ZERO-SHOT CERTIFIED DEFENSE AGAINST ADVERSARIAL PATCHES WITH VISION TRANSFORMERS

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ABSTRACT

Adversarial patch attack aims to fool a machine learning model by arbitrarily modifying pixels within a restricted region of an input image. Such attacks are a major threat to models deployed in the physical world, as they can be easily realized by presenting a customized object in the camera view. Defending against such attacks is challenging due to the arbitrariness of patches, and existing provable defenses suffer from poor certified accuracy. In this paper, we propose PatchVeto, a zero-shot certified defense against adversarial patches based on Vision Transformer (ViT) models. Rather than training a robust model to resist adversarial patches which may inevitably sacrifice accuracy, PatchVeto reuses a pretrained ViT model without any additional training, which can achieve high accuracy on clean inputs while detecting adversarial patched inputs by simply manipulating the attention map of ViT. Specifically, each input is tested by voting over multiple inferences with different attention masks, where at least one inference is guaranteed to exclude the adversarial patch. The prediction is certifiably robust if all masked inferences reach consensus, which ensures that any adversarial patch would be detected with no false negative. Extensive experiments have shown that PatchVeto is able to achieve high certified accuracy (e.g. 67.1% on ImageNet for 2%-pixel adversarial patches), significantly outperforming state-of-the-art methods. The clean accuracy is the same as vanilla ViT models (81.8% on ImageNet) since the model parameters are directly reused. Meanwhile, our method can flexibly handle different adversarial patch sizes by simply changing the masking strategy.

1 INTRODUCTION

Deep neural networks (DNNs) are increasingly deployed in the physical world for safety-critical computer vision tasks. Examples include face authentication on smartphones (Sun et al., 2016), driving assistance on autonomous cars (Wei et al., 2019), and intruder detection on surveillance cameras (Chung et al., 2017). Unfortunately, DNNs are widely known to be vulnerable against evasion attacks (Szegedy et al., 2014; Papernot et al., 2018), where an adversary can easily induce misclassifications by adding a small perturbation to the input image. How to defend against such attacks has been a challenging research problem due to the poor interpretability of DNNs.

Among all types of evasion attacks, adversarial patch attacks (Brown et al., 2017; Karmon et al., 2018) have attracted much attention due to their practicality in the physical world. Unlike classic adversarial attacks that seek to generate a global $L_p$-bounded perturbation ($p = 1, 2, \infty, ...$), an adversarial patch can arbitrarily modify the pixels within a restricted region of the input image. For example, an attacker can fool the DNN in a self-driving car by attaching a printed sticker onto the road signs (Eykholt et al., 2018), or bypass face authentication by presenting a customized object in front of the camera (Komkov & Petiushko, 2021). Various heuristic defenses (Naseer et al., 2019; Rao et al., 2020) have been designed for adversarial patch attacks. However, these heuristic approaches are unable to guarantee robustness against unseen adaptive attacks (Chiang et al., 2020).

There are several provable defenses proposed for adversarial patches. Most of them (Zhang et al., 2020; Levine & Feizi, 2020; Xiang et al., 2021; Metzen & Yatsura, 2021) aim to design a model that can guarantee to make consistent predictions on images with or without an adversarial patch. These
approaches are mostly based on the insight that the prediction can be made by aggregating local features extracted from small independent receptive fields. The certified robustness is achieved by ensuring that the aggregated result will not be dominated by a small number of potentially adversarial receptive fields. As a result, they have to significantly compromise the prediction accuracy due to the lack of global features. The most recent work (Metzen & Yatsura, 2021) in this type can only achieve a certified accuracy of 26.0% on ImageNet under 2%-pixel adversarial patches.

Instead of attempting to hazardously make imprecise predictions in presence of adversarial patches, we argue that it might be more reasonable to find a boundary of when the inference can be trusted. For example, imagine a DNN is used for driving assistance, it would be desirable for the model to promise reliability and precision when it gives a driving suggestion, while informing the driver about the potential risk if the input is potentially harmful. Such defense can be viewed as a provable detection technique, which attempts to guarantee the perfect recall (i.e., no false negative) of adversarial input detection. The Minority Reports Defense (McCoyd et al., 2020), PatchGuard++ (Xiang & Mittal, 2021), and ScaleCert (Han et al., 2021) are designed for such purpose, which partially occludes the image around each candidate patch location and analyzes the predictions of all occluded images to detect adversarial patches. However, the Minority Reports Defense cannot scale to complex high-resolution images (e.g. ImageNet) due to the training difficulty and heavy computation overhead, and PatchGuard++ and ScaleCert are based on CNN backbones with small receptive fields (e.g. BagNet), which cannot sufficiently utilize the global feature. As a result, how to achieve accurate and scalable certified defense against adversarial patches remains an open problem.

To this end, we introduce PatchVeto, a detection-based provable defense against adversarial patches that can flexibly and accurately scale to complex images and different adversarial patch sizes. PatchVeto is inspired by the recently-proposed Vision Transformer (ViT) architecture (Dosovitskiy et al., 2021), which is based on the self-attention mechanism widely used in natural language processing (Vaswani et al., 2017). PatchVeto is zero-shot (aka. requires no additional training) by directly reusing a pretrained ViT backbone for certification.

In a ViT model, the input image is partitioned into small patches. The patches are fed into several Transformer encoder layers to exchange local information by attending to each other. The global feature is obtained after the Transformer layers and used to classify the whole image. Such an attention mechanism enables a convenient way to exclude local patches from an inference pass - a patch can be excluded by masking the attentions of other patches towards it. The remaining patches can still interact with each other to obtain sufficient global information for prediction.

The certified defense ability of PatchVeto is obtained by manipulating the attention map of ViT. Given an input image that may contain an adversarial patch, PatchVeto first makes a prediction using the original ViT, then verify the prediction with a batch of parallel forwarding passes. Each forwarding pass uses a different attention mask to exclude certain local patches, and the masks are designed to guarantee at least one forwarding pass will not attend to the adversarial patch. The prediction is verified if all masked forwarding passes produce the same classification.

We evaluate PatchVeto on popular datasets including ImageNet and CIFAR-10 with adversarial patch sizes ranging from 0.4% to 25%. The results show that PatchVeto is able to achieve significantly higher clean accuracy and certified accuracy than existing certified defenses. Specifically, PatchVeto is able to stably remain a high test accuracy in the verified image subset under different adversarial patch sizes, although the ratio of verifiable inputs decreases under larger adversarial patches.

2 BACKGROUND AND RELATED WORK

2.1 VISION TRANSFORMERS VS. CONVOLUTION NEURAL NETWORKS

The Vision Transformer (ViT) architecture (Dosovitskiy et al., 2021) is proposed recently as an alternative to Convolution Neural Networks (CNNs for short) (Szegedy et al., 2015) in computer vision tasks. ViT is inspired by the scaling success of self-attention-based architectures (in particular Transformer (Vaswani et al., 2017)) on NLP tasks. In a ViT, an image is split into patches and converted to a sequence of linear embeddings of these patches, which is then fed into a Transformer as the input. Image patches are treated the same way as tokens (words) in an NLP application. By pre-training the model on large amounts of data, it is able to attain excellent results as compared to
convolutional networks. Later studies have found that the Transformer architecture can outperform CNN as the backbone network on most downstream CV tasks (Liu et al., 2021).

Splitting the input image into patches is not new in ViT. (Brendel & Bethge, 2019) introduced a variant of the ResNet architecture (He et al., 2016) called BagNet, which classifies an image based on the occurrences of small local image features. BagNet can achieve reasonable accuracy on ImageNet, although the accuracy is inferior to ViT due to the lack of model interactions between the patches. Unlike most existing certified defenses against adversarial patches that are based on BagNet, ours is based on ViT.

2.2 Adversarial Patches vs. Adversarial Perturbations

DNNs are widely known to be vulnerable against adversarial attacks (Szegedy et al., 2014; Goodfellow et al., 2015). Classic adversarial attacks are known as adversarial perturbations, which aim to generate a perturbation added to the pixels of an image that can lead to misclassification.

An adversarial patch is a special case of adversarial attack where the pixel modification is performed within a restricted region in the image. Brown et al. (2017) first demonstrated the feasibility of fooling an image classifier with a specifically crafted physical patch. Numerous other approaches (Karmon et al., 2018; Eykholt et al., 2018) have been proposed afterward to achieve more practical and effective patch attacks.

Whole-image perturbations, as argued in Chiang et al. (2020), are unrealistic in the real world, while patch attack scenario is more reasonable for modeling physical adversary (Eykholt et al., 2018).

2.3 Certified Detection vs. Certified Recovery

There are lots of techniques proposed to defend against adversarial patches, including heuristic defenses and certified defenses. Heuristic defenses (Naseer et al., 2019; Rao et al., 2020) are mostly based on the empirical understanding of existing attacks, which may fail on strong adaptive attacks (Chiang et al., 2020). Certified defenses, instead, aim to rigorously guarantee the robustness of a given model to patch attacks. Due to the ability to prevent future adaptive adversaries, certified defenses have attracted many researchers’ interests in recent years.

The certified defenses can further be classified as certified recovery (Chiang et al., 2020; Xiang et al., 2021; Levine & Feizi, 2020; Zhang et al., 2020; Metzen & Yatsura, 2021) and certified detection (McCoyd et al., 2020; Xiang & Mittal, 2021; Han et al., 2021). Certified recovery aims to recover the correct prediction on images with adversarial patches, while certified detection aims to detect adversarial images with no false negative.

Although certified recovery is usually believed to be more advanced than certified detection, we argue that certified detection may be more practical. First, recovering the correct prediction under the presence of adversarial patches is difficult or even impossible in some cases, e.g. when the critical area of interest (AOI) is hidden by an adversarial patch. Second, optimizing the model for both clean and adversarial inputs would inevitably decrease the model’s accuracy in all existing certified recovery approaches, which may harm the user experience in normal settings. The focus of this paper is certified detection.

3 Problem Setup

Our work shares the same threat model as existing certified defenses against adversarial patches (Xiang et al., 2021; Levine & Feizi, 2020; Chiang et al., 2020; Zhang et al., 2020).

The attack and defense are both focused on image classification. We use $\mathcal{X} \subset \mathbb{R}^{W \times H \times C}$ to denote the distribution of images where each image $x \in \mathcal{X}$ has width $W$, height $H$, number of channels $C$. We take $\mathcal{Y} = \{0, 1, \ldots, N - 1\}$ as the label space, where the number of classes is $N$. We use $f : \mathcal{X} \rightarrow \mathcal{Y}$ to denote the model that takes an image $x \in \mathcal{X}$ as input and predicts the class label $y \in \mathcal{Y}$.

Attacker capability. The attacker can arbitrarily modify pixels within a restricted region, and this region can be anywhere on the image, even over the salient object. We assume that all manipulated...
pixels are within a square region, and the defender has a conservative estimate (i.e., upper bound) of the region size. Our method can be generalized to other patch shapes, as long as the patch can be covered by a restricted rectangle, but we focus on square-shaped patches for simplicity.

Formally, we assume the attacker can arbitrarily modify an image $x$ within a constraint set $\mathcal{A}(x)$. We use a binary pixel block $p \in \mathcal{P} \subset \{0, 1\}^{W \times H}$ to represent the restricted region, where the pixels within the region are set to 1. Then, the constraint set $\mathcal{A}(x)$ can be expressed as $\{x' = (1 - p) \odot x + p \odot x''\} | x, x'' \in \mathbb{R}^{W \times H \times C}, p \in \mathcal{P}\}$, where $\odot$ refers to the element-wise product operator, and $x''$ is the content of the adversarial patch.

**Attack objective.** We focus on the adversarial patch attacks against image classification models. Given a deep learning model $f$, an image $x$, and its true class label $y$, the goal of the attacker is to find an image $x' \in \mathcal{A}(x) \subset \mathcal{X}$ such that $f(x') = y'$, where $y'$ is an arbitrary incorrect class label defined by the attacker and $y' \neq y$.

**Defense objective.** The job of the defender is to design a defended model $g = (f, v) : \mathcal{X} \rightarrow \mathcal{Y} \times \{0, 1\}$, where $g(x) = (f(x), v(x))$, $f(x) \in \mathcal{Y}$ is the classification result, and $v(x) \in \{0, 1\}$ is the verification result indicating whether the prediction $f(x)$ can be verified (1 stands for “verified”). For a given input, the defender decides whether the input can be verified ($v(x) = 1$). The verifiable input subset is named as “robust domain” and noted as $\mathcal{X}_{\text{trust}} = \{x \in \mathcal{X} | v(x) = 1\}$. The predictions of PatchVeto should be resistant to adversarial patches in the robust domain, i.e., any adversarial example generated by the attacker either is ineffective or can be detected (cannot pass the verification). Formally, for any certified clean data point $x \in \mathcal{X}_{\text{trust}}$ and any adversarial example $x' \in \mathcal{A}(x)$, we ensure either $f(x') = f(x)$ or $v(x') = 0$.

The defender aims to improve the quality of the defended model. The clean accuracy $\text{acc}_{\text{clean}}$ (the accuracy of $f$ on the original dataset $\mathcal{X}$ without considering verification) and the certified accuracy $\text{acc}_{\text{certified}}$ (the ratio of images in $\mathcal{X}$ that are correctly and provably classified) are frequently used in prior work to describe the performance of certified defenses. Formally,

\[
\text{acc}_{\text{clean}} = \mathbb{E}_{x \in \mathcal{X}}[l(f(x), y)]
\]

(1)

\[
\text{acc}_{\text{certified}} = \mathbb{E}_{x \in \mathcal{X}}[l(f(x), y) v(x)]
\]

(2)

where $l$ is the 0/1 error function.

In other words, the defender wants to maximize the ratio of verifiable inputs, measured by

\[
 r_{\text{trust}} = \frac{|\mathcal{X}_{\text{trust}}|}{|\mathcal{X}|}
\]

(3)

and the model accuracy in the trust domain

\[
\text{acc}_{\text{in-trust}} = \mathbb{E}_{x \in \mathcal{X}_{\text{trust}}} [l(f(x), y)]
\]

(4)

so that it can retain high test accuracy and guarantee reliability on most inputs ($\mathcal{X}_{\text{trust}}$), while raising a warning if the input $x$ is potentially malicious ($v(x) = 0$). The concept is similar to the selective prediction approaches that try to integrate a reject option in the neural network (Geifman & El-Yaniv, 2019). Such a rejection mechanism is helpful in many perception tasks where a fall-back solution is available. For example, a driving assistance model can ask the human driver to take over or perform a conservative operation when it’s not confident about the current situation.

4 **OUR APPROACH: PATCHVETO**

We introduce PatchVeto, a detection-based certified defense against adversarial patch attacks. Our method is developed upon the Vision Transformer (ViT) architecture, by utilizing its input partition nature and self-attention mechanism. By simply manipulating the attention masks of ViT and voting over different masked predictions, PatchVeto can produce high-precision prediction on the input images and certify robustness on a large portion of them.

4.1 **THE DEFENDED MODEL**

The conceptual model architecture of PatchVeto is shown in Figure 1. It can be viewed as a paired function $g = (f, v)$, where $f$ is a pretrained ViT model for prediction, and $v$ is a verification function...
based on the ViT model. Given an input image \( x \), PatchVeto produces a pair \( (f(x), v(x)) \), where \( f(x) \) is the predicted class of \( x \) and \( v(x) \) represents whether the prediction is verified.

In PatchVeto, the input image is split into non-overlapping patches as in vanilla ViT models. Suppose the input patch size is \( P \times P \) in pixels, then the input image \( x \in \mathcal{X} \subseteq \mathbb{R}^{W \times H \times C} \) is partitioned into a sequence of patches \( \mathcal{P} = \{ p_i \}_{i=1}^{n} \), where \( n = n_w \times n_h = \frac{W}{P} \times \frac{H}{P} \) is the number of patches. Each patch \( p_i \) is then flattened, passed through a linear projection layer, and added a position embedding to generate a patch embedding \( q_i \). A learnable \([\text{class}]\) embedding \( q_0 \) is prepended to the sequence of embeddings, which is used to produce the class prediction after passing through later layers.

Specifically, the patch embeddings are fed into multiple parallel Transformer encoder layers \( T = \{ t_0, t_1, ..., t_k \} \) to exchange information between local patches. The encoders share the same weights of the ViT model \( f \), while are used with different attention masks. Each Transformer encoder \( t_j \) will produce an encoding of the \([\text{class}]\) node, which is then passed through the MLP head to produce a class prediction \( y_j \). We call the predictions produced with the masked attention maps (i.e. \( y_1, y_2, ..., y_k \)) as masked predictions. The class prediction \( f(x) \) is produced by the Transformer encoder without attention masking (i.e. \( y_0 \)), which is equivalent to a direct inference using the base ViT model. The verification result \( v(x) \) is produced by voting over all of the masked predictions \( (y_1, y_k) \). We ensure at least one of the masked predictions is benign (i.e. can completely mask the adversarial patch out), which will veto the adversary’s target output even if all other predictions are compromised. The prediction is verified if all Transformer encoders reach consensus (i.e. agreeing on the same class prediction).

For example, as illustrated in Figure 1, suppose we use a ViT model with 30×30 input resolution and 10×10 input patch resolution as the base model. An input image will be partitioned into 3×3 patches. To defend against adversarial patches with 5×5 resolution, we let each mask to exclude 2×2 local patches, i.e. a square region with 20×20 resolution. By sliding the 2×2 mask over all local patches in the image, we can get four (2×2) possible mask locations and guarantee at least one of the mask locations can completely hide the 5×5-pixel adversarial patch. A certified prediction is produced if the four masked predictions vote for the same class as the non-masked prediction.

### 4.2 Masking Strategy

The certification ability of PatchVeto is achieved by ensuring that at least one of the masked predictions is not influenced by the adversarial patch. The key to design the attention masks is to determine how many local input patches might be tainted by the adversarial patch (i.e. containing pixels belonging to the adversarial patch). Since the input partition plan is fixed and the adversarial patch is at an arbitrary location in the image, we need to consider the worst case, i.e. the maximum number of input patches that may be tainted by the adversary.
Our masking strategy is based on the observation that, in an image that is partitioned into non-overlapping $P \times P$-pixel patches, an adversarial patch with $W_{\text{adv}} \times H_{\text{adv}}$ resolution can affect at most $N_{W} \times N_{H}$ input patches, where $N_{W} = \left\lceil \frac{W_{\text{adv}}}{P} \right\rceil + 1$ and $N_{H} = \left\lceil \frac{H_{\text{adv}}}{P} \right\rceil + 1$. For example, as illustrated in Figure 2, if the width $W_{\text{adv}}$ of a square adversarial patch is smaller than the input patch width $P$, four input patches may be tainted (if the adversarial patch is at the joint of $2 \times 2$ input patches). Similarly, a square adversarial patch with $W_{\text{adv}} \in (2P, 3P)$ may affect at most $4 \times 4$ input patches.

Specifically, given the maximum rectangle shape $W_{\text{adv}} \times H_{\text{adv}}$ of the adversarial patch, we can compute the minimum size $N_{W} \times N_{H}$ for the attention mask. By sliding the mask over the whole input patch grid with a stride of 1, we can enumerate all $k$ possible locations of the mask, where

$$k = (\frac{W}{P} - N_{W} + 1) \times (\frac{H}{P} - N_{H} + 1)$$

We can guarantee that at least one of the $k$ masks can cover the arbitrary adversarial patch.

### 4.3 Certification Analysis

In this subsection, we prove that PatchVeto can achieve the defender’s objective described in Section 3. After obtaining the regular prediction of the ViT base model $f(x)$, the verification result of PatchVeto is obtained by

$$v(x) \triangleq \begin{cases} 1, & \text{if } f_{1}(x) = f_{2}(x) = \ldots = f_{k}(x) = f(x); \\ 0, & \text{otherwise} \end{cases}$$

where $f_{j}(x)$ represents the prediction obtained by the ViT base model with the $j$-th mask position on the attention map.

For any verified clean data point $x \in X_{\text{trust}}$ and any adversarial example $x' \in A(x)$, we need to ensure the adversarial patch is either ineffective or can be detected. Specifically, assuming $x'$ can pass the verification, we have

$$f_{1}(x') = f_{2}(x') = \ldots = f_{k}(x') = f(x')$$

Based on our masking strategy (Section 4.2), at least one of the masked predictions will exclude the adversarial patch in $x'$, i.e.

$$\exists j \in \{1, 2, \ldots, k\}, \text{ s.t. } f_{j}(x') = f_{j}(x)$$

Since $x$ is a verified input, we have $f(x) = f_{j}(x)$, and thus

$$f(x') = f_{j}(x') = f_{j}(x) = f(x)$$

meaning the adversarial patch attack on $x'$ is ineffective. Therefore, we can guarantee that any effective adversarial patch added to a trusted input image would not pass the verification.

## 5 Evaluation

We evaluated PatchVeto on both CIFAR-10 (Krizhevsky, 2009) and ImageNet (Krizhevsky et al., 2012) datasets under different adversarial patch sizes. The PatchVeto implementation used for
evaluation was based on a pretrained ViT-Base model variant with $16 \times 16$ input patch size (ViT-B/16) (Wightman, 2019), which achieves 81.8% test accuracy on ImageNet. When testing on CIFAR-10, the ViT-B/16 base model is fine-tuned on the resized CIFAR-10 dataset first to reach 98.7% test accuracy. The base ViT model can also be replaced with other model variants. All the experiments were conducted on a Linux server with 4 Nvidia V100 GPU nodes.

**Baselines.** Most existing approaches on certified adversarial patch defense are focused on “certified recovery” (as described in Section 2). We compared our approach PatchVeto (PV for short) with the well-known and/or state-of-the-art defenses, including recovery-based defenses like Interval Bound Propogation (IBP) (Chiang et al., 2020), (De) randomized Smoothing (DS) (Levine & Feizi, 2020), PatchGuard (PG) (Xiang et al., 2021), and BagCert (BC) (Metzen & Yatsura, 2021). Detection-based methods include Minority Report (MR) (McCoyd et al., 2020), PatchGuard++ (PG++) (Xiang & Mittal, 2021) and (Han et al., 2021), whose certified detection is also achieved by voting over multiple inferences. PG++ is based on the BagNet architecture (Brendel, 2020), which cannot reach optimal accuracy due to the lack of global feature. MR is based on directly training (fine-tuning) a CNN model to classify the images with a square region occluded, thus can achieve higher clean and certified accuracy. However, the original design of MR needs to enumerate a lot of occlusion positions, which is computationally intensive for high-resolution images. Thus we additionally implement a more advanced version of MR, named MR+, by porting our masking strategy to reduce its number of occlusion positions to the same as in Equation 5. We also replaced the CNN backbone of MR+ to a pretrained ResNet50 (Wightman, 2019) that has similar performance (81.1% accuracy on ImageNet) as the ViT backbone used in PatchVeto. Unlike our approach that requires no training, MR+ needs to fine-tune the model for each adversarial patch size. Unless otherwise noted, MR+ is fine-tuned for 5 epochs (around 4 hours) on the default training split for each adversarial patch size.

### 5.1 Defense Effectiveness

We first compared our approach with existing certified defense approaches in terms of clean accuracy and certified accuracy. As shown in Table 1, our approach was able to significantly outperform the other approaches with a clean accuracy of 81.8% and a certified accuracy of 67.1% on ImageNet with $32 \times 32$-pixel adversarial patches. Due to the design of PatchVeto, its clean accuracy remains the same as the base ViT model, which can be further improved by using better base models.
The results of detection-based approaches (including ours) are not directly comparable with the recovery-based approaches because they are designed for different goals. However, we can notice that our approach was able to achieve a much higher certified accuracy than recovery-based methods, thus it may be more practical to use in real world. The main reason is that the certified detection is based on voting over predictions with small number of patches excluded, which can still provide sufficient global features, rather than in recovery-based approaches where each voter is based on a small local patch.

As compared to other certified detection approaches, PatchVeto could achieve higher clean accuracy and certified accuracy, especially on the ImageNet dataset. This is because of the advantage of self-attention mechanisms in Vision Transformers, which can better tolerate the absence of individual local patches by simply not attending to them. MR+ or other training-based approaches would inevitably sacrifice accuracy since the model has to be fitted on different augmented data.

Meanwhile, MR+ requires to be fine-tuned on an augmented dataset for each adversarial patch size. We have tested the performance of MR+ on ImageNet under 2%-pixel patches with number of epoches ranging from 3 to 24, which took 2 to 16 hours for training. The clean accuracy and certified accuracy increased slowly from 72.9% and 52.8% to 78.1% and 61.1% respectively, which are still lower than the results of PatchVeto achieved with no training effort.

We further tested the defense effectiveness of PatchVeto and MR+ under different adversarial patch sizes. The results are shown in Table 2. To support the defense against different adversarial patch sizes, MR+ requires fine-tuning the model for each size, while PatchVeto only needs to slightly adjust the masking strategy, including the size of masks and the number of mask positions as described in Section 4.2.

The results show that the certified accuracy of PatchVeto dropped from 72.0% to 37.1% as the adversarial patch size increased from 0.5% to 25.0%, which is an intuitive result since the stronger adversary (with the ability to modify a larger region in the image) is harder to defend. Meanwhile, it is interesting to notice that the accuracy of PatchVeto in the trust domain (acc\textsubscript{in-trust}) remained high (even slightly increases) under larger adversarial patch sizes. This means that PatchVeto can retain a high usability under strong adversaries - even though PatchVeto may raise more warnings (i.e. report more unverifiable input images) when defending against stronger adversaries, it can still promise a high accuracy when it gives verified predictions.

5.2 Ablation Study

PatchVeto does not require fine-tune the model, while MR+ requires fine-tuning by default. To understand the effect of fine-tuning for both PatchVeto and MR+, we tested them by adding/removing the fine-tuning phase. The results on CIFAR-10 are visualized in Figure 3. By adding a four-hour fine-tuning phase to PatchVeto for each adversarial patch size, the clean accuracy was almost not changed, and the certified accuracy was slightly increased. For example, the certified accuracy of PatchVeto on CIFAR-10 with 2.4%-pixel adversarial patch was increased from 84.1% to 88.3%. In practice, using PatchVeto in the zero-shot manner (without fine-tuning) is already effective enough. However, if we remove the fine-tuning process in MR+ (i.e. directly using the original model for
The certified accuracy of MR+ became higher than PatchVeto under larger adversarial patches, e.g., in Figure 3, the certified accuracies of MR+ and PV were 65.6% and 48.5% respectively under 25%-pixel adversarial patches. This means that ViT may be less effective than fine-tuned CNN when a large portion of local features are missing. We further tested the performance of MR+ on ImageNet under 2%-pixel patches with the number of epochs ranging from 3 to 24, which took 2 to 16 hours for training. The clean accuracy and certified accuracy increased slowly from 72.9% and 52.8% to 78.1% and 61.1% respectively, which were still lower than the results of PatchVeto achieved with no training effort. This again demonstrates the robustness of ViT architectures to tolerant the absence of a small portion of local features.

We also evaluated the performance of PatchVeto with other ViT variants, including a more accurate backbone ViT_b16_224 ($\text{acc}_{\text{clean}} = 83.1\%$) and a more coarse-grained ViT_b32_384 ($\text{acc}_{\text{clean}} = 81.7\%$). The result is shown in Figure 4. The certified accuracy remains high for different ViT backbones, and stronger backbones produce slightly higher certified accuracy as expected.

5.3 Overhead

Since the verification part of PatchVeto is based on a big batch of masked predictions which might be time-consuming, we further measured the latency of PatchVeto to verify an input image against different adversarial patch sizes on a V-100 GPU. As shown in Figure 5, the verification latency is around 240 ms per sample to defend against 0.5%-pixel patches (which requires to enumerate $k = 169$ possible mask positions) and 126 ms for 25%-pixel patches ($k = 49$). The verification latency is obviously higher than the regular inference latency of ViT (around 12 ms per sample), also
higher than MR+ with the ResNet50 backbone. However, we think the latency is still acceptable given the great benefits of zero-shot certification it provides.

6 CONCLUSION AND FUTURE WORK

In this paper, we presented a simple yet effective certified defense against adversarial patches, by utilizing the novel connection between adversarial patches and input patches in Vision Transformers. We demonstrated the effectiveness and practicality of the defense on ImageNet and CIFAR-10, as well as its flexibility to support different sizes of adversarial patches. The current form of this defense is only designed for a single square adversarial patch, while other shapes of patches and multiple patches are not handled yet. A problem with multiple adversarial patches might be that the number of possible mask positions may be too large, in order to ensure at least one mask can hide the adversarial patches. More advanced masking strategies and voting mechanisms might be needed in the future to tackle this problem.

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