0.441	0.447	0.072	0.279	0.623
toilet	0.513	0.723	0.587	0.119	0.409	0.587	0.527	0.631	0.632	0.114	0.489	0.714
tv	0.485	0.682	0.558	0.040	0.452	0.642	0.459	0.585	0.585	0.059	0.544	0.759
laptop	0.525	0.721	0.605	0.080	0.424	0.665	0.506	0.590	0.594	0.090	0.460	0.752
mouse	0.228	0.302	0.297	0.046	0.355	0.707	0.236	0.257	0.257	0.043	0.402	0.800
remote	0.133	0.212	0.154	0.050	0.358	0.528	0.123	0.193	0.193	0.061	0.522	0.757
keyboard	0.421	0.674	0.479	0.068	0.422	0.545	0.410	0.526	0.526	0.100	0.518	0.672
cell phone	0.223	0.348	0.237	0.062	0.387	0.548	0.255	0.320	0.320	0.101	0.558	0.708
microwave	0.441	0.607	0.507	0.180	0.377	0.634	0.527	0.567	0.567	0.175	0.524	0.733
oven	0.282	0.513	0.264	0.000	0.269	0.346	0.347	0.431	0.432	0.000	0.390	0.511
toaster	0.122	0.191	0.177	0.000	0.176	0.227	0.256	0.311	0.311	0.000	0.380	0.450
sink	0.262	0.441	0.264	0.075	0.338	0.382	0.312	0.403	0.403	0.083	0.466	0.630
refrigerator	0.469	0.692	0.555	0.000	0.182	0.556	0.450	0.568	0.577	0.000	0.304	0.662
book	0.078	0.169	0.064	0.041	0.179	0.255	0.052	0.134	0.171	0.087	0.369	0.570
clock	0.304	0.475	0.330	0.076	0.470	0.575	0.294	0.374	0.374	0.098	0.562	0.687
vase	0.220	0.346	0.242	0.065	0.295	0.495	0.195	0.317	0.333	0.093	0.447	0.704
scissors	0.213	0.328	0.247	0.000	0.386	0.293	0.222	0.258	0.258	0.000	0.444	0.379
teddy bear	0.383	0.615	0.436	0.058	0.331	0.549	0.303	0.484	0.488	0.056	0.431	0.681
hair drier	0.017	0.061	0.008	0.031	0.009	0.071	0.118	0.182	0.182	0.060	0.133	0.433
toothbrush	0.126	0.269	0.091	0.064	0.240	0.447	0.156	0.186	0.186	0.094	0.289	0.667
Total	0.293	0.460	0.318	0.077	0.352	0.478	0.260	0.383	0.392	0.097	0.466	0.646

Table 4: Evaluation results for non-adversarial images under rainy conditions (p=0.7)

Class	AP_all	AP_50	AP_75	AP_small	AP_medium	AP_large	AR_all_1	AR_all_10	AR_all_100	AR_small	AR_medium	AR_large
person	0.353	0.576	0.369	0.121	0.470	0.586	0.154	0.385	0.416	0.150	0.536	0.670
bicycle	0.169	0.339	0.156	0.033	0.231	0.473	0.159	0.237	0.248	0.046	0.341	0.590
car	0.192	0.316	0.206	0.067	0.375	0.485	0.109	0.248	0.255	0.093	0.484	0.642
motorcycle	0.279	0.522	0.288	0.066	0.246	0.480	0.197	0.344	0.359	0.088	0.325	0.575
airplane	0.382	0.644	0.403	0.222	0.440	0.463	0.370	0.478	0.483	0.240	0.495	0.579
bus	0.471	0.652	0.552	0.129	0.314	0.630	0.406	0.535	0.538	0.136	0.380	0.704
train	0.465	0.712	0.500	0.000	0.058	0.518	0.491	0.551	0.551	0.000	0.206	0.601
truck	0.214	0.396	0.203	0.076	0.230	0.341	0.238	0.366	0.369	0.126	0.387	0.562
boat	0.105	0.223	0.087	0.039	0.134	0.307	0.083	0.160	0.176	0.053	0.239	0.464
traffic light	0.068	0.150	0.055	0.033	0.226	0.320	0.060	0.109	0.109	0.051	0.336	0.521
fire hydrant	0.445	0.627	0.519	0.029	0.513	0.663	0.416	0.483	0.483	0.044	0.543	0.711
stop sign	0.470	0.539	0.530	0.032	0.550	0.840	0.476	0.489	0.489	0.030	0.600	0.863
parking meter	0.303	0.439	0.339	0.044	0.332	0.457	0.242	0.337	0.337	0.050	0.348	0.526
bench	0.104	0.178	0.110	0.030	0.118	0.204	0.146	0.192	0.197	0.035	0.208	0.410
bird	0.181	0.288	0.199	0.069	0.399	0.571	0.138	0.223	0.227	0.081	0.474	0.688
cat	0.384	0.648	0.384	0.000	0.409	0.395	0.447	0.503	0.503	0.000	0.484	0.520
dog	0.378	0.564	0.435	0.093	0.421	0.403	0.403	0.493	0.493	0.089	0.497	0.547
horse	0.415	0.638	0.453	0.089	0.460	0.584	0.317	0.520	0.528	0.149	0.550	0.704
sheep	0.327	0.540	0.345	0.121	0.412	0.463	0.112	0.368	0.419	0.153	0.491	0.620
cow	0.259	0.408	0.297	0.043	0.375	0.485	0.142	0.341	0.349	0.078	0.483	0.627
elephant	0.396	0.642	0.413	0.110	0.353	0.469	0.217	0.474	0.493	0.118	0.401	0.602
bear	0.439	0.633	0.496	0.000	0.668	0.433	0.434	0.537	0.537	0.000	0.715	0.543
zebra	0.525	0.785	0.597	0.263	0.540	0.676	0.249	0.580	0.597	0.269	0.589	0.745
giraffe	0.555	0.805	0.615	0.198	0.589	0.652	0.332	0.614	0.625	0.200	0.607	0.742
backpack	0.048	0.110	0.033	0.023	0.089	0.131	0.091	0.144	0.146	0.056	0.250	0.362
umbrella	0.233	0.405	0.237	0.063	0.295	0.415	0.174	0.342	0.357	0.107	0.415	0.587
handbag	0.046	0.095	0.045	0.023	0.094	0.064	0.074	0.132	0.132	0.048	0.233	0.440
tie	0.132	0.235	0.134	0.058	0.312	0.265	0.155	0.219	0.224	0.075	0.430	0.567
suitcase	0.155	0.286	0.153	0.019	0.178	0.309	0.106	0.235	0.251	0.040	0.268	0.495
frisbee	0.332	0.436	0.396	0.172	0.580	0.708	0.321	0.384	0.384	0.181	0.645	0.787
skis	0.106	0.243	0.097	0.100	0.246	0.042	0.146	0.197	0.201	0.119	0.441	0.325
snowboard	0.150	0.248	0.186	0.053	0.330	0.204	0.223	0.236	0.236	0.055	0.487	0.480
sports ball	0.079	0.101	0.086	0.051	0.217	0.602	0.085	0.095	0.095	0.056	0.278	0.643
kite	0.136	0.227	0.143	0.096	0.326	0.248	0.129	0.198	0.205	0.100	0.414	0.505
baseball bat	0.138	0.307	0.098	0.133	0.233	0.000	0.174	0.218	0.218	0.138	0.328	0.150
baseball glove	0.122	0.219	0.121	0.056	0.255	0.065	0.140	0.160	0.160	0.057	0.327	0.467
skateboard	0.287	0.461	0.331	0.128	0.452	0.284	0.324	0.356	0.356	0.138	0.532	0.488
surfboard	0.202	0.355	0.201	0.042	0.329	0.301	0.197	0.284	0.290	0.059	0.413	0.567
tennis racket	0.300	0.542	0.279	0.130	0.439	0.343	0.325	0.381	0.381	0.140	0.509	0.568
bottle	0.166	0.273	0.187	0.055	0.332	0.449	0.116	0.228	0.238	0.092	0.443	0.635
wine glass	0.154	0.265	0.162	0.027	0.262	0.601	0.104	0.209	0.213	0.044	0.341	0.700
cup	0.178	0.264	0.198	0.047	0.302	0.380	0.158	0.284	0.285	0.075	0.455	0.602
fork	0.168	0.291	0.174	0.060	0.284	0.283	0.190	0.248	0.248	0.081	0.370	0.518
knife	0.062	0.121	0.051	0.041	0.144	0.149	0.093	0.129	0.129	0.058	0.265	0.308
spoon	0.073	0.135	0.078	0.042	0.139	0.206	0.091	0.134	0.134	0.059	0.273	0.357
owl	0.222	0.347	0.228	0.051	0.233	0.403	0.200	0.358	0.368	0.085	0.400	0.623
banana	0.120	0.257	0.096	0.047	0.162	0.209	0.089	0.210	0.262	0.072	0.312	0.456
apple	0.076	0.122	0.069	0.029	0.112	0.193	0.076	0.169	0.191	0.049	0.266	0.400
sandwich	0.198	0.348	0.203	0.021	0.116	0.284	0.233	0.372	0.372	0.044	0.231	0.516
orange	0.166	0.242	0.180	0.015	0.247	0.300	0.111	0.289	0.333	0.046	0.439	0.602
broccoli	0.125	0.297	0.099	0.013	0.147	0.191	0.079	0.233	0.288	0.044	0.308	0.431
carrot	0.107	0.214	0.095	0.029	0.190	0.148	0.071	0.185	0.213	0.073	0.345	0.326
hot dog	0.157	0.268	0.160	0.022	0.218	0.270	0.157	0.254	0.271	0.047	0.358	0.426
pizza	0.384	0.563	0.436	0.028	0.308	0.546	0.342	0.500	0.503	0.040	0.454	0.687
donut	0.217	0.310	0.247	0.110	0.275	0.491	0.097	0.315	0.352	0.126	0.463	0.730
cake	0.179	0.308	0.183	0.056	0.215	0.290	0.197	0.330	0.338	0.071	0.352	0.566
chair	0.115	0.221	0.105	0.054	0.167	0.189	0.101	0.227	0.239	0.090	0.294	0.472
couch	0.192	0.340	0.193	0.000	0.101	0.232	0.234	0.340	0.340	0.000	0.176	0.405
potted plant	0.155	0.320	0.133	0.069	0.197	0.263	0.168	0.289	0.294	0.108	0.327	0.509
bed	0.209	0.400	0.176	0.000	0.107	0.222	0.352	0.409	0.410	0.000	0.136	0.439
dining table	0.184	0.328	0.172	0.033	0.084	0.274	0.295	0.377	0.381	0.057	0.209	0.545
toilet	0.319	0.509	0.330	0.000	0.268	0.362	0.371	0.460	0.461	0.000	0.357	0.526
tv	0.295	0.433	0.319	0.009	0.269	0.395	0.311	0.374	0.374	0.015	0.333	0.502
laptop	0.367	0.520	0.417	0.027	0.255	0.490	0.376	0.435	0.439	0.035	0.296	0.587
mouse	0.128	0.178	0.167	0.043	0.203	0.267	0.137	0.143	0.143	0.042	0.225	0.344
remote	0.087	0.148	0.101	0.031	0.227	0.418	0.096	0.128	0.128	0.042	0.327	0.564
keyboard	0.280	0.442	0.325	0.000	0.273	0.404	0.300	0.388	0.388	0.000	0.359	0.551
cell phone	0.168	0.270	0.177	0.041	0.320	0.378	0.194	0.235	0.235	0.057	0.460	0.483
microwave	0.258	0.388	0.287	0.180	0.260	0.297	0.293	0.313	0.313	0.175	0.291	0.383
oven	0.180	0.314	0.176	0.000	0.180	0.209	0.236	0.278	0.278	0.000	0.245	0.332
toaster	0.058	0.076	0.057	0.000	0.088	0.126	0.200	0.256	0.256	0.000	0.260	0.500
sink	0.169	0.299	0.158	0.066	0.262	0.189	0.231	0.286	0.286	0.073	0.353	0.397
refrigerator	0.293	0.500	0.319	0.000	0.148	0.342	0.335	0.422	0.436	0.000	0.207	0.506
book	0.056	0.125	0.043	0.031	0.137	0.156	0.039	0.098	0.127	0.061	0.295	0.391
clock	0.283	0.435	0.316	0.064	0.458	0.540	0.274	0.349	0.349	0.088	0.532	0.638
vase	0.178	0.292	0.183	0.060	0.248	0.423	0.166	0.292	0.300	0.080	0.390	0.667
scissors	0.128	0.224	0.124	0.000	0.303	0.127	0.150	0.169	0.169	0.000	0.300	0.243
teddy bear	0.280	0.475	0.297	0.027	0.311	0.375	0.229	0.379	0.384	0.023	0.396	0.517
hair drier	0.006	0.013	0.005	0.000	0.008	0.022	0.064	0.127	0.127	0.000	0.133	0.333
toothbrush	0.055	0.146	0.025	0.060	0.060	0.303	0.081	0.119	0.119	0.075	0.150	0.467
Total	0.219	0.357	0.232	0.057	0.273	0.353	0.208	0.306	0.314	0.072	0.373	0.530

Table 5: Evaluation results for normal adversarial images under normal conditions

Class	AP_all	AP_50	AP_75	AP_small	AP_medium	AP_large	AR_all_1	AR_all_10	AR_all_100	AR_small	AR_medium	AR_large
person	0.126	0.228	0.124	0.014	0.216	0.365	0.117	0.331	0.362	0.123	0.482	0.578
bicycle	0.017	0.042	0.011	0.001	0.037	0.146	0.127	0.219	0.227	0.061	0.331	0.440
car	0.022	0.042	0.021	0.003	0.089	0.207	0.099	0.223	0.229	0.074	0.461	0.561
motorcycle	0.077	0.197	0.052	0.012	0.108	0.122	0.137	0.273	0.284	0.070	0.338	0.375
airplane	0.023	0.048	0.021	0.003	0.043	0.137	0.217	0.378	0.387	0.227	0.453	0.416
bus	0.101	0.169	0.105	0.002	0.034	0.329	0.337	0.458	0.460	0.092	0.302	0.618
train	0.089	0.198	0.069	0.000	0.007	0.145	0.272	0.403	0.403	0.000	0.228	0.431
truck	0.060	0.123	0.052	0.013	0.093	0.089	0.191	0.321	0.324	0.074	0.374	0.482
boat	0.008	0.022	0.004	0.001	0.018	0.085	0.064	0.156	0.188	0.061	0.292	0.406
traffic light	0.010	0.026	0.007	0.002	0.154	0.156	0.059	0.106	0.110	0.046	0.378	0.458
fire hydrant	0.198	0.300	0.211	0.000	0.296	0.376	0.326	0.384	0.384	0.000	0.433	0.586
stop sign	0.173	0.238	0.174	0.001	0.215	0.596	0.367	0.403	0.403	0.019	0.538	0.681
parking meter	0.074	0.122	0.076	0.002	0.057	0.326	0.215	0.278	0.280	0.031	0.267	0.465
bench	0.002	0.004	0.001	0.000	0.002	0.045	0.125	0.187	0.194	0.044	0.214	0.379
bird	0.008	0.014	0.007	0.001	0.034	0.049	0.088	0.173	0.182	0.066	0.422	0.465
cat	0.099	0.209	0.073	0.000	0.048	0.155	0.371	0.451	0.454	0.000	0.519	0.450
dog	0.067	0.123	0.064	0.002	0.051	0.130	0.356	0.454	0.457	0.095	0.419	0.525
horse	0.108	0.190	0.105	0.004	0.145	0.243	0.225	0.388	0.392	0.095	0.439	0.503
sheep	0.114	0.210	0.109	0.020	0.205	0.126	0.081	0.311	0.362	0.140	0.465	0.448
cow	0.117	0.188	0.130	0.010	0.243	0.194	0.117	0.303	0.310	0.073	0.446	0.529
elephant	0.167	0.303	0.163	0.002	0.156	0.325	0.177	0.431	0.458	0.124	0.394	0.542
bear	0.154	0.289	0.145	0.000	0.200	0.170	0.287	0.414	0.414	0.000	0.569	0.415
zebra	0.188	0.347	0.177	0.068	0.179	0.274	0.139	0.430	0.451	0.231	0.446	0.550
giraffe	0.145	0.252	0.143	0.002	0.119	0.299	0.243	0.466	0.469	0.092	0.495	0.535
backpack	0.018	0.042	0.012	0.009	0.043	0.024	0.088	0.136	0.137	0.054	0.232	0.329
umbrella	0.013	0.025	0.011	0.001	0.032	0.097	0.132	0.278	0.302	0.079	0.372	0.477
handbag	0.011	0.026	0.007	0.004	0.037	0.012	0.078	0.130	0.130	0.051	0.232	0.335
tie	0.039	0.074	0.042	0.008	0.239	0.081	0.135	0.191	0.192	0.064	0.365	0.505
suitcase	0.039	0.080	0.031	0.002	0.053	0.111	0.124	0.246	0.258	0.038	0.275	0.510
frisbee	0.043	0.057	0.055	0.009	0.212	0.543	0.237	0.300	0.300	0.145	0.470	0.750
skis	0.017	0.042	0.012	0.006	0.081	0.009	0.125	0.174	0.176	0.077	0.469	0.250
snowboard	0.006	0.011	0.007	0.001	0.017	0.024	0.151	0.178	0.217	0.070	0.479	0.140
sports ball	0.000	0.000	0.000	0.000	0.015	0.249	0.058	0.067	0.071	0.039	0.222	0.500
kite	0.004	0.008	0.004	0.002	0.009	0.015	0.087	0.160	0.173	0.093	0.340	0.382
baseball bat	0.014	0.036	0.009	0.008	0.037	0.003	0.151	0.179	0.179	0.120	0.254	0.300
baseball glove	0.031	0.060	0.024	0.003	0.157	0.085	0.097	0.116	0.116	0.022	0.267	0.433
skateboard	0.018	0.033	0.015	0.003	0.099	0.015	0.261	0.314	0.314	0.138	0.476	0.318
surfboard	0.018	0.038	0.015	0.001	0.041	0.100	0.128	0.219	0.236	0.058	0.329	0.454
tennis racket	0.013	0.025	0.011	0.001	0.061	0.096	0.226	0.278	0.288	0.126	0.376	0.400
bottle	0.017	0.030	0.017	0.003	0.082	0.144	0.108	0.209	0.217	0.083	0.403	0.600
wine glass	0.017	0.033	0.015	0.001	0.051	0.254	0.102	0.199	0.200	0.037	0.347	0.600
cup	0.011	0.017	0.012	0.001	0.040	0.241	0.150	0.267	0.272	0.074	0.413	0.637
fork	0.007	0.014	0.005	0.001	0.034	0.043	0.163	0.214	0.214	0.077	0.337	0.341
knife	0.005	0.011	0.003	0.001	0.032	0.032	0.106	0.142	0.144	0.068	0.289	0.346
spoon	0.008	0.018	0.006	0.003	0.024	0.032	0.096	0.159	0.166	0.098	0.284	0.393
bowl	0.050	0.082	0.053	0.002	0.127	0.311	0.189	0.325	0.333	0.074	0.385	0.540
banana	0.016	0.040	0.009	0.001	0.042	0.116	0.076	0.199	0.246	0.072	0.297	0.416
apple	0.002	0.004	0.002	0.000	0.015	0.204	0.087	0.183	0.195	0.044	0.220	0.549
sandwich	0.019	0.041	0.016	0.000	0.009	0.131	0.186	0.319	0.323	0.044	0.225	0.436
orange	0.036	0.055	0.039	0.001	0.172	0.272	0.084	0.281	0.320	0.076	0.407	0.557
broccoli	0.021	0.050	0.016	0.000	0.045	0.044	0.055	0.190	0.241	0.036	0.289	0.274
carrot	0.009	0.020	0.007	0.001	0.084	0.098	0.071	0.204	0.227	0.108	0.351	0.262
hot dog	0.028	0.054	0.021	0.000	0.167	0.176	0.143	0.246	0.246	0.022	0.388	0.364
pizza	0.124	0.211	0.130	0.000	0.125	0.319	0.255	0.394	0.396	0.027	0.381	0.530
donut	0.040	0.063	0.043	0.004	0.102	0.325	0.101	0.277	0.305	0.110	0.399	0.636
cake	0.068	0.127	0.066	0.006	0.092	0.207	0.174	0.301	0.309	0.082	0.338	0.482
chair	0.009	0.020	0.006	0.001	0.019	0.066	0.093	0.225	0.248	0.096	0.311	0.465
couch	0.147	0.267	0.148	0.000	0.093	0.184	0.280	0.416	0.416	0.000	0.274	0.477
potted plant	0.004	0.010	0.003	0.000	0.010	0.024	0.140	0.234	0.257	0.078	0.328	0.336
bed	0.061	0.144	0.046	0.000	0.006	0.122	0.290	0.374	0.375	0.000	0.186	0.395
dining table	0.149	0.273	0.144	0.019	0.051	0.245	0.270	0.339	0.343	0.035	0.218	0.482
toilet	0.100	0.179	0.099	0.000	0.058	0.191	0.306	0.416	0.422	0.000	0.332	0.480
tv	0.214	0.342	0.241	0.002	0.204	0.331	0.377	0.453	0.453	0.041	0.458	0.562
laptop	0.130	0.207	0.141	0.003	0.088	0.288	0.384	0.468	0.471	0.105	0.361	0.594
mouse	0.027	0.038	0.036	0.000	0.270	0.721	0.224	0.233	0.233	0.030	0.361	0.800
remote	0.009	0.017	0.009	0.002	0.051	0.098	0.102	0.155	0.155	0.054	0.427	0.493
keyboard	0.121	0.218	0.130	0.003	0.136	0.246	0.314	0.421	0.421	0.100	0.424	0.518
cell phone	0.044	0.083	0.039	0.008	0.116	0.125	0.163	0.210	0.210	0.072	0.394	0.381
microwave	0.050	0.078	0.055	0.002	0.067	0.132	0.342	0.425	0.425	0.175	0.385	0.556
oven	0.073	0.146	0.069	0.000	0.042	0.133	0.238	0.309	0.310	0.000	0.263	0.377
toaster	0.002	0.004	0.001	0.000	0.012	0.000	0.089	0.144	0.144	0.000	0.260	0.000
sink	0.109	0.196	0.099	0.037	0.168	0.136	0.224	0.303	0.303	0.053	0.357	0.471
refrigerator	0.065	0.122	0.054	0.000	0.007	0.161	0.285	0.409	0.416	0.000	0.179	0.489
book	0.010	0.027	0.006	0.004	0.031	0.063	0.040	0.110	0.137	0.072	0.297	0.418
clock	0.024	0.043	0.024	0.001	0.132	0.194	0.221	0.272	0.275	0.068	0.441	0.460
vase	0.008	0.017	0.008	0.001	0.035	0.116	0.132	0.246	0.254	0.078	0.333	0.535
scissors	0.002	0.005	0.002	0.000	0.008	0.006	0.119	0.144	0.144	0.000	0.289	0.221
teddy bear	0.049	0.108	0.041	0.000	0.040	0.129	0.164	0.295	0.309	0.033	0.329	0.405
hair drier	0.003	0.016	0.000	0.021	0.000	0.011	0.082	0.082	0.082	0.060	0.000	0.200
toothbrush	0.000	0.001	0.000	0.000	0.000	0.011	0.047	0.060	0.061	0.053	0.028	0.367
Total	0.054	0.098	0.052	0.004	0.085	0.165	0.174	0.272	0.281	0.067	0.348	0.455

Table 6: Evaluation results for normal adversarial images under rainy conditions (p=0.7)

Class	AP_all	AP_50	AP_75	AP_small	AP_medium	AP_large	AR_all_1	AR_all_10	AR_all_100	AR_small	AR_medium	AR_large
person	0.156	0.286	0.151	0.019	0.233	0.358	0.116	0.317	0.348	0.118	0.464	0.552
bicycle	0.018	0.042	0.011	0.001	0.034	0.165	0.116	0.186	0.196	0.045	0.268	0.442
car	0.027	0.048	0.026	0.003	0.101	0.209	0.087	0.189	0.195	0.059	0.398	0.488
motorcycle	0.079	0.207	0.050	0.025	0.090	0.121	0.123	0.249	0.259	0.063	0.272	0.379
airplane	0.045	0.089	0.042	0.003	0.067	0.146	0.233	0.365	0.369	0.193	0.421	0.413
bus	0.136	0.232	0.139	0.003	0.038	0.314	0.316	0.428	0.428	0.044	0.265	0.593
train	0.097	0.218	0.073	0.000	0.006	0.142	0.275	0.387	0.387	0.000	0.172	0.419
truck	0.057	0.116	0.049	0.018	0.086	0.087	0.167	0.277	0.278	0.054	0.320	0.423
boat	0.009	0.024	0.004	0.001	0.014	0.096	0.050	0.120	0.141	0.038	0.189	0.392
traffic light	0.011	0.027	0.009	0.003	0.143	0.129	0.053	0.095	0.095	0.044	0.321	0.311
fire hydrant	0.248	0.395	0.269	0.005	0.321	0.400	0.329	0.374	0.374	0.030	0.423	0.552
stop sign	0.280	0.366	0.309	0.001	0.415	0.569	0.371	0.393	0.393	0.022	0.538	0.652
parking meter	0.087	0.145	0.101	0.005	0.054	0.328	0.202	0.277	0.278	0.031	0.281	0.448
bench	0.001	0.003	0.001	0.000	0.001	0.036	0.094	0.142	0.149	0.036	0.165	0.287
bird	0.010	0.020	0.008	0.002	0.036	0.042	0.085	0.153	0.159	0.051	0.379	0.433
cat	0.087	0.189	0.064	0.000	0.047	0.132	0.307	0.380	0.383	0.000	0.441	0.379
dog	0.060	0.113	0.054	0.005	0.054	0.090	0.285	0.361	0.361	0.095	0.361	0.399
horse	0.123	0.238	0.113	0.010	0.112	0.228	0.189	0.353	0.353	0.100	0.329	0.504
sheep	0.117	0.226	0.113	0.039	0.201	0.115	0.070	0.265	0.312	0.097	0.409	0.401
cow	0.113	0.204	0.114	0.038	0.224	0.147	0.109	0.276	0.284	0.061	0.422	0.475
elephant	0.108	0.197	0.105	0.003	0.116	0.248	0.182	0.377	0.401	0.135	0.316	0.492
bear	0.142	0.226	0.140	0.000	0.218	0.179	0.258	0.346	0.346	0.000	0.554	0.328
zebra	0.226	0.406	0.234	0.075	0.218	0.322	0.153	0.451	0.470	0.263	0.452	0.571
giraffe	0.182	0.333	0.176	0.016	0.132	0.347	0.251	0.484	0.490	0.192	0.467	0.582
backpack	0.012	0.029	0.008	0.008	0.032	0.009	0.066	0.102	0.103	0.046	0.173	0.212
umbrella	0.016	0.034	0.013	0.001	0.031	0.080	0.126	0.243	0.258	0.066	0.319	0.407
handbag	0.010	0.021	0.007	0.003	0.032	0.008	0.065	0.113	0.114	0.042	0.213	0.245
tie	0.033	0.066	0.030	0.008	0.223	0.083	0.129	0.181	0.185	0.067	0.340	0.476
suitcase	0.024	0.051	0.018	0.001	0.040	0.071	0.079	0.171	0.173	0.022	0.192	0.338
frisbee	0.099	0.133	0.114	0.020	0.389	0.442	0.232	0.283	0.286	0.130	0.457	0.738
skis	0.029	0.075	0.019	0.014	0.111	0.012	0.112	0.158	0.163	0.076	0.420	0.200
snowboard	0.007	0.012	0.009	0.001	0.022	0.010	0.130	0.161	0.190	0.040	0.454	0.120
sports ball	0.000	0.000	0.000	0.000	0.020	0.246	0.050	0.059	0.059	0.032	0.181	0.457
kite	0.007	0.013	0.007	0.004	0.014	0.019	0.079	0.147	0.158	0.075	0.316	0.414
baseball bat	0.017	0.042	0.011	0.010	0.042	0.000	0.133	0.155	0.155	0.100	0.234	0.000
baseball glove	0.032	0.068	0.026	0.005	0.143	0.123	0.091	0.111	0.111	0.033	0.231	0.433
skateboard	0.028	0.051	0.026	0.005	0.107	0.010	0.231	0.266	0.266	0.106	0.420	0.235
surfboard	0.027	0.055	0.023	0.002	0.053	0.080	0.119	0.189	0.197	0.043	0.282	0.372
tennis racket	0.024	0.047	0.019	0.001	0.079	0.113	0.213	0.258	0.264	0.083	0.349	0.484
bottle	0.020	0.038	0.020	0.004	0.088	0.148	0.103	0.205	0.211	0.085	0.393	0.538
wine glass	0.027	0.049	0.025	0.001	0.074	0.301	0.090	0.185	0.188	0.032	0.329	0.569
cup	0.012	0.020	0.013	0.001	0.047	0.215	0.140	0.250	0.255	0.067	0.391	0.587
fork	0.009	0.018	0.007	0.001	0.048	0.035	0.140	0.177	0.177	0.049	0.290	0.300
knife	0.004	0.008	0.003	0.001	0.023	0.005	0.066	0.097	0.099	0.048	0.216	0.100
spoon	0.005	0.013	0.003	0.002	0.019	0.027	0.070	0.101	0.105	0.048	0.209	0.271
owl	0.043	0.074	0.044	0.002	0.093	0.249	0.162	0.277	0.284	0.069	0.300	0.489
banana	0.016	0.037	0.010	0.001	0.035	0.103	0.065	0.174	0.212	0.071	0.247	0.364
apple	0.002	0.003	0.002	0.000	0.015	0.160	0.073	0.136	0.148	0.038	0.200	0.326
sandwich	0.017	0.038	0.013	0.000	0.008	0.100	0.170	0.265	0.273	0.032	0.202	0.363
orange	0.048	0.069	0.054	0.001	0.115	0.174	0.075	0.198	0.238	0.062	0.326	0.365
broccoli	0.022	0.056	0.016	0.000	0.040	0.049	0.052	0.174	0.227	0.024	0.254	0.318
carrot	0.006	0.018	0.003	0.001	0.045	0.055	0.053	0.138	0.168	0.082	0.259	0.188
hot dog	0.069	0.124	0.067	0.000	0.164	0.145	0.123	0.201	0.201	0.013	0.339	0.283
pizza	0.150	0.256	0.148	0.002	0.149	0.298	0.258	0.389	0.392	0.044	0.378	0.518
donut	0.041	0.061	0.047	0.006	0.096	0.205	0.089	0.220	0.240	0.098	0.320	0.464
cake	0.064	0.120	0.063	0.006	0.087	0.131	0.148	0.239	0.244	0.056	0.273	0.382
chair	0.007	0.016	0.004	0.001	0.014	0.042	0.075	0.171	0.186	0.062	0.232	0.377
couch	0.088	0.164	0.077	0.000	0.053	0.104	0.179	0.265	0.265	0.000	0.148	0.312
potted plant	0.004	0.011	0.003	0.000	0.009	0.022	0.119	0.197	0.215	0.061	0.267	0.313
bed	0.052	0.120	0.033	0.000	0.003	0.078	0.262	0.318	0.318	0.000	0.093	0.341
dining table	0.131	0.246	0.123	0.018	0.036	0.210	0.254	0.311	0.316	0.032	0.165	0.459
toilet	0.068	0.125	0.063	0.000	0.053	0.120	0.199	0.263	0.265	0.000	0.200	0.304
tv	0.106	0.186	0.106	0.000	0.092	0.187	0.227	0.285	0.285	0.000	0.247	0.391
laptop	0.082	0.136	0.088	0.002	0.052	0.206	0.261	0.319	0.319	0.065	0.226	0.415
mouse	0.092	0.132	0.117	0.030	0.158	0.170	0.125	0.126	0.126	0.028	0.216	0.267
remote	0.009	0.018	0.007	0.002	0.045	0.082	0.084	0.124	0.124	0.055	0.318	0.336
keyboard	0.083	0.163	0.078	0.004	0.054	0.214	0.222	0.284	0.284	0.089	0.226	0.425
cell phone	0.045	0.077	0.049	0.012	0.087	0.119	0.120	0.152	0.152	0.053	0.272	0.297
microwave	0.030	0.046	0.033	0.004	0.025	0.118	0.204	0.244	0.244	0.200	0.194	0.344
oven	0.046	0.091	0.048	0.000	0.022	0.085	0.172	0.208	0.209	0.000	0.157	0.267
toaster	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
sink	0.071	0.129	0.063	0.026	0.141	0.075	0.156	0.207	0.207	0.042	0.261	0.289
refrigerator	0.039	0.090	0.028	0.000	0.005	0.110	0.214	0.294	0.305	0.000	0.143	0.355
book	0.008	0.022	0.004	0.004	0.023	0.025	0.027	0.075	0.098	0.054	0.221	0.225
clock	0.029	0.049	0.028	0.001	0.194	0.193	0.217	0.279	0.282	0.060	0.464	0.470
vase	0.009	0.018	0.009	0.000	0.040	0.101	0.126	0.229	0.243	0.043	0.346	0.535
scissors	0.004	0.007	0.005	0.000	0.013	0.005	0.147	0.175	0.175	0.000	0.344	0.250
teddy bear	0.047	0.107	0.037	0.000	0.038	0.112	0.138	0.259	0.265	0.018	0.302	0.342
hair drier	0.002	0.005	0.000	0.000	0.012	0.002	0.073	0.073	0.073	0.000	0.133	0.133
toothbrush	0.000	0.001	0.000	0.000	0.000	0.009	0.033	0.063	0.063	0.053	0.017	0.467
Total	0.055	0.100	0.053	0.006	0.083	0.138	0.147	0.227	0.235	0.057	0.292	0.380

Table 7: Evaluation results for RainPGD under normal conditions

Class	AP_all	AP_50	AP_75	AP_small	AP_medium	AP_large	AR_all_1	AR_all_10	AR_all_100	AR_small	AR_medium	AR_large
person	0.135	0.243	0.133	0.016	0.187	0.362	0.113	0.337	0.373	0.132	0.503	0.574
bicycle	0.014	0.034	0.011	0.001	0.026	0.172	0.150	0.237	0.245	0.063	0.352	0.494
car	0.021	0.039	0.021	0.003	0.076	0.283	0.103	0.228	0.234	0.077	0.462	0.594
motorcycle	0.125	0.287	0.094	0.050	0.138	0.194	0.156	0.292	0.309	0.079	0.331	0.441
airplane	0.093	0.164	0.087	0.011	0.236	0.186	0.293	0.394	0.399	0.213	0.519	0.407
bus	0.175	0.275	0.191	0.006	0.061	0.408	0.346	0.467	0.472	0.092	0.324	0.628
train	0.141	0.282	0.139	0.000	0.026	0.190	0.341	0.457	0.457	0.000	0.300	0.485
truck	0.065	0.129	0.067	0.018	0.083	0.100	0.194	0.329	0.336	0.104	0.368	0.499
boat	0.029	0.073	0.017	0.006	0.055	0.141	0.078	0.181	0.199	0.071	0.286	0.453
traffic light	0.010	0.023	0.006	0.002	0.205	0.162	0.064	0.103	0.103	0.044	0.364	0.358
fire hydrant	0.248	0.437	0.268	0.048	0.412	0.340	0.307	0.362	0.369	0.044	0.457	0.509
stop sign	0.194	0.262	0.206	0.000	0.189	0.532	0.361	0.377	0.377	0.000	0.538	0.630
parking meter	0.034	0.051	0.038	0.001	0.061	0.410	0.232	0.298	0.298	0.094	0.238	0.496
bench	0.002	0.005	0.001	0.000	0.002	0.066	0.114	0.192	0.201	0.053	0.230	0.374
bird	0.017	0.029	0.016	0.005	0.034	0.086	0.092	0.186	0.196	0.087	0.364	0.565
cat	0.106	0.218	0.087	0.000	0.041	0.171	0.374	0.470	0.470	0.000	0.457	0.485
dog	0.085	0.146	0.081	0.002	0.072	0.146	0.344	0.443	0.443	0.047	0.434	0.502
horse	0.151	0.268	0.150	0.004	0.207	0.241	0.243	0.397	0.400	0.066	0.449	0.530
sheep	0.152	0.277	0.152	0.045	0.219	0.193	0.089	0.353	0.397	0.148	0.496	0.525
cow	0.121	0.193	0.128	0.011	0.236	0.213	0.126	0.291	0.303	0.061	0.446	0.520
elephant	0.300	0.524	0.304	0.174	0.334	0.331	0.199	0.467	0.477	0.218	0.438	0.537
bear	0.260	0.399	0.273	0.000	0.227	0.353	0.396	0.489	0.489	0.000	0.554	0.519
zebra	0.210	0.379	0.222	0.122	0.180	0.316	0.148	0.455	0.461	0.212	0.445	0.579
giraffe	0.094	0.162	0.103	0.003	0.093	0.200	0.207	0.483	0.497	0.188	0.547	0.525
backpack	0.019	0.046	0.013	0.013	0.032	0.052	0.090	0.137	0.138	0.055	0.224	0.388
umbrella	0.027	0.051	0.026	0.002	0.052	0.160	0.163	0.330	0.346	0.101	0.410	0.557
handbag	0.013	0.032	0.008	0.006	0.034	0.012	0.086	0.137	0.137	0.052	0.244	0.405
tie	0.022	0.039	0.024	0.001	0.112	0.116	0.132	0.175	0.175	0.045	0.349	0.490
suitcase	0.066	0.133	0.059	0.005	0.108	0.148	0.138	0.249	0.259	0.054	0.281	0.490
frisbee	0.199	0.252	0.247	0.101	0.313	0.521	0.235	0.290	0.290	0.163	0.435	0.637
skis	0.040	0.098	0.026	0.047	0.091	0.041	0.127	0.171	0.173	0.094	0.398	0.400
snowboard	0.010	0.017	0.012	0.004	0.025	0.016	0.184	0.222	0.228	0.095	0.458	0.180
sports ball	0.001	0.001	0.001	0.000	0.037	0.246	0.070	0.073	0.077	0.039	0.293	0.471
kite	0.012	0.023	0.012	0.009	0.026	0.016	0.098	0.182	0.193	0.098	0.421	0.314
baseball bat	0.017	0.039	0.013	0.009	0.041	0.001	0.153	0.186	0.186	0.122	0.274	0.100
baseball glove	0.035	0.065	0.032	0.006	0.176	0.173	0.132	0.141	0.141	0.045	0.287	0.567
skateboard	0.019	0.035	0.018	0.003	0.084	0.011	0.227	0.274	0.274	0.109	0.425	0.288
surfboard	0.058	0.112	0.057	0.007	0.108	0.200	0.183	0.264	0.274	0.087	0.378	0.485
tennis racket	0.023	0.042	0.020	0.001	0.067	0.065	0.237	0.301	0.305	0.099	0.404	0.532
bottle	0.011	0.020	0.011	0.002	0.050	0.163	0.117	0.219	0.231	0.088	0.427	0.662
wine glass	0.025	0.046	0.024	0.002	0.063	0.183	0.101	0.203	0.204	0.045	0.352	0.577
cup	0.011	0.019	0.011	0.001	0.035	0.184	0.154	0.277	0.281	0.080	0.443	0.584
fork	0.021	0.042	0.019	0.003	0.063	0.054	0.180	0.245	0.249	0.079	0.402	0.400
knife	0.015	0.032	0.012	0.006	0.058	0.076	0.116	0.165	0.165	0.081	0.334	0.315
spoon	0.015	0.031	0.012	0.008	0.041	0.099	0.111	0.158	0.160	0.091	0.290	0.350
bowl	0.086	0.140	0.089	0.006	0.164	0.379	0.210	0.362	0.373	0.113	0.423	0.584
banana	0.043	0.102	0.028	0.004	0.098	0.123	0.073	0.194	0.254	0.076	0.317	0.400
apple	0.004	0.008	0.003	0.000	0.035	0.106	0.081	0.161	0.191	0.033	0.257	0.467
sandwich	0.028	0.059	0.026	0.000	0.013	0.158	0.192	0.333	0.333	0.000	0.244	0.455
orange	0.039	0.060	0.041	0.002	0.165	0.225	0.097	0.260	0.285	0.079	0.366	0.469
broccoli	0.038	0.086	0.028	0.000	0.070	0.078	0.065	0.229	0.275	0.025	0.303	0.400
carrot	0.011	0.027	0.008	0.001	0.116	0.092	0.060	0.191	0.222	0.078	0.373	0.265
hot dog	0.042	0.088	0.027	0.002	0.115	0.229	0.150	0.252	0.258	0.060	0.361	0.379
pizza	0.150	0.252	0.157	0.001	0.126	0.349	0.270	0.402	0.408	0.025	0.339	0.576
donut	0.049	0.079	0.049	0.006	0.131	0.344	0.089	0.290	0.327	0.121	0.453	0.635
cake	0.067	0.131	0.062	0.013	0.091	0.122	0.175	0.312	0.320	0.093	0.350	0.492
chair	0.009	0.021	0.007	0.001	0.020	0.096	0.097	0.233	0.252	0.108	0.313	0.458
couch	0.205	0.379	0.196	0.000	0.118	0.253	0.287	0.445	0.446	0.000	0.334	0.500
potted plant	0.005	0.012	0.004	0.000	0.011	0.040	0.169	0.276	0.281	0.083	0.334	0.451
bed	0.120	0.280	0.082	0.000	0.008	0.169	0.323	0.407	0.407	0.000	0.129	0.436
dining table	0.141	0.262	0.127	0.013	0.041	0.261	0.273	0.358	0.362	0.056	0.220	0.508
toilet	0.238	0.418	0.238	0.000	0.170	0.300	0.378	0.492	0.492	0.000	0.402	0.553
tv	0.331	0.492	0.372	0.022	0.319	0.440	0.365	0.464	0.464	0.041	0.466	0.578
laptop	0.313	0.501	0.341	0.051	0.269	0.399	0.390	0.466	0.466	0.095	0.361	0.586
mouse	0.187	0.244	0.238	0.027	0.304	0.658	0.234	0.241	0.241	0.043	0.377	0.733
remote	0.017	0.030	0.018	0.003	0.069	0.228	0.096	0.140	0.140	0.045	0.380	0.514
keyboard	0.250	0.423	0.266	0.040	0.260	0.341	0.327	0.417	0.417	0.100	0.431	0.498
cell phone	0.084	0.143	0.091	0.017	0.173	0.302	0.192	0.234	0.234	0.073	0.435	0.458
microwave	0.054	0.085	0.058	0.005	0.061	0.141	0.331	0.369	0.369	0.175	0.358	0.433
oven	0.117	0.245	0.095	0.000	0.091	0.172	0.251	0.315	0.315	0.000	0.269	0.383
toaster	0.092	0.151	0.139	0.000	0.189	0.000	0.156	0.211	0.211	0.000	0.380	0.000
sink	0.138	0.238	0.139	0.036	0.213	0.169	0.234	0.302	0.302	0.064	0.349	0.471
refrigerator	0.215	0.335	0.249	0.000	0.042	0.289	0.321	0.425	0.431	0.000	0.204	0.501
book	0.017	0.043	0.011	0.007	0.053	0.078	0.040	0.107	0.137	0.068	0.316	0.396
clock	0.038	0.061	0.040	0.001	0.231	0.235	0.242	0.311	0.314	0.066	0.516	0.528
vase	0.011	0.021	0.011	0.001	0.041	0.072	0.140	0.263	0.272	0.082	0.385	0.522
scissors	0.004	0.009	0.004	0.000	0.013	0.011	0.158	0.194	0.194	0.000	0.356	0.271
teddy bear	0.093	0.193	0.080	0.001	0.083	0.170	0.201	0.326	0.341	0.018	0.396	0.438
hair drier	0.012	0.029	0.004	0.000	0.013	0.038	0.082	0.164	0.164	0.000	0.133	0.467
toothbrush	0.001	0.002	0.000	0.000	0.003	0.012	0.098	0.126	0.126	0.056	0.217	0.433
Total	0.084	0.147	0.085	0.013	0.112	0.193	0.187	0.287	0.295	0.071	0.366	0.471

Table 8: Evaluation results of RainPGD under rainy conditions (p=0.7)

Class	AP_all	AP_50	AP_75	AP_small	AP_medium	AP_large	AR_all_1	AR_all_10	AR_all_100	AR_small	AR_medium	AR_large
person	0.118	0.221	0.112	0.013	0.160	0.311	0.103	0.302	0.335	0.113	0.459	0.516
bicycle	0.013	0.030	0.009	0.001	0.018	0.114	0.123	0.202	0.215	0.049	0.307	0.454
car	0.018	0.033	0.018	0.002	0.065	0.250	0.095	0.206	0.212	0.069	0.417	0.539
motorcycle	0.109	0.263	0.076	0.038	0.130	0.162	0.140	0.266	0.283	0.062	0.303	0.408
airplane	0.057	0.110	0.054	0.005	0.167	0.101	0.216	0.305	0.310	0.170	0.416	0.306
bus	0.124	0.210	0.124	0.005	0.039	0.310	0.293	0.409	0.412	0.089	0.268	0.555
train	0.101	0.215	0.089	0.000	0.008	0.139	0.303	0.395	0.395	0.000	0.161	0.430
truck	0.044	0.089	0.042	0.009	0.062	0.069	0.161	0.268	0.276	0.062	0.299	0.436
boat	0.017	0.045	0.009	0.002	0.031	0.105	0.052	0.120	0.132	0.038	0.181	0.347
traffic light	0.008	0.018	0.006	0.002	0.154	0.144	0.059	0.089	0.089	0.041	0.298	0.321
fire hydrant	0.219	0.387	0.221	0.044	0.388	0.288	0.271	0.332	0.339	0.041	0.427	0.461
stop sign	0.192	0.264	0.199	0.000	0.226	0.491	0.353	0.369	0.369	0.000	0.510	0.630
parking meter	0.042	0.056	0.050	0.002	0.089	0.226	0.185	0.225	0.225	0.100	0.224	0.313
bench	0.001	0.002	0.001	0.000	0.001	0.028	0.088	0.137	0.143	0.033	0.146	0.291
bird	0.013	0.021	0.013	0.004	0.027	0.065	0.085	0.161	0.169	0.070	0.318	0.506
cat	0.057	0.132	0.041	0.000	0.025	0.091	0.272	0.352	0.352	0.000	0.322	0.368
dog	0.047	0.086	0.042	0.001	0.053	0.074	0.244	0.323	0.323	0.047	0.350	0.349
horse	0.136	0.245	0.138	0.004	0.179	0.220	0.215	0.383	0.388	0.056	0.442	0.512
sheep	0.121	0.233	0.111	0.031	0.167	0.164	0.089	0.299	0.330	0.115	0.394	0.483
cow	0.088	0.151	0.088	0.009	0.170	0.137	0.116	0.249	0.261	0.053	0.382	0.449
elephant	0.222	0.414	0.201	0.100	0.249	0.244	0.162	0.367	0.373	0.124	0.317	0.443
bear	0.147	0.226	0.156	0.000	0.192	0.197	0.292	0.341	0.341	0.000	0.438	0.349
zebra	0.207	0.380	0.207	0.082	0.176	0.315	0.143	0.435	0.447	0.146	0.434	0.585
giraffe	0.094	0.173	0.097	0.001	0.082	0.185	0.198	0.471	0.482	0.127	0.506	0.546
backpack	0.011	0.028	0.005	0.009	0.017	0.050	0.069	0.103	0.103	0.047	0.157	0.292
umbrella	0.020	0.040	0.018	0.001	0.039	0.092	0.142	0.283	0.298	0.085	0.364	0.464
handbag	0.009	0.020	0.005	0.003	0.025	0.004	0.068	0.111	0.111	0.033	0.215	0.290
tie	0.024	0.044	0.026	0.001	0.108	0.090	0.122	0.163	0.165	0.038	0.339	0.467
suitcase	0.032	0.063	0.031	0.004	0.065	0.054	0.085	0.160	0.164	0.042	0.191	0.284
frisbee	0.170	0.234	0.207	0.105	0.260	0.359	0.202	0.254	0.254	0.151	0.378	0.500
skis	0.030	0.067	0.022	0.034	0.075	0.034	0.106	0.151	0.154	0.069	0.400	0.325
snowboard	0.005	0.009	0.005	0.001	0.015	0.015	0.145	0.149	0.152	0.028	0.354	0.180
sports ball	0.000	0.001	0.001	0.000	0.033	0.164	0.060	0.060	0.063	0.034	0.226	0.371
kite	0.009	0.016	0.009	0.007	0.019	0.013	0.092	0.161	0.173	0.084	0.383	0.314
baseball bat	0.014	0.033	0.012	0.008	0.035	0.000	0.137	0.153	0.157	0.109	0.228	0.000
baseball glove	0.027	0.057	0.024	0.007	0.115	0.116	0.107	0.117	0.117	0.042	0.229	0.500
skateboard	0.014	0.028	0.013	0.002	0.064	0.008	0.200	0.239	0.239	0.077	0.377	0.300
surfboard	0.039	0.075	0.039	0.003	0.082	0.134	0.147	0.207	0.217	0.057	0.303	0.405
tennis racket	0.023	0.042	0.024	0.001	0.066	0.061	0.232	0.284	0.288	0.094	0.384	0.479
bottle	0.007	0.015	0.006	0.001	0.032	0.093	0.093	0.173	0.183	0.065	0.339	0.555
wine glass	0.015	0.034	0.010	0.001	0.044	0.092	0.084	0.160	0.164	0.032	0.293	0.454
cup	0.008	0.014	0.008	0.000	0.028	0.125	0.129	0.238	0.241	0.051	0.406	0.484
fork	0.014	0.027	0.013	0.002	0.033	0.036	0.127	0.167	0.172	0.051	0.268	0.332
knife	0.007	0.016	0.005	0.004	0.021	0.027	0.077	0.101	0.101	0.058	0.185	0.185
spoon	0.009	0.019	0.007	0.004	0.029	0.046	0.080	0.121	0.123	0.064	0.221	0.343
bowl	0.060	0.104	0.062	0.003	0.105	0.265	0.169	0.279	0.288	0.069	0.322	0.476
banana	0.032	0.079	0.022	0.004	0.071	0.096	0.066	0.152	0.201	0.070	0.243	0.317
apple	0.002	0.005	0.002	0.000	0.018	0.064	0.059	0.109	0.136	0.040	0.170	0.318
sandwich	0.017	0.038	0.013	0.000	0.006	0.104	0.142	0.251	0.252	0.000	0.148	0.361
orange	0.028	0.045	0.029	0.001	0.094	0.166	0.089	0.235	0.251	0.067	0.300	0.457
broccoli	0.028	0.069	0.022	0.000	0.051	0.053	0.057	0.196	0.237	0.029	0.253	0.357
carrot	0.006	0.018	0.003	0.001	0.062	0.070	0.050	0.134	0.156	0.064	0.246	0.203
hot dog	0.025	0.055	0.015	0.001	0.065	0.152	0.105	0.211	0.211	0.047	0.321	0.294
pizza	0.123	0.212	0.126	0.000	0.112	0.295	0.241	0.368	0.372	0.023	0.330	0.514
donut	0.044	0.067	0.048	0.006	0.081	0.265	0.079	0.251	0.281	0.119	0.354	0.561
cake	0.043	0.082	0.042	0.007	0.081	0.064	0.155	0.252	0.261	0.062	0.327	0.361
chair	0.005	0.012	0.004	0.001	0.011	0.047	0.071	0.169	0.185	0.070	0.231	0.358
couch	0.085	0.170	0.084	0.000	0.040	0.112	0.161	0.244	0.246	0.000	0.183	0.276
potted plant	0.003	0.008	0.002	0.000	0.007	0.028	0.142	0.223	0.232	0.053	0.272	0.411
bed	0.056	0.148	0.037	0.000	0.005	0.078	0.226	0.284	0.284	0.000	0.114	0.302
dining table	0.103	0.202	0.082	0.006	0.025	0.195	0.236	0.298	0.302	0.038	0.160	0.436
toilet	0.145	0.266	0.144	0.000	0.095	0.189	0.273	0.351	0.351	0.000	0.296	0.391
tv	0.179	0.274	0.187	0.004	0.140	0.263	0.215	0.272	0.272	0.008	0.244	0.364
laptop	0.200	0.329	0.206	0.051	0.173	0.253	0.261	0.316	0.316	0.060	0.233	0.405
mouse	0.107	0.140	0.130	0.033	0.159	0.304	0.150	0.157	0.157	0.043	0.225	0.489
remote	0.009	0.020	0.007	0.002	0.032	0.157	0.064	0.103	0.103	0.040	0.245	0.436
keyboard	0.165	0.298	0.153	0.033	0.151	0.263	0.256	0.304	0.304	0.050	0.306	0.381
cell phone	0.044	0.081	0.046	0.006	0.090	0.213	0.123	0.145	0.145	0.032	0.268	0.344
microwave	0.023	0.037	0.023	0.005	0.028	0.056	0.213	0.244	0.244	0.200	0.236	0.267
oven	0.067	0.140	0.060	0.000	0.053	0.103	0.161	0.202	0.202	0.000	0.186	0.237
toaster	0.004	0.008	0.000	0.000	0.017	0.000	0.056	0.056	0.056	0.000	0.100	0.000
sink	0.097	0.181	0.091	0.051	0.183	0.077	0.179	0.229	0.229	0.061	0.290	0.306
refrigerator	0.157	0.272	0.175	0.000	0.049	0.204	0.265	0.362	0.364	0.000	0.182	0.422
book	0.009	0.024	0.004	0.005	0.023	0.027	0.027	0.069	0.096	0.055	0.198	0.263
clock	0.037	0.061	0.038	0.001	0.231	0.153	0.215	0.273	0.276	0.061	0.448	0.468
vase	0.008	0.015	0.007	0.000	0.029	0.056	0.130	0.229	0.234	0.056	0.340	0.469
scissors	0.002	0.004	0.001	0.000	0.009	0.004	0.114	0.125	0.125	0.000	0.278	0.143
teddy bear	0.058	0.127	0.046	0.001	0.051	0.113	0.150	0.257	0.266	0.026	0.327	0.329
hair drier	0.004	0.008	0.000	0.000	0.010	0.011	0.036	0.082	0.082	0.000	0.133	0.167
toothbrush	0.000	0.001	0.000	0.000	0.000	0.003	0.047	0.053	0.053	0.036	0.061	0.200
Total	0.058	0.106	0.056	0.010	0.080	0.132	0.147	0.226	0.233	0.055	0.289	0.378

B Normal PGD vs RainPGD Applied on Images

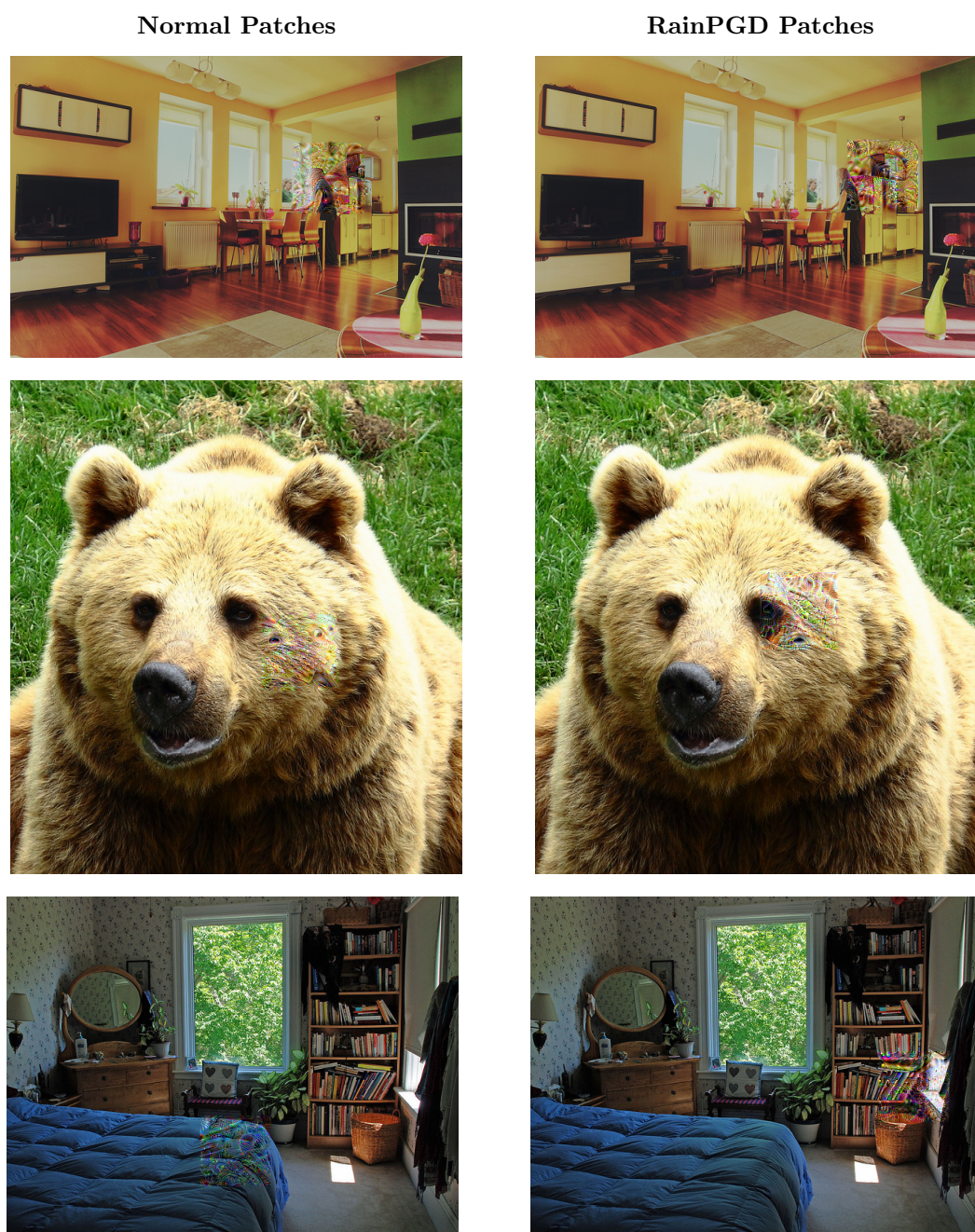


Figure 6: Comparison of normal and RainPGD patches applied to 3 images (Left is normal PGD, Right is RainPGD)

C RainyCOCO Images



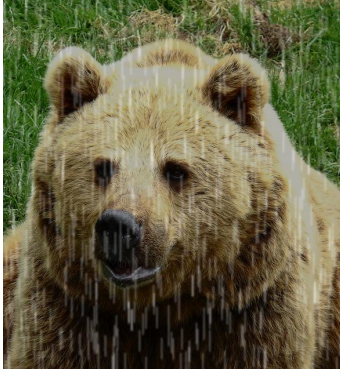
(a) Weak rain



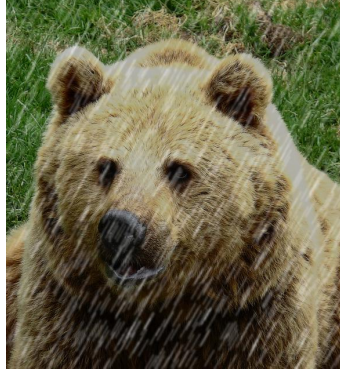
(b) Heavy rain



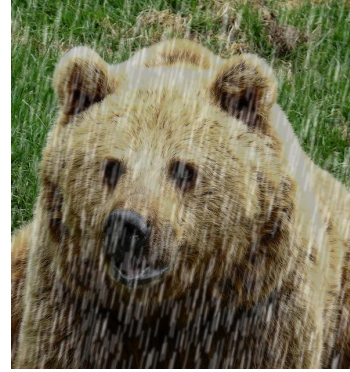
(c) Torrential rain



(d) Weak rain



(e) Heavy rain



(f) Torrential rain



(g) Weak rain



(h) Heavy rain



(i) Torrential rain

Figure 7: Weak, heavy, and torrential rain from the RainyCOCO dataset, labeled by rain type.