Task-agnostic Defense against Adversarial Patch Attacks

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Abstract. Adversarial patch attacks mislead neural networks by injecting adversarial pixels within a designated local region. Patch attacks can be highly effective in a variety of tasks and physically realizable via attachment (e.g., a sticker) to the real-world objects. Despite the diversity in attack patterns, adversarial patches tend to be highly textured and different in appearance from natural images. We exploit this property and present PatchZero, a task-agnostic defense against white-box adversarial patches. Specifically, our defense detects the adversarial pixels and "zeros out" the patch region by repainting with mean pixel values. We formulate the patch detection problem as a semantic segmentation task such that our model can generalize to patches of any size and shape. We further design a two-stage adversarial training scheme to defend against the stronger adaptive attacks. We thoroughly evaluate PatchZero on the image classification (ImageNet, RESISC45), object detection (PASCAL VOC), and video classification (UCF101) datasets. Our method achieves SOTA robust accuracy without any degradation in the benign performance.

Keywords: Adversarial Robustness, Recognition, Classification

1 Introduction

Adversarial patch attacks inject adversarial pixels within a specified local region and cause incorrect predictions of neural networks. Several effective patch attacks have been proposed, from the early Adversarial Patch [4], LaVAN [24], Masked CW [5], and Masked PGD [34] attacks to the more recent DPatch [29], Robust DPatch [26], and Masked AutoPGD [9] attacks. Compared with the full image perturbation attacks [13, 5, 33], patch attacks are local perturbations but still highly effective in a variety of tasks. Patch attacks are also physically realizable since they can be printed and placed into the scene, whereas perturbations to the entire image cannot be deployed in such a manner. Real-world computer vision systems, such as autonomous driving and security surveillance, can be attacked by adversarial patches placed in the targeted scenes.

To tackle adversarial patch attacks in different domains, many patch defense methods have been proposed, from the image classification defenses [18, 35, 15, 27, 8, 49, 45, 48, 46], to the more recent object detection [51, 7, 47] and video
Fig. 1: Task-agnostic defense for adversarial patch attacks. PatchZero takes an adversarial image (top) as input and outputs a preprocessed image (bottom) with adversarial pixels effectively removed. Our approach can be applied to the image classification (left), object detection (middle), and video classification (right) tasks without any retraining or modification of the downstream classifiers. Green and red denote correct and incorrect predictions.

Our defense is based on the observation that, for all considered tasks, the generated adversarial patches “look” very different from the benign pixels in the image, as shown in the first column of Figure 1. Noted that adversarial attack patterns are different from image forensics. Image forensic manipulations often utilize pieces from another nature image, while adversarial attacks use model gradients to generate perturbations. To achieve effective attacks, the patch attacks have to create strong pixel perturbations that have distinct distributions from nature pixels. Our defense exploits these observations and formulates the patch pixel detection problem as a semantic segmentation task. To this end, we utilize the PSPNet [50] due to its simplicity and the multi-scale pyramid architecture for detecting patches of different sizes. After detection, our model repaints the patch region with the mean pixel values (zero values after image classification defenses [1, 30, 32]. While prior work has made significant progress in adversarial patch defense, the methods remain specific to the task and the defenses remain weak. Some of them [45, 46] also require prior knowledge, such as adversarial patch size, to be effective. In this paper, we focus on adversarial patch attacks under the white-box setting, since they are stronger [2, 43] than the black-box and physical patch attacks. We aim to design a task-agnostic patch defense that holds strong under any white-box patch attacks (including adaptive ones) and does not require any prior knowledge.

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normalization). Empirically, this process effectively “zeros out” the adversary and restores most of the accuracy for the downstream tasks. Therefore, we name our network “PatchZero”.

While the patch detector is highly effective in finding the adversarial pixels, the detector itself is vulnerable to adversarial attack. Besides considering the Downstream-only (DO) attacks, we also train our network to defend against stronger adaptive attacks. Our patch detector outputs a binary mask which is non-differentiable during the backpropagation. To this end, we approximate the gradient of the binary mask using the Backward Pass Differential Approximation (BPDA) \cite{3} technique. To efficiently train our PatchZero under BPDA attacks, we further propose a two-stage adversarial training scheme. The patch detector is first trained with DO attack examples and then reinforced with BPDA joint attack examples in stage two. It is not obvious that this attacker-defender race should reach an equilibrium but we find that it does stabilize after some number of iterations and the adversary can no longer produce more destructive patches. We do not retrain the downstream classifiers so our model maintains high benign accuracy.

We evaluate the PatchZero under the Masked PGD (MPGD), Masked AutoPGD (MAPGD), and Masked CW (MCW) attacks since they give a good coverage of the white-box patch attacks. We evaluate our defense across three different tasks. For image classification, we report the robust performance on the ImageNet \cite{10} and RESISC-45 \cite{6} datasets. For object detection, we test on the PASCAL VOC \cite{12} dataset. For the task of video classification, we evaluate on the UCF101 \cite{42} dataset. PatchZero achieves state-of-the-art performances on all three tasks compared with the previous work. Under the stronger BPDA adaptive attacks, the advantage margin of our defense method is even larger. To summarize, our contributions are three-fold:

1. We present PatchZero, an effective and task-agnostic defense against white-box adversarial patch attacks across the tasks of image classification, object detection, and video classification.
2. We introduce a two-stage training scheme that reinforces PatchZero’s robustness under the stronger adaptive attacks and accelerates training in the early stages.
3. We qualitatively and quantitatively evaluate our defense on multiple datasets and demonstrate significant improvements on both the benign and robust performances compared with the baselines.

2 Related Work

Perturbation Attacks: Perturbation attacks manipulate the whole image to mislead neural networks. Goodfellow et al. \cite{13} introduce the first perturbation attack called Fast Gradient Sign Method (FGSM) by estimating adversarial perturbations from gradients. Carlini and Wagner \cite{5} design the CW attack with the optimization objective to minimize the perturbation magnitude. Later, Madry et al. \cite{34} introduce Projected Gradient Descent (PGD) attack, one of
the strongest perturbation attacks among recent designs. Croce and Hein [9] further extend PGD to Auto PGD with automatic step size tuning and a refined objective function. Compared with PGD, Auto PGD is more effective under the same attack budget and does not require parameter tuning.

**Patch Attacks:** Patch Attacks, on the other hand, only modify a restricted region of the image. Brown et al. [4] first introduce the Adversarial Patch attack that generates a universal and physically realizable patch to mislead the image classification models. LaVAN [24] is proposed at the same time but focuses on the digital patch. After the introduction of the full-image PGD and AutoPGD attacks, Masked PGD and Masked AutoPGD are two extensions to patch attacks by restricting the attack region. All of the above mentioned patch attacks are task-agnostic and can be easily extended to the object detection and video classification tasks.

We would also like to mention some task-specific patch attacks. In the object detection domain, Liu et al. [29] design DPatch against popular object detectors. Lee et al. [26] investigate failure cases of DPatch and later introduce the Robust DPatch. Furthermore, Saha et al. [39] introduce a blindness attack against the classifier inside an object detector, while Rao et al. [37] propose localization-optimized attacks. In the video classification domain, the only patch attack we can find besides Masked PGD and Masked AutoPGD attacks is the MultAV attack by Lo et al. [31]. MultAV is very similar to Masked PGD, but uses multiplication instead of summation when applying the perturbation.

We select Masked PGD and Masked AutoPGD for our experiments, since they are task-agnostic and can be easily applied across different tasks. Empirically, we also find them to be stronger than the task-specific attacks.

**Patch Defenses for Image Classification:** Digital Watermark (DW) [19] and Local Gradient Smoothing (LGS) [35] are among the early patch defenses. Both are later proved to be ineffective by Chiang et al. [8], who propose the first certified defense call Interval Bound Propagation (IBP). IBP limits the values of activation maps to guarantee a robustness lower bound. More recently, Xiang et al. [45] put forward PatchGuard, a network with small receptive field and outlier masking. It requires non-trivial modification of the backbone classifier. The same authors later propose another defense called PatchCleanser [46] that can be applied to any classifier. PatchCleanser uses an ensemble and exhaustive masking technique to identify the patch region. Both PatchGuard and PatchCleanser require the prior knowledge of the attack patch size to compute the optimal mask size. According to the paper, their certified robustness do not hold well for large patches. In comparison, our approach can defend against patch attacks of any patch size without any prior knowledge.

**Patch Defenses for Object Detection:** Similar to the image classification defense, object detection patch defense also receives a lot of attention recently. Liang et al. [28] uses Grad-Cam to detect and filter out the unusual area of the image. However, Grad-Cam can only provide a coarse map and is subject to miss detection and false positives. Zhou et al. [52] combine Grad-Cam gradient map and discrete entropy to locate the adversarial pixels, but the detection
results are still coarse and limited. A more recent model, DetectorGuard [47] uses small receptive field CNN to output a robust objectness map that indicates the probability of objects being present at different locations. If the map results are different from the basic predictions, they will raise an alert for adversary. However, this work only identifies but does not defend against patch attacks.

**Patch Defenses for Video Classification:** Adversarial patch defense is a relatively new research direction in video classification. To the best of our knowledge, we find three related works. Anand et al. [1] propose Inpainting with Laplacian Prior (ILP) to detect and inpaint adversarial pixels in the Laplacian space. However, the method only works for optical-flow based video classifiers.

Lo et al. propose to replace each Batch Normalization (BN) [22] layer of a regular video classifier with three BNs. The network needs to be retrained adversarially to learn a “switch mechanism” to connect to the correct BN module. The same authors later propose OUDefend [32] module as a embedding feature denoiser to be inserted between the layers of a video classifier. Both methods from Lo et al. require modification and retraining of the downstream classifiers, while our approach can be plugged into any classifier. Compared with all the above video defense methods, our approach is task-agnostic and more effective.

### 3 Defense Against Adversarial Patch Attacks

In this section, we first introduce some related background in Section 3.1. Then we explain PatchZero defense in Section 3.2. Lastly, we elaborate on the two-stage training scheme for robustness against the stronger adaptive patch attacks in Section 3.3.

#### 3.1 Background

**Projected Gradient Descent (PGD) and AutoPGD:** Introduced by Madry et al. [33], PGD attack is one of the strongest perturbation attacks proven to be effective against image classification models. Given an input image $X$, its ground-truth label $Y^*$, model weights $\theta$ and the loss function $\ell$, PGD attack is generated by maximizing the loss function in an iterative manner:

$$
X^{(0)}_{adv} = X, \quad X^{(t+1)}_{adv} = C_\epsilon \{ X^{(t)}_{adv} + \alpha \text{Sign}(\nabla_X \ell(X^{(t)}_{adv}, Y^*, \theta)) \}.
$$

Note that the clipping function $C$ is utilized to prevent the per-pixel modification from going beyond the threshold $\epsilon$. In addition, random initialization and restarts are adopted to further strengthen the attack. AutoPGD [9] is later proposed as a PGD with auto step size tuning and a refined objective function. It is shown to be more effective than PGD under the same attack budget.

**Masked PGD and Masked AutoPGD:** Although the original PGD attack is designed for the full-image perturbation attacks, it can be easily converted into a patch attack. As shown in Eq. 2, only pixels inside the patch region $[x, y, h, w]$ will be modified by the PGD:

$$
X^{(t+1)}_{adv}[\text{patch}] = C_\epsilon \{ X^{(t)}_{adv} + \alpha \text{Sign}(\nabla_X \ell(X^{(t)}_{adv}, Y^*, \theta)) \}[\text{patch}].
$$
Fig. 2: Pipeline of PatchZero. The patch detector $d$ takes one or multiple attack images $X$ and predicts pixel-wise adversarial binary mask $M$ (black for adversarial pixels and white for benign pixels). We “zero out” the patch by multiplying $X$ with $M$ and fill the identified patch region with the mean pixel values. The preprocessed image $X'$ is passed to the downstream classifier $f$ for final predictions $Y$.

Here patch refers to the region defined as $[x : x + h, y : y + w]$ with the given $[x, y, h, w]$. Masked PGD can attack object detectors and video classifiers by deriving the gradients from corresponding loss functions. AutoPGD can be converted to its patch attack counterpart Masked AutoPGD in a similar manner.

Adversarial Training: Adversarial training [13, 33] has proven to be effective against various adversarial attacks. The key idea is to generate adversarial examples and inject them into the mini-batches during training. Generally, the effectiveness of adversarial training depends on the strength of adversarial examples. In practice, several researches [41, 23, 40] have studied PGD attack and achieved significant robustness through adversarial training. To tackle adversarial patch attacks, we propose a two-stage training scheme that adversarially trains our models in two stages with samples produced by Masked PGD and Masked AutoPGD. The details are provided in Section 3.3.

3.2 PatchZero Network

The full pipeline of PatchZero is shown in Fig. 2. Our method consists of two steps. In the first step, the input image $X \in \mathbb{R}^{H \times W \times C}$ is processed by the patch detector $d: \mathbb{R}^{H \times W \times C} \rightarrow [0, 1]^{H \times W}$, which yields a probability map describing the possibilities for each pixel not being manipulated. We then binarize through a threshold $\epsilon_p$ the probability map to a binary mask $M \in \{0, 1\}^{H \times W}$, where patch pixels are denoted zeros. For the second step, we remove the identified patch region via element-wise multiplication between $X$ and $M$. The masked region is then filled with mean pixel value $\overline{X}$ computed from the dataset to generate:

$$X' = X \odot M + \overline{X} \odot \neg M.$$  \hfill (3)
After the zero-out step, the downstream model $f$ takes the sanitized image $X'$ and makes the final prediction $Y$.

We generate adversarial patches of random locations and sizes and the corresponding ground truth binary mask for each image. We construct the training set for $d$ by equally mixing attack images and benign images. During the patch detector training, we follow the loss function of PSPNet [50], which consists of a main cross entropy loss and two auxiliary loss terms. During inference, the patch detector can detect and “zero out” the adversarial pixels most of the time, but occasionally misses some pixels at the border. To this end, we use morphological dilation to slightly enlarge the predicted mask by a few pixels.

3.3 Adaptive Attack and Two-stage Training

When generating adversarial patches, there are two attack strategies. In the Downstream-only (DO) attack, only gradients from the downstream classifier $f$ is considered. However, the patch detector $d$ itself is vulnerable to adversarial attacks, especially under the white-box setting, where attackers have full knowledge of the pipeline. In the stronger adaptive attack, both the gradients from the downstream classifier $f$ and from the patch detector $d$ are considered. As defined in Eq. 3, the zero-out step includes the non-differentiable binarization operation. The pixel-level gradient $\nabla_X \ell(X^{(t)}_{\text{adv}}, Y^*, \theta)$ cannot be computed directly through back-propagation.

**BPDA Adaptive Attack:** Proposed by Athalye et al. [3], BPDA is an approximation strategy to bypass non-differentiable layers inside a network and achieve effective adaptive attacks. Given a non-differentiable operation $h$, BPDA finds a differentiable approximation $h'$ that satisfies $h(x) \approx h'(x)$. The original operation $h$ is used in the forward pass but replaced by the approximation $h'$ in the backward pass. To apply BPDA to PatchZero, we approximate the binarization operation by the Sigmoid function, since the binarization is essentially a Step function.

**Two-stage Adversarial Training:** The BPDA adaptive attack introduces some difficulty to the training process of the patch detector. In the early stages, the patch detector is immature and creates random gradients. Since the adaptive attack passes the gradients from the downstream classifier through the patch detector, the resulting gradients will be misleading. To resolve this issue, we propose a two-stage training scheme as described below:

- **Training Stage 1:** As shown in the green box of Figure 2, we first generate adversarial patches using the DO attack, which only consider the gradients from the downstream classifier $f$. We train the patch detector $d$ with a mixture of benign and adversarial images.
- **Training Stage 2:** When the patch detector starts to converge on the DO attack images, we switch to the 2nd stage of training. We generate adversarial patches using the BPDA adaptive attack, which consider gradients from both parts of the pipeline. We generate online adversarial attacks at every training step with updated model weights instead of pre-computing the entire training
set when training starts. This practice creates an attacker-defender race and further fortifies the effectiveness of the patch detector. Stage 2 is illustrated in the blue box of Figure 2.

The two-stage training mechanism greatly accelerates the training process and improves the robustness of PatchZero under the stronger BPDA adaptive attacks.

4 Experiments

We adopt the PSPNet [50] with the ResNet-50 [20] backbone as the patch detector of PatchZero. We initialize the PSPNet with weights pre-trained on the ImageNet [10] and follow the loss function for image segmentation. We train our PSPNet patch detector through the two-stage adversarial training introduced in Section 3.3. Regarding the binarization threshold, we set $\epsilon_p$ as 0.5. We developed the PatchZero and the two-stage training scheme in PyTorch [36] and use the Adversarial Robustness Toolbox (ART)\footnote{https://github.com/Trusted-AI/adversarial-robustness-toolbox} for generating attacks. For the two-stage training, we use a learning rate of 0.0001, the Adam [25] optimizer, and a batch size of 64 for image classification, 16 for object detection, and 36 for video classification.

4.1 Image Classification

**Implementation Details:** We conduct our image classification experiments on two datasets. We use the validation split of the ImageNet [10] dataset with 50,000 images and 1000 classes. We also evaluate on the RESISC-45 [6] remote sensing dataset that contains 31,500 images and 45 scene classes. Compared with the ImageNet, RESISC-45 has larger image size (256x256) and provides a remote sensing perspective. On the ImageNet, we use ResNetV2-50x1 as the backbone image classifier for all the defense methods. On the RESISC-45, we use DenseNet-121 [21] as the image classifier. We use the top1 accuracy for evaluation.

**Attacks:** For the Masked PGD [34] attack, we use a perturbation strength of 1.0, a step size of 0.01 and 100 iterations. For the Masked AutoPGD attack [9], we use a perturbation strength of 0.3, a step size of 0.1 and 100 iterations. Following the same settings as the previous works, we use 2% rectangular patches for ImageNet and 9% square patches for RESISC-45. The patch sizes are w.r.t. the image area and patch locations are random.

**Baseline Defenses:**

- **PatchGuard:** PatchGuard [45] is a certified defense with small receptive field and outlier masking. We empirically evaluate the robustness under the same attack settings. Note that the method requires prior knowledge of the attack patch size to estimate the defense mask window size.
Table 1: **Benign and robust accuracy on the ImageNet benchmark.** Adversarial patches are generated with random locations and 2% patch size. The middle portion of the defense methods are evaluated under the DO attacks.

| Defense Method          | No Attack | MPGD  | MAPGD | MCW  |
|-------------------------|-----------|-------|-------|------|
| Undefended              | 81.62%    | 14.35%| 9.40% | 49.57%|
| GT Mask                 | 81.60%    | 81.42%| 81.34%| 81.37%|
| PatchGuard [45]         | 60.40%    | 49.41%| 48.91%| 56.95%|
| PatchCleanser [46]      | 80.54%    | 64.30%| 63.57%| 73.12%|
| PatchZero (Separate)    | 81.47%    | 75.60%| 76.80%| 74.24%|
| PatchZero (Joint)       | **81.58%**| 80.74%| **80.92%**| 71.01%|
| PatchZero (BPDA)        | 81.48%    | 55.46%| 70.02%| -    |

– **PatchCleanser:** PatchCleanser [46] is another certified defense against adversarial patches via two rounds of exhaustive masking and ensemble. We empirically evaluate the robustness under the same attack settings. This defense method also requires prior knowledge of attack patch size.

– **JPEG Compression:** Guo et al. [16] propose to defend against adversarial attacks through image transformations, including JPEG compression. Here we use JPEG compression as a preprocessor defense.

– **Adversarial Training:** For each downstream model $f$, we follow a typical adversarial training scheme [33] and train the downstream classifier with a mixture of clean and adversarial images.

**Defense Results:** We first present the undefended baseline and GT Mask baseline which assume perfect adversarial patch detection. As shown in Table 1, the GT baseline recovers most of the robustness accuracy compared with no attack, showing the potential of our approach. The two certified defense baselines, PatchGuard and PatchCleanser, both require prior knowledge of attack patch size and the robustness declines as the patch size increases. Our method’s performance is not strongly dependent on the patch size (except for occlusion effects) but we tested with 2% patch size for fair comparison. We trained two versions of PatchZero under the DO attack setting. PatchZero (Separate) is trained separately for each type of attack, while PatchZero (Joint) is trained with a mixture of all three attacks.

PatchZero (Separate) outperforms PatchGuard by 27% and PatchCleanser by 13% on the MPGD and MAPGD attacks. PatchZero (Separate) has similar performance as PatchCleanser and both outperform PatchGuard on the MCW attack. PatchZero jointly trained with all attacks has 5% improvement on the PGD-based attacks but 3% lower on the MCW attack. Compared with the GT Mask results, PatchZero has almost no drop in accuracy in all attacks except for MCW under the DO attack, but larger gaps under the stronger BPDA adaptive
Table 2: **Benign and robust accuracy on the RESISC-45 benchmark.** Adversarial patches are generated with random locations and 9% patch sizes. The middle portion of the defense methods are evaluated under the DO attacks.

| Defense Method    | No Attack | MPGD  | MAPGD |
|-------------------|-----------|-------|-------|
| Undefended        | 92.9%     | 3.0%  | 1.7%  |
| GT Mask           | 92.9%     | 87.8% | 87.2% |
| JPEG Comp [11]   | 91.0%     | 4.1%  | 1.7%  |
| Adv Training [14] | 83.9%     | 71.8% | 67.2% |
| PatchZero         | 92.9%     | 87.5% | 85.0% |
| PatchZero(BPDA)   | 92.9%     | 81.2% | 76.4% |

attack. Note that neither PatchGuard nor PatchCleanser can be easily adapted for adaptive attack.

We also evaluated PatchZero on the RESISC-45 dataset to test robustness under higher image resolution and much larger patch sizes (9% of image size), as shown in Table 2. We compare with JPEG compression and adversarial training baselines. JPEG compression performs poorly; adversarial training shows much better defense but PatchZero performs better by a large margin, even under the stronger BPDA adaptive attack. Also, adversarial training reduces benign accuracy substantially (by 9%), while PatchZero maintains the benign accuracy of the undefended model.

For both datasets, we can see that the BPDA accuracy drops from GT accuracy, more seriously in ImageNet than in RESISC-45, likely due to much larger variety in the former. Nonetheless, substantial improvements are achieved over undefended model and available alternatives. Further improvements in the patch detection performance will be a consideration in our future research.

### 4.2 Object Detection

**Implementation Details:** For the object detection task, we evaluate on the PASCAL VOC [12] dataset, which has 20 object categories. Following the same setting as previous works [44], our models are trained on VOC 2007 plus VOC 2012 and tested on VOC 2007. We use the Faster-RCNN [38] with ResNet-50 [20] as the downstream detector. For evaluation, we use the standard Average Precision (AP), AP50, and AP75 metrics.

**Attacks:** We defend against Masked PGD attack with a perturbation strength of 0.3, step size of 0.1, and 100 iterations. Patch sizes are 120 × 120 and patch locations are random.

**Baseline Defense:** We adopt Adversarial Training, JPEG Compression as the baseline defense methods, since we are unable to find any other patch defense baselines and the two image classification baselines do not obviously transfer to the detection task.
Table 3: **Benign and robust AP on the PASCAL VOC benchmark.** All adversarial patches are generated with random locations and 8% patch sizes. The middle portion of the defense methods are evaluated under the DO attacks.

| Defense Method | No Attack AP | AP50 | AP75 | Masked PGD AP | AP50 | AP75 |
|----------------|--------------|------|------|---------------|------|------|
| Undefended     | 49.20%       | 76.4%| 52.6%| 6.5%          | 10.9%| 6.7% |
| GT Mask        | 49.2%        | 76.4%| 52.6%| 43.0%         | 68.8%| 44.4%|
| JPEG Compress [11] | 47.7%       | 75.0%| 51.4%| 30.0%         | 48.1%| 32.3%|
| Adv Training [14] | 47.7%       | 75.1%| 51.7%| 16.8%         | 31.9%| 15.2%|
| PatchZero      | 48.4%        | 75.3%| 51.8%| 41.5%         | 66.1%| 43.8%|
| PatchZero(BPDA)| 48.4%        | 75.3%| 51.8%| 35.1%         | 60.0%| 35.5%|

**Defense Results:** Table 3 shows evaluation results against the Masked PGD attack on PASCAL VOC. Similarly, the GT Mask baseline assumes perfect adversarial patch detection and recovers most of the robustness accuracy compared with no attack. PatchZero achieves an AP of 41.5%, around 8% lower than the benign performance, while JPEG compression and adversarial training only get 30.0% and 16.8% AP, respectively. The DO attack results of PatchZero are very close to the GT Mask results. PatchZero also outperforms the other baselines on the benign images. The BPDA results are lower compared with our DO results, but still 5% higher than the JPEG Compression and 18% higher than Adversarial Training, even though they use the much weaker DO attack.

### 4.3 Video Classification

**Implementation Details:** We conduct our video classification experiments on the UCF101, an action recognition dataset that has 13,320 short trimmed videos from 101 action categories. Since adversarial defense is computationally expensive on the video domain, we randomly select 202 video from the test dataset. We adopt the MARS [21] model as the downstream classifier. We use the top1 and top5 classification accuracy as the evaluation metrics.

**Attacks:** For video classification, we consider the Masked PGD and Masked AutoPDG attacks, with perturbation strength of 1.0, step size of 0.2, and 20 iterations. All attacks use BPDA and have patch sizes of 5% and 10%. The patch locations are fixed for all frames of the same video but random for each video.

**Baseline Defenses:** Due to the lack of reliable adversarial patch defense methods in video classification, we pick the H.264 video compression [17] as the baseline defense.

**Defense Results:** We compare the defense performance of different defense methods in Table 4. All methods use the MARS model as the downstream classifier. The GT baseline assumes perfect patch detection and recovers most of the
Table 4: **Benign and robust accuracy on the UCF101 benchmark.** All adversarial patches are generated with random locations. Video Compression defense is evaluated under the DO attack.

| Defense Method       | No Attack | MPGD 5% | MPGD 10% | MAPGD 5% | MAPGD 10% |
|----------------------|-----------|---------|----------|----------|----------|
| Undefended           | 94.55%    | 8.42%   | 3.96%    | 18.81%   | 0.00%    |
| GT Mask              | 94.55%    | 91.58%  | 93.07%   | 91.58%   | 93.07%   |
| Video Compress [17]  | 94.55%    | 21.29%  | 6.44%    | 12.87%   | 0.99%    |
| PatchZero(BPDA)      | 94.55%    | 81.68%  | 82.67%   | 73.27%   | 76.24%   |

Robustness accuracy compared with no attack. For the benign videos, neither PatchZero nor the video compression degrade accuracy compared with the undefended MARS classifier. For the attack scenarios, Masked AutoPGD attack is stronger than the Masked PGD attack and attacks with larger patch sizes (10%) are stronger. PatchZero significantly outperforms the video compression baseline under all attack combinations. The margin is even larger for the stronger Masked AutoPGD attacks and larger patch sizes. For example, for the 10% Masked AutoPGD attacks, our method outperforms the Video Compression baseline by a margin of 75.25% on the top1 accuracy. Compared with the GT Mask, PatchZero still has some performance gap, but already outperforms the other baseline by a large margin.

Lo et al. proposed “3-BN” [22] and “OUDefend” [32] modules as defense for multiple video attacks. The authors do not provide implementation for either method, so we cannot thoroughly compare with them. In their only patch attack experiment, they use a much weaker, Downstream-only Masked PGD attack with patch size of 1.2%, perturbation strength of 1.0, and 5 iterations. The “3-BN” achieves a 63.8% accuracy and OUDefend achieves a 42.00% accuracy. In comparison, we use the adaptive version of Masked PGD attack and with stronger attack parameters: patch sizes of 5% and 10%, perturbation strength of 1.0, and 20 iterations. PatchZero achieves 81.68% top1 accuracy, almost 20% higher. Also, both methods require modification and adversarial training of the downstream video classifier. Neither of them can be easily applied across tasks.

### 4.4 Discussion

**Effectiveness of the Patch Detector:** To figure out how the patch detector performs in identifying the corrupted pixels, we conduct quantitative evaluations on the RESISC-45 dataset. Attacks are generated by Masked AutoPGD under the DO and BPDA attack modes. We report the precision, recall, accuracy, and F1 of the adversarial pixel segmentation task on attack images. According to Table 5 part (a), our patch detector can effectively identify manipulated pixels under both attack modes, although there is a 1% drop in Recall from DO attack
Table 5: (a) Adversarial pixel segmentation performance of the patch detector on the DO and BPDA Masked PGD attacked images on RESISC-45. (b) The models' total number of parameters, GPU memory usage, and inference time in mins on the entire ImageNet validation dataset with one Nvidia 2080Ti GPU.

(a) Patch detector effectiveness.  

|      | Recall | Prec  | Acc   | F1   |
|------|--------|-------|-------|------|
| DO   | 99.8%  | 99.1% | 99.9% | 99.5%|
| BPDA | 98.8%  | 99.1% | 99.8% | 99.0%|

(b) Memory cost and speed.

| Model      | Time | GPU   | Param |
|------------|------|-------|-------|
| ResNet-50  | 8 mins | 1.96 GB | 25.5M |
| PatchCleanser | 758 mins | 7.32 GB | 25.5M |
| PatchZero  | 12 mins | 3.33 GB | 72.2M |

to the stronger BPDA attack. Empirically, we observe that these 1% uncovered pixels, especially at the patch border, can have some influence on the overall accuracy. We also evaluated our patch detector on the benign images. The false positive detection rate is 5.05e-06.

Computation Overhead: We analyze the memory cost and inference speed of PatchZero in Table 5 part (b). Both PatchZero and PatchCleanser use ResNet-50 as backbone. Although Patchzero has more model parameters, it actually has a faster (60x) inference speed and lower (2x) GPU memory footprint.

DO vs. BPDA Attack Patterns: We compare the DO (top) and BPDA adaptive attack patterns (bottom) in Figure 3. The left column shows adversarial patches in the image classification task. The BPDA attack pattern seems to be more colorful and granular than the DO attack pattern. For the object detection task (middle), BPDA attack patterns are more structured, rather than a seemingly random appearance. For the video classification task (right). Under DO attack, the adversarial patch shows some “grid-like” pattern, which we later verify is specific to the MARS video classifier. Under the BPDA attack, the ‘pattern is denser and more granular pattern.

In all cases, the two types of attack patterns are very different for the same images. The BPDA attack patterns start with the DO patterns and gradually evolve into the granular patterns. The changing appearance requires the patch detector to be updated at each iteration. It is not at all obvious that the process should converge but we find that the process does converge and that the trained patch detector becomes robust against the changing patches.

Failure Cases and Limitations: We present three common failure cases of PatchZero in Figure 4. As shown in part (a), missed detection can lead to failure of our defense method, since repainting cannot be effectively applied without a correct patch detection. Leaking adversarial pixels in (b) is another failure case though morphological operations applied to the detected binary mask can reduce the effects. Final failure cases in part (c) can arise due to significant occlusion caused by random patch location falling on top of the main object in the scene, regardless of correct patch detection.
5 Conclusions

In this paper, we proposed PatchZero, a task-agnostic defense against white-box patch attacks. PatchZero first detects the adversarial pixels and then “zeros out” the patch region by repainting with mean pixel values. We further propose a Two-stage training scheme to defend against the stronger adaptive attacks. Extensive experiments demonstrate the state-of-the-art robustness of PatchZero under across the tasks of image classification, object detection, and video classification. We hope PatchZero can inspire new research towards task-agnostic adversarial defenses.
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