Minority Reports Defense: Defending Against Adversarial Patches

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Abstract

Deep learning image classification is vulnerable to adversarial attack, even if the attacker changes just a small patch of the image. We propose a defense against patch attacks based on partially occluding the image around each candidate patch location, so that a few occlusions each completely hide the patch. We demonstrate on CIFAR-10, Fashion MNIST, and MNIST that our defense provides certified security against patch attacks of a certain size.

1 Introduction

An attacker with knowledge of a neural network model can construct, from any normal image \( x \), an adversarial example \( x^* \) that looks to humans like \( x \) but that the model classifies differently from the normal image [SZS⁺¹⁴, GSS¹⁵, HJN⁺¹¹, CW¹⁷].

Recently, researchers have proposed the adversarial patch attack [BMR⁺¹⁷, KZG¹⁸], where the attacker changes just a limited rectangular region of the image, for example by placing a sticker over a road sign or other object. Others have expanded on the vulnerability to this type of attack [EEF⁺¹⁷, TRG¹⁹, XZL⁺¹⁹]. In this paper, we propose a defense against this attack.

The idea of our defense is to occlude part of the image and then classify the occluded image. First, we train a classifier that properly classifies occluded images. Then, if we knew the location of the adversarial patch, we could occlude that region of the image (e.g., overwriting it with a uniform grey rectangle) and apply the classifier to the occluded image. This would defend against patch attacks, as the attacker’s contribution is completely overwritten and the input to the classifier (the occluded image) cannot be affected by the attacker in any way.

In practice, we do not know the location of the adversarial patch, so a more sophisticated defense is needed. Our approach is to...
(b) Attack

Figure 2: Prediction grids for a benign image (left) and an undefended attack image (right). Each cell in the grid is colored based on the prediction made by the classifier when fed an image obscured at that position in the grid. A cluster of identical minority predictions, as seen in the right image, suggests an attack. In the attack image on the right, green hashes mark the nine predictions where the adversarial patch was fully occluded.

proach works by occluding an area larger than the maximum patch size and striding the occlude area across the image, making an occluded prediction at each stride. We then analyze the classifier’s predictions on these occluded images. If the occlusion region is sufficiently larger than the adversarial patch, several of the occluded images will completely obscure the adversarial patch and thus the classifier’s prediction on those images will be unaffected by the adversary and should match the correct label. Thus, we expect the correct label to appear multiple times among the predictions from occluded images. We show how to use this redundancy to detect adversarial patch attacks. We call our scheme the minority reports defense because no matter where the patch is located, there will always be a minority of predictions that cannot be influenced by the attacker and vote for the correct label.

Figure 1 illustrates our defense. We take the input image (Figure 1a) and construct a grid of partially occluded images (Figure 1b) with occlusions at different locations, chosen so that any attack will be occluded in a cluster of several predictions. We then apply the classifier to each occluded image to obtain a grid of predictions. When under attack, we can expect most predictions to differ from the true label, but there will always be a cluster of locations where the adversarial patch is fully obscured and thus the labels are all expected to agree with the true label; in Figure 1, the 3rd and 4th images in the 4th row obscure the adversarial patch and thus vote for the true label. Our defense analyzes the grid of predicted labels to detect this pattern. If there is a cluster of predictions that all match each other but are in the minority for the prediction grid overall, then this suggests an attack. Figure 2 visualizes the prediction grid for a benign image (on the left) and a malicious image containing an undefended adversarial patch (on the right).1

We evaluate our scheme on the CIFAR-10 [KH09], Fashion MNIST [XRV17], and MNIST [LBBH98] datasets with a stride of one. We show that our defense does not harm accuracy much. We also evaluate its security against adaptive attacks. In particular, we show how to bound the success of any possible attack on a given image, and using this we are able to demonstrate certified security for a large fraction of images. In particular, we are able to prove a security theorem: for a large fraction of images in the validation set, we can prove that no patch attack will succeed, no matter where the patch is placed or how the patch is modified, so long as the size of the patch is limited.

Our contributions are:
- We quantify the vulnerability of undefended networks for Fashion MNIST and MNIST against patch attacks with patches of different sizes (§3.2).
- We propose a novel method for detecting patch attacks, based on differently occluded views of the input image (§4).
- We provide a worst-case analysis of security against adaptive attacks for CIFAR-10, Fashion MNIST, and MNIST (§5 and §7).

2 Data and Inner Model Training

Our defense sends partially occluded images to an inner model, which returns a normal logit prediction for the dataset classes. For this inner model, we use a standard convolutional architecture, trained with data augmentation and random 90/10 train/validation splits: for CIFAR-10, we use SimpNet’s 600K parameter version [HRF+18] trained for 700 epochs, though we do not yet reproduce all details of their training; for Fashion MNIST, a VGG-16 model [SZ14] trained for 50 epochs; for MNIST, the Deotte model [Deo18] ([32C3-32C3-32C5S2] - [64C3-64C3-64C5S2] - 128), with 40% dropout and batch normalization and 45 epochs.

As our defense will partially occlude the image, we train these inner models with occluded images. Each time an image is presented in training, a randomly placed \( n \times n \) square is occluded and the model receives the occluded image. This is similar to cutout from Devries et al. [DT17], who used occlusion as a regularizer. We differ in that we also provide the model an additional input containing a sparsity mask that indicates which pixels are occluded. For instance, the input to the CIFAR-10 model is an image, with dimensions \( 32 \times 32 \times 3 \), and a mask, with dimensions \( 32 \times 32 \times 1 \). In the mask, a 0 indicates an occluded position and a 1 indicates a non-occluded position. To better handle the missing pixels, convolutions in the inner model architecture are replaced with sparsity invariant convolutions [USS+17]. If the mask indicates no occlusions,

1 For the eagle eyed reader, our illustrations are still for a \( 6 \times 6 \) patch.
the sparsity invariant convolutions behave as normal convolutions; but, when occlusions are indicated, the occluded pixels are handled better. We report inner model accuracies in §8.

3 Patch Attack

Patch attacks [BMR+17] work by replacing a small part of the image with something of the attacker’s choosing, e.g., by placing a small sticker on an object or road sign. Figure 1a shows a patch attack. Patch attacks represent a practical method of executing an attack in the physical world. It is not uncommon to see stickers on road signs in the real world, without preventing humans from understanding the signs nor prompting the immediate removal of the patch. We see patch attacks partly as a practical concern, and partly as a stepping stone toward defending against full image attacks.

3.1 Attack model

We assume the attacker, with complete knowledge of the model, may select a square area of limited size anywhere within the digital image and arbitrarily modify all pixels within that square to any values in the pixel range. For simplicity, we restrict the attacker to a square patch. Our approach can handle other shapes as well so long as they are known in advance.

3.2 Patch sizes

We first studied how large a patch is needed to successfully attack our models. We test multiple patch sizes and measure the attacker’s success rate for each patch size.

Setup We conduct a targeted attack against our Fashion MNIST and MNIST models from §2. We attack the first 300 validation images for Fashion MNIST and the first 100 validation images for MNIST, and report the fraction of images for which we are able to successfully mount a patch attack. For each image, we select a target label by choosing randomly among the classes that are least likely, according to the softmax outputs of the classifier (namely, we find the least likely class, identify all classes whose confidence is within 0.1% of the least likely, and select the target class uniformly at random among this set). That target is used for all attacks on that image. For each base image and its chosen target class, we enumerate all possible patch positions and try at each position to find an attack patch at that position.

Attack algorithm To generate patch attacks, we iterate over all possible locations for the patch, and use a projected gradient descent (PGD) attack for each location. We consider the attack a success if we find any location where we can place a patch that changes the model’s prediction to the target label. The resulting adversarial patch is specific to one particular image and one particular location.

The standard PGD attack uses a constant step size, but we found it was more effective to use a schedule that varies the step size among iterations. In our experiments, a cyclic learning rate was more effective than a constant step size or an exponential decay rate, so we used it in all experiments. We used a cyclic learning rate with 10 steps per cycle, with step sizes from 0.002 to 0.3, for a maximum of 150 steps. We stopped early at the end of a cycle if the attack achieved confidence 0.6 or higher for the target class, or if the confidence had not improved by at least 0.002 in the last 20 steps from the best so far. For each image, we attacked in parallel across all possible patch locations.

Results For our MNIST model, a 6×6 patch is large enough to successfully attack 45% of the images. The success rate for 4×4 patches was 19%, and for 8×8 patches 80%. When an image can be attacked, there are often many possible locations where an adversarial patch can be placed: for a 6×6 patch, out of all images where a patch attack is possible, there were on average of 41 different positions where the patch can be placed.

For our Fashion MNIST model, the success rate for patch attacks was as follows: 4×4 patch: 27% success, 5×5 patch: 50% success, 6×6 patch: 60% success.

These results indicate that, on MNIST, an attacker needs to control a 6×6 patch to have close to a 50% chance of success, while a 5×5 patch is large enough for Fashion MNIST, occupying 5% and 3% of the images respectively.

As recent work [CNA+20] focuses on 5×5 patches for MNIST and CIFAR-10, we use 5×5 patches for all datasets.

4 Our Defense

The basic idea of the minority reports defense is to occlude part of the image and classify the resulting image. If the occlusion completely covers the adversarial patch, then the attacker will be unable to influence the classifier’s prediction. We don’t know where the adversarial patch might be located, so we stride the occlusion area across the image. Because we use an occlusion area sufficiently larger than the adversarial patch, no matter where the adversarial patch is placed there should be a cluster of occlusion positions that all yield the same prediction.

4.1 Creating a prediction grid

Our defense first generates a prediction grid, then analyzes it for patterns that indicate an attack. We generate the prediction grid as follows. For defending MNIST images against a 5×5 adversarial patch, we use a 7×7 occlusion region. We slide the 7×7 occlusion region over the 28×28 image with a stride of one pixel, yielding 22×22 possible locations for the occlusion region. The prediction grid is a 22×22 array that records, for each location, the classifier’s output. At each
Figure 3: In (a) and (c), we show the prediction grids for two benign images. (b) and (d) show the corresponding vote grids. We must decide if the minority votes (yellow) are benign errors or what remains of the truth after an attack has influenced the other predictions. Unanimous voting classifies the top example as benign and the bottom as an attack.

location, we mask out the corresponding occlusion region of the image, classify the occluded image, obtain the confidence scores from the classifier’s softmax layer, and record that in the corresponding cell of the prediction grid. Cell \((i, j)\) of the prediction grid contains the confidence scores for all 10 classes, when the pixels in the square \((i, j), \ldots, (i+7, j+7)\) of the image are masked out.

We visualize the pattern of occlusions in Figure 1b, though with a large stride for illustration. A stride of one on MNIST produces prediction grids such as figure 2 and figures 3a and 3c.

If the image contains an adversarial patch centered at location \((i, j)\), then obscuring at each of the 9 locations centered at \((i-1, j-1), \ldots, (i+1, j+1)\) yields nine images where the adversarial patch has been completely overwritten, and the predictions in those cells of the prediction grid are completely unaffected by the attacker. If the classifier is sufficiently accurate on occluded images, we can hope that all of those 9 predictions match the true label. Thus, within the prediction grid, we can expect to see a 3 x 3 region where the predictions are uninfluenced by the attacker and (hopefully) all agree with each other. Our defense takes advantage of this fact.

4.2 Detection

In a benign image, typically every cell in the prediction grid predicts for the same label. In contrast, in a malicious image, we expect there will be a 3 x 3 region in the prediction grid (where the adversarial patch is obscured) that predicts a single label, and some or all of the rest of the prediction grid will have a different prediction. We use this to detect attacks.

In our simplest defense, we look at all 3 x 3 regions in the prediction grid that vote unanimously for the same label (i.e., all 9 cells yield the same classification). If there are two different labels that both have a 3 x 3 unanimous vote, then we raise an alarm and treat this as a malicious image.

Equivalently, we categorize each 3 x 3 region within the prediction grid as either unanimously voting for a class (if all 9 cells in that region vote for that class) or abstaining (if they don’t all agree). We construct a 20 x 20 voting grid recording these votes. If the voting grid consists of solely a single class and abstentions, then we treat the image as benign, and we use that class as the final prediction of our scheme. Otherwise, if the voting grid contains more than one class, we treat it as malicious.

The idea behind this defense is twofold. First, in a benign image, we expect it to be rare for any 3 x 3 region in the prediction grid to vote unanimously for an incorrect class: that would require the classifier to be consistently wrong on 9 occluded images. Therefore, the voting grid for benign images will likely contain only the correct class and abstentions. Second, for a malicious image, no matter where the adversarial patch is placed, there will be a 3 x 3 region in the prediction grid that is uninfluenced by the attack and thus can be expected to vote unanimously for the true class. This means that the voting grid for malicious images will likely contain the correct class at least once. This places the attacker in an impossible bind: if the attack causes any other class to appear in the voting grid, the attack will be detected; but if it does not, then our scheme will classify the image correctly. Either way, the defender wins.

We can formulate our defense mathematically as follows. Let \(x\) denote an image, \(m_{i,j}\) denote the mask that occludes pixels in \([i, i+7] \times [j, j+7]\), and \(x \odot m_{i,j}\) denote the result of masking image \(x\) with mask \(m_{i,j}\). Then the prediction grid \(p\) is constructed as

\[
p_{i,j} = C(x \odot m_{i,j}, m_{i,j}),
\]

where the classifier \(C\) outputs a vector of confidence scores.
The voting grid is defined as

\[ v_{i,j} = \begin{cases} 
  c & \text{if } c = \arg \max_{c'} p_{i+u,j+v,c'} \quad \forall u, v \in \{0, 1, 2\} \\
  \omega & \text{otherwise}.
\end{cases} \]  

(2)

If there exists a single class \( c \) such that \( v_{i,j} = c \) or \( v_{i,j} = \omega \) for all \( i, j \), then our scheme treats the image as benign and outputs the class \( c \); otherwise, our scheme treats the image as malicious.

We illustrate how the defense works with two examples. For instance, if the prediction grid is as shown in figure 3a then it yields the voting grid in figure 3b. This will be treated as benign, with classification 7. We show another example of a prediction grid in figure 3c and the resulting voting grid in figure 3d. This image will be treated as malicious, and our scheme will decline to classify it. In particular, it is possible that the true label is 5, but an adversarial patch was placed in the upper-left that caused most of the classifications to be shifted to 3, except for a few cases where the patch was partly or wholly obscured. It is of course also possible that the image was benign and a cluster of classification errors caused this pattern, which is the case here.

4.3 Visualization

To give some intuition, we visualize a few sample prediction grids in figure 4. The \( 22 \times 22 \) prediction grid is displayed as a Hinton diagram with \( 22 \times 22 \) squares. The color of each square indicates which class had highest confidence at that location in the prediction grid (i.e., the class predicted by the classifier). The size of each square is proportional to the confidence of that class.

We show a representative example from each of four different common cases that we have seen:

(a) Most benign images have a prediction grid that predicts all for the same label or has just scattered minority predictions and looks like case (a): the predictions almost always agree with the true label, for almost all positions of the occlusion region, but there are a few locations that when occluded cause classification errors (non-black squares). These will be correctly classified and treated as benign by our scheme.

(b) A few benign images have prediction grids that are more noisy and contain large clusters of incorrect predictions in the prediction grid. These will be (incorrectly) categorized as malicious by our scheme, i.e., they will cause a false positive.

(c) We show the prediction grid resulting from a typical attack image, with an adversarial patch placed near the center of the image. The green cross-hatching represents the locations that completely occlude the adversarial patch. Those locations in the prediction grid, as well as some other locations in a broader ring around this, vote unanimously for the true label (1). Occlusion regions placed elsewhere fail to occlude the adversarial patch and cause the classifier to mis-classify the image as the attacker’s target class (2). Our scheme correctly recognizes this as malicious, because the voting grid contains both unanimous votes for 1 and for 2.

(d) Other attack images have even more noise outside the fully occluded area. These too are correctly recognized
as malicious, because the voting grid contains unanimous votes for multiple labels, here 3, 2, and 6.

4.4 The full minority reports defense

We found that the above defense can be improved by incorporating two refinements: (a) using soft agreement instead of hard unanimity, and (b) tolerating outliers.

First, instead of checking whether a $3 \times 3$ region in the prediction grid votes unanimously for the same label, we check whether the confidence for that label, averaged over the region, exceeds some threshold. For instance, with a 90% threshold, if the confidence scores for class $c$ within that $3 \times 3$ region average to 0.9 or larger, then we’d record a vote for $c$ in the voting grid; if no class exceeds the threshold, then we record an abstention.

Second, when computing the average, we discard the lowest score before computing the average. This allows us to tolerate a single outlier when checking for agreement in a $3 \times 3$ region.

Mathematically, we fix a threshold $\tau$, and then form the voting grid as

$$v_{i,j} = \begin{cases} c & \text{if } \text{avg}(\{p_{i+u,j+v,c} \forall u, v \in \{0, 1, 2\}\}) \geq \tau \\ \omega & \text{otherwise.} \end{cases} \tag{3}$$

Here we define $\text{avg}(S)$ to be the average of $S \setminus \{\min S\}$, i.e., the average of all but the lowest score in the multiset $S$.

The threshold $\tau$ is a hyper-parameter that can be used to control the trade-off between false positives and false negatives. Increasing $\tau$ reduces the number of false positives, but also risks failing to detect some attacks; decreasing $\tau$ increases detection power, at the cost of increasing the false positive rate.

The size of the occlusion region is another hyper-parameter of our defense. In our experiments, we always chose an occlusion region that is two pixels larger than the largest adversarial patch we seek to defend. Thus our occlusion region will be $7 \times 7$ and we provide certified results against adversarial patches up to $5 \times 5$ in size. Our approach can generalize to other shapes, such as rectangles or even to arbitrary shapes, so long as they are known in advance. We can defend against a rectangular $w \times h$ sticker, with a $(w + 2) \times (h + 2)$ occlusion region. To defend against stickers with some other known shape $S$, the occlusion region can be obtained as the union of 9 translations of $S$, where we translate independently by $-1$, 0, or 1 pixels in each dimension.

We visualize the operation of our final defense in figure 5.

5 Security Evaluation

One benefit of our design is that it enables us to guarantee the security of our scheme on some images. We describe our certified security analysis in this section.

The core observation is: if the adversarial patch is completely occluded, then the adversary cannot have any influence on the prediction made by the classifier on the corresponding occluded image. For certified security, we make a very conservative assumption: we assume that the adversary might be able to completely control the classifier’s prediction for all other occluded images (i.e., where the patch is only partly occluded, or is not occluded at all). This assumption lets us make a worst-case analysis of whether the classification a particular image could change in the presence of an adversarial patch of a particular size.

Notice that wherever the sticker is placed, there will be a $3 \times 3$ grid in the prediction grid that is unaffected by the sticker. (This is because with a stride of one we use an occlusion region that is 2 pixels larger than the maximum possible sticker size.) It follows that there will be some cell in the voting grid that is not changed by the sticker.

If the voting grid for an image $x$ is completely filled with votes for a single class $c$, with no abstentions, then any image $x'$ that differs by introduction of a single sticker will either be classified by our defense as class $c$ or will be detected by our defense as malicious. (This follows because at least one element of the voting grid is unaffected by the sticker, so at least one element of the voting grid for $x'$ will vote for $c$. If no other class appears in the voting grid, then our defense will classify $x'$ as class $c$; if some other class appears, then our defense will treat $x'$ as malicious.) Thus, such images can be certified safe—there is no way to attack them without being detected. If the prediction is also correct, we classify the image as certified accurate.

In contrast, if the voting grid has even one region that does not vote, or votes as the attacker would like, then our conser-
6 Higher Resolution Images

For higher resolution images, a stride of one pixel becomes prohibitive. Increasing the stride lets us manage the cost. For a patch of size $p \times p$ pixels and a stride of $s$ pixels, an occlude area of $(p + 2s) \times (p + 2s)$ produces nine full occlusions of any patch, if the patch is aligned to our stride grid. This mirrors what we have done with a stride of one. To account for patches not aligned to our stride grid, we increase our occlude by one stride. Thus our occlude area is $(p + 3s) \times (p + 3s)$ pixels for a stride of $s$, for $s > 1$.

As an example, if CIFAR-10 had twice the resolution, our $5 \times 5$ pixel patch would be $10 \times 10$ pixels. With a stride of two, our occlude area would be $16 \times 16$, or $(10+3 \times 2) \times (10+3 \times 2)$.

7 Experiments

We evaluate the effectiveness of our defense by measuring the clean accuracy (the images that when unmodified are classified correctly by class and as benign) and the certified accuracy (the images that when unmodified are classified correctly by class and as benign and where any attack – targeted or un-targeted – will either not change the classification or will be detected).

**Method** We measure the clean and the certified accuracy on the 5000 or 6000 validation images. We perform multiple trials, using a different random 90/10 train/validation split for each trial. For each dataset we perform $n = 4$ trials. The standard deviation is relatively low (for clean and certified accuracy they are CIFAR-10: $0.2 – 0.8\%$ $0.5 – 1.1\%$, Fashion MNIST: $0.2–0.4\%$ $0.2–0.6\%$, MNIST: $0.0 – 0.1\%$ $0.1–0.5\%$). We report results for different points in the tradeoff between clean and certified accuracy, and compare with recent related work using Interval Bounds Propagation (IBP) [CNA+20].

**Results** Our results, table 1, show that our defense achieves relatively high clean and certified accuracy and outperforms the previous state of the art.

| Dataset | Defense | Lit. Clean | Cert. |
|---------|---------|------------|-------|
| CIFAR-10 IBP [CNA+20] | 47.8% | 30.3% |
| MR (Our) | 94.0% | 78.8% | 77.6% |
| | 90.6% | 62.1% | 92.4% | 43.8% |
| Fashion MR | 93.8% | 85.4% | 84.3% |
| | 93.0% | 69.4% |
| | 93.9% | 42.0% |
| MNIST IBP [CNA+20] | 92.9% | 62.0% |
| MR | 99.6% | 95.1% | 94.9% |
| | 99.0% | 75.8% |
| | 99.4% | 64.2% |

For CIFAR-10, we achieve a clean accuracy of 92.4% and 43.8% of images can be certified accurate (no matter where a sticker is placed, the resulting image will either be classified correctly or the attack will be detected) for $5 \times 5$ stickers. This is significantly better than recent work by Chiang et al. [CNA+20], which achieves clean accuracy of 47.8% and certified accuracy of 30.3% for CIFAR-10 against $5 \times 5$ stickers.
8 Effects of Occlude Training

Our defense requires the inner model to handle occluded images well. To assess the effect of this requirement, we trained models with and without occlusions for all three inner-model architectures.

Training on occluded images appears to have only a small change on the accuracy of the inner model on non-occluded images, see table 2. The change is at worst the standard deviation of our measurements. Note from table 1 that the clean accuracy of our defense might have either a small or no drop from the accuracy of our inner-model.

Table 2: The effect of training on occluded images, on the inner model’s accuracy on non-occluded images. We show the difference (last column) and the standard deviation ($n = 4$).

| Dataset   | Type of training images | Non-occluded | Occluded | $\Delta$ |
|-----------|-------------------------|--------------|----------|----------|
| CIFAR-10  | Non-occluded            | 92.5 ± 0.3%  | 92.5 ± 0.2% | -0.0%  |
| Fashion   | Non-occluded            | 94.1 ± 0.4%  | 93.8 ± 0.3% | -0.3%  |
| MNIST     | Non-occluded            | 99.58 ± 0.08% | 99.63 ± 0.33% | +0.05% |

Note that this does not measure the accuracy of our defense as a whole. Our defense feeds the inner model occluded images at test time, and accuracy on occluded images is slightly lower than on non-occluded images.

9 Related Work

In earlier work, Hayes proposes a defense against sticker attacks using inpainting of a suspected sticker region to remove the sticker from the image [Hay18]. This is similar to our defense. However, Hayes uses a heuristic to identify the region to inpaint (based on unusually dense regions within the saliency map), so any attack that fools the heuristic could defeat their defense. One could use inpainting in our scheme instead of occlusion, and it is possible this might improve accuracy, though our work can be viewed as showing that simple occlusion suffices to get strong results. Naseer et al. propose a defense against sticker attacks by smoothing high frequency image details to remove the sticker [NKP18]. They limit accuracy loss by using windows that overlap by a third, but their windows are smaller than the attack patch. Chiang et al. broke both of these defenses [CNA+20], so neither is effective against adaptive attacks; in contrast, we guarantee security against adaptive attack.

In concurrent work, Wu et al. defend against adversarial patches with adversarial training [WTW20]. The primary advantage of our approach is that it provides certified security.

In concurrent work, Chiang et al. study certified security against patch attacks using interval bounds propagation [CNA+20]. As discussed above, our defense achieves significantly better certified accuracy on both MNIST and CIFAR than their scheme. They also examine how their defense generalizes to other shapes of stickers and how to achieve security against $L_0$-bounded attacks, topics that we have not examined.

10 Conclusion

We propose the minority reports defense, a network architecture designed specially to be robust against patch attacks. We show experimentally that it is successful at defending against these attacks for a significant fraction of images.

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