Essential Features: Content-Adaptive Pixel Discretization to Improve Model Robustness to Adaptive Adversarial Attacks

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Abstract—To remove the effects of adversarial perturbations, preprocessing defenses such as pixel discretization are appealing due to their simplicity but have so far been shown to be ineffective except on simple datasets such as MNIST, leading to the belief that pixel discretization approaches are doomed to failure as a defense technique. This paper revisits the pixel discretization approaches. We hypothesize that the reason why existing approaches have failed is that they have used a fixed codebook for the entire dataset. In particular, we find that this can lead to situations where images become more susceptible to adversarial perturbations and also suffer significant loss of accuracy after discretization. We propose a novel image preprocessing technique called Essential Features that uses an adaptive codebook that is based on per-image content and threat model. Essential Features adaptively selects a separable set of color clusters for each image to reduce the color space while preserving the pertinent features of the original image, maximizing both separability and representation of colors. Additionally, to limit the adversary’s ability to influence the chosen cluster colors, Essential Features takes advantage of spatial correlation with an adaptive blur that moves pixels closer to their original value without destroying original edge information. We design several adaptive attacks and find that our approach is more robust than previous baselines except on simple datasets such as MNIST that largely consist of black and white pixels.

I. INTRODUCTION

Machine learning models have been used for a large diversity of tasks including robots, automatic speech recognition systems, and the development of self-driving cars. These models, however, have been shown to be vulnerable to subtle adversarial attacks [4], [9], [13], [14], [19], [22] that threaten the safety and real-world practicality of such systems. Attacks now range from digital attacks such as the Fast Gradient Sign Method (FGSM) [13] and Projected Gradient Descent (PGD) [24] to physical-world attacks such as Expectation over Transformation (EoT) [4] and Robust Physical Perturbations (RP₂) [13] that generate physical stickers to carry out an attack.

Understanding how to defend machine learning models remains a challenge despite an increasingly large literature of defense design [12], [15], [24], [57], [59], [41]–[43]. As attack and defense algorithms have evolved over the years, a somewhat patch-work approach has prevented us from closing the gap between what machine learning models versus humans think is important for a small change in an input. Adversarial training [24], [41]–[43] is widely considered to be the best technique to increase model robustness, but a large gap between clean accuracy and adversarial accuracy still remains.

In addition to adversarial training, early approaches to designing image classification defenses to adversarial attacks included image preprocessing techniques such as JPEG compression [11], [12], [15], color-bit reduction [15], [59], and blurring [39]. However, these works did not consider adaptive attacks that took the added preprocessing into account; they were broken in subsequent papers with a technique known as Backwards Pass Differentiable Approximation (BPDA) [3]. When using BPDA, the backwards gradient calculation for the (non-differentiable) preprocessing function is estimated with a differentiable function. Oftentimes, the identity function suffices for this purpose [3].

Another intellectual limitation of these preprocessing defenses is that they failed to consider the content of individual images, limiting their ability to balance a tradeoff between representation, or allowing the defense to recreate or preserve essential features of the natural image, and separability, or reducing an adversary’s ability to add adversarial noise that can persist through the preprocessing transformation.

Chen et al. [9] try to overcome the above limitations by discretizing the color space based on the training set, but they still used a fixed codebook across the dataset. They concluded that for most datasets, approaches based on pixel discretization remain unsuccessful as a defense against adaptive adversarial inputs since it is difficult to find globally-separated codeword colors except on simple datasets such as MNIST that largely consist of black and white pixels.

In this paper, we revisit the pixel discretization approach. We show that pixel discretization can indeed yield a significantly improved defense against adaptive adversarial inputs for diverse datasets on which prior pixel discretization preprocessing approaches failed. Unlike prior approaches that relied on a single codebook for the entire dataset, we find that it is useful to select the codebook adaptively based on the image content for a more robust defense. The insight is that individual images can have good color separability while having poor separability collectively — no single codebook may suffice across all images. For instance, a STOP traffic sign is predominantly red and white and has good separability.
Similarly, an image of a pig against a natural background may have good separability, but will utilize a different set of colors than a traffic sign.

To this end, we introduce a $k$-means color reduction inspired transform to reduce a given image into $k$ separable color clusters, where $k$ is chosen adaptively at test time and the resulting discretized colors are also specific to the image. In adaptive attack scenarios, we find that this significantly limits the adversary’s ability to add arbitrary textural changes within areas of similar color profiles, improving robustness for a wider set of datasets.

An adaptive codebook-based defense does have a potential weakness on some images where color separation is relatively poor in that an adaptive adversary can inject adversarial noise that causes a change in the choice of codebook that results in a significant change in the resulting image after pixel discretization. We propose a secondary preprocessing defense, called adaptive blurring, to limit an attacker’s ability to influence shift in colors chosen for the codebook. Adaptive blurring takes advantage of spatial correlation to bias pixels towards their original color values and is applied prior to adaptive pixel discretization. In order to preserve important edge features of the original content, we adaptively choose smaller blur kernels around strong edges and larger blur kernels in the absence of edges. The thresholds are set based on the strength of edge possible under the expected $L_\infty$ norm ball restrictions to prevent the adversary from being able to arbitrarily add features wherever they want.

We empirically find that using our adaptive discrete pixelization, combined with adaptive blurring on many datasets, and then adversarially training the entire pipeline results in a model that is significantly more robust to BPDA and other adaptive attacks than defenses based on state-of-the-art adversarial training of a model alone. We apply adaptive attack lessons learned in [33] when evaluating our proposed defense towards ensuring that we are selecting state-of-the-art adaptive adversarial attack strategies that factor in our defense approach. To demonstrate the efficacy of our method, we perform experiments on six common datasets. We test on adaptive PGD attacks as well as a black-box soft-label attack (Square Attack [1]). Essential Features raised adversarial robustness on adversarial robustness on datasets for which prior pixel discretization attempts failed to improve robustness. In particular, compared to baselines, we raised robustness on CIFAR-10 [18], from 52.33% to 57.47%, GTSRB from 77.71% to 78.59%, RESISC45 from 44.2% to 66.73%, and ImageNet from 16% to 22.59%.

**Contributions:**

1) We propose a novel, content-aware transformation called Essential Features that reduces the attack space by applying adaptive blurring and adaptive discretization to pixels on a per-image basis to blunt the impact of adversarial perturbations. Essential Features balances high representation accuracy by preserving important edges and high separability between color clusters on a per-image basis to make it harder to find successful adversarial perturbations that survive the pixel preprocessing.

2) We develop adaptive attacks to our Essential Features approach and use this robust feature space in combination with adversarial training.

3) We evaluate our defense against adaptive white-box and black-box attacks and show that our defense is more robust to $L_\infty$ and $L_2$ attacks than state-of-the-art adversarially trained models.

In Section 2, we describe the most relevant related work in adversarial image defenses. Sections 3 and 4 motivate and detail the Essential Features approach. In Section 5, we describe the experimentation, including results on adaptive attacks. Finally, we discuss the implication of our approach and summarize our findings.

**II. RELATED WORK**

Our work is primarily related to image preprocessing defenses and adversarial training. We aim to address the flaws of current image preprocessing defenses and leverage adversarial training to achieve increased robustness. We briefly describe these and the relation to our work.

**Image Preprocessing Defenses:** Image preprocessing approaches seek to remove adversarial perturbations through image processing techniques (e.g., image blurring or sharpening). Once processed, the resulting image is handed to the machine learning model. The goal of such image preprocessing techniques is to both not affect the accuracy in classifying non-adversarial images as well as improving the classification accuracy of adversarially tampered images.

Several preprocessing defenses include color-bit reduction [15], [39], JPEG compression [11], [12], [15], and a non-differentiable pixel deflection approach [25]. These image preprocessing algorithm defenses were broken with simple applications of BPDA with the identity function as the backwords approximation [2], [3]. Xu et al. additionally propose filtering defenses but do not present adaptive attacks. Unlike our adaptive blurring, their filters are fixed. Liang et al. propose a per image adaptive detection approach that blurs each image based on its entropy [23]. In contrast, we propose a defense that outputs correct predictions in the face of attacks and blurs adaptively within an image.

More recently, Chen et al. propose a dataset tuned color codebook discretization transformation that reduces each image to the same set of separable codebook colors [9]. The authors also do theoretical analysis and suggest that such techniques are fundamentally doomed on complex datasets such as CIFAR-10 or ImageNet due to a lack of color separation in the dataset. However, we overcome the pessimistic findings of Chen et al. by applying Essential Features on a per-image basis, allowing us to tune the pixel discretization transform based on the color profile of the given image at test time.

Jalalpour et al. [17] first proposed the notion of using $k$-means color reduction to thwart adversarial attacks. We will also use a variant $k$-means color reduction; however, unlike Jalalpour et al., we will choose number of colors $k$ adaptively
on a per-image basis such that chosen clusters are highly separable. Further, Jalalpour et al. did not adversarially train networks with \( k \)-means color reduced images. We additionally add adaptive Gaussian blurring in front of the color reduction rather than normal Gaussian blurring, which preserves more of the original edge features. Finally, we also note that color-bit reduction effectively truncates color bits to decrease the number of colors while we select \( k \) representative colors to reduce to based on the dominant colors in the image. The key difference is that standard color-bit reduction splits the color space into evenly spaced values, some of which may not be in the image itself. Our proposed color discretization approach adapts the chosen colors to the image itself.

**Adversarial Training:** Adversarial training is a commonly used class of defense approaches that train classifiers under attacked images to raise robustness. The goal is that training on adversarial images will result in a hardened classifier. Adversarial training poses a min-max problem where we minimize the classifier’s loss over the strongest perturbations \( \delta \). The goal is that training adversarial images to raise robustness. The goal is that training adversarial training while retaining comparable accuracy \[28\], hard to scale \[20\], so other approaches have tried to speed up \( \delta \) attacks generated at each epoch. While effective, one limitation of adversarial training is that it is slow and hard to scale \[20\], so other approaches have tried to speed up adversarial training while retaining comparable accuracy \[28\], \[37\], \[41\]–\[43\].

**III. Motivation**

We assume a threat model in which perturbation space \( S \) is defined by a bounded \( L_{\infty} \) (or, alternatively, \( L_2 \)) perturbation to an input, i.e., \( ||\delta||_{\infty} < \epsilon \) (or alternatively, \( ||\delta||_2 < \epsilon \)). The goal of our proposed **Essential Features** approach is to minimize the attack surface through image preprocessing techniques, allowing the response to be tailored to both the expected adversary and the underlying image. This transformation can be seen as one that creates a more robust feature space that can then be adversarially trained on. We motivate the necessary components to limit the attack surface of adversaries, including motivating color reduction, outlining our mathematical goal, and demonstrating how each step limits the attack surface. Fundamentally, any algorithm will need to trade-off reducing the attack surface available to adversaries and the ability to classify images. We note that when adversaries are given sufficient movement of color values, no algorithm can recover sufficient signal to thwart an adversary. Similarly, if the noise level available to the adversary is above the signal level needed to classify a particular image, there is little hope in thwarting the adversary.

At a high level, we introduce two key principles that any successful color reducing defense must balance: (i) representation, which we use to refer to the defense’s ability to consider properties of the data and to faithfully reconstruct its essential features, and (ii) separability, which we use to refer to the ability for an attacker to change a pixel’s color to create an unwanted feature. A trivial solution with high representation uses all of the color space, and a trivial solution with high separability uses extremely few colors. We propose a content-based transformation for each image to achieve both principles.

**A. Choosing representative colors wisely**

The original color-bit reduction algorithm \[39\] quantized the color space at set intervals and discretized colors to the nearest quantized value. The goal of the approach was to reduce the colors available to an adversary by limiting the choices of color. One primary limitation of this technique is that the set of chosen colors is largely independent of the actual colors occurring in the image. This can lead to poor representation. Chen et al. \[9\] observe this weakness and propose a solution that calculates \textit{per-dataset} separable color codebooks to discretize the color space to a small set of colors. However, Chen et al. found that a dataset-specific codebook is only successful in simple datasets like MNIST. With more complex datasets such as CIFAR-10 and ImageNet, color discretization, even when based on the dataset, fails to improve robustness over standard adversarial training. The fundamental problem that Chen et al. found is that many datasets, including CIFAR-10 and ImageNet, do not have enough color separability to achieve good representation and separability at the same time.
Our hypothesis is that the limitation of Chen et al. was that they did not chose discretized colors on a per image basis; rather, they calculated a set of discretized colors for the whole dataset. Our hypothesis is based on the intuition that most images in real-world datasets do indeed have sufficient color separability even if the dataset as a whole does not. Furthermore, using an appropriate adaptive pixel discretization algorithm, it should be possible to exploit image-specific color separability to achieve higher robustness on a wide variety of datasets on which prior pixel discretization approaches failed.

The original color-bit reduction algorithm [39] and Chen et al.’s dataset-specific pixel discretization algorithm [9] both remain vulnerable to cases where pixels with similar colors fall between two codebook colors, which then allows an adversary to switch the color assignment for pixels in that set with small perturbations.

As a simple example, suppose colors are in the range 0 (black) to 1 (white) and that we have a central box as one of the classes in the dataset as shown in Fig. 2a. In (a), a foreground square with color 0.75 and background of color 0.25 (The histogram of the colors is shown to the right). Further, suppose the codebook values were selected at 0, 0.5, and 1 and that (generally) images in the dataset consist primarily of these values.

Suppose now that at test time you are given a slightly perturbed sample with a bimodal distribution with a background of values in [0.2, 0.3] and a light gray box with values in [0.7, 0.8] (e.g., Fig 2b). That is, the adversary is able to add noise of up to +/- 0.05 to each pixel. For each peak, half of the value range is closer to 0.5 and half of the value range is closer to the relative extreme (0 or 1). As a result, because the colors were chosen based upon the dataset in general rather than tailored to each image, you get the messy result in Fig 3. A better set of equally separable codebook colors for this particular image’s content would have been 0.25 and 0.75, which would assign all the pixels in each peak to the same codebook color.

The example illustrates the need for the defense to consider per-image content and representation. In particular, it shows that a per-image pixel discretization transform that chooses the codebook based on the test image content can provide a stronger defense against adversarial perturbations that other codebooks. We also note that this is a simple example but the principle generalizes to color clusters in images broadly.

It is important to note that as the epsilon budget available to the adversary increases towards 0.25, the distance at which an adversary could then take a pixel in one cluster and make it closer to the other cluster, the ability to recover or adapt to the adversary is necessarily lost.

**B. An Adaptive Color Reduction Transform**

To combat the shortcomings of prior discretization techniques, we apply a per-image adaptive color reduction transform. The goal of this transformation is to reconstruct the input image as faithfully as possible (high representation) with separable colors (high separability). This can be formulated as solving the following optimization problem, where $T_c$ takes each pixel in an image $x$ and sets it to the nearest color in the cluster palette $C$, and where $d$ represents a minimum distance between any two clusters:

$$
\arg\min_C \|T_C(x) - x\|_2
$$

s.t. $\forall i, \forall j, ||C_i - C_j||_2 > d$

(1)

In the previously introduced example with the light gray box, an adaptive per-image color reduction palette of two colors should select 0.25 and 0.75 clusters as previously argued in Section III-A. Ideally, Fig. 2b would be transformed to Fig. 3 instead of Fig. 3.

Now that we apply a per-image adaptive color reduction transform at test time, there is some opportunity for the attacker to slightly influence the palette by 1) shifting large amounts of pixels assigned to a cluster in a certain direction or 2) by adding edges / changing which pixels belong to which clusters arbitrarily. We can mitigate this effect by taking advantage of spatial correlation to attempt to recover the true cluster these attacked pixels belong to as described below.

**C. An Adaptive Blurring Operator**

The fact that the transformation is applied at test time allows an adversary to create a noisy signal (within small $L_p$ bounds)
Fig. 4. An example attack where an adversary has inserted a feature into a flat region. While an adversary would typically hide this in the noise, we show it directly to allow for easier understanding of this approach.

Fig. 5. Example of the importance of blurring kernel sizes.

(a) Applying a blur kernel of size 3 to Fig. 4.

(b) Applying a blur kernel of size 13 to Fig. 4.

Fig. 6. Adaptive blurring sets the blur high enough inside the square to suppress edges within the adversary’s budget while preserving the original edge of the square before passing the image off to color reduction.

In contrast, if we apply a large amount of blur uniformly on the entire image as in Fig. 5b, we can reduce the noise within the central box and the featureless areas of the background. However, the large blur causes a loss in the defining edges of the original square (Fig. 2), which could be necessary for classification. This is shown both visually in the image (right) and the mixing of the two clusters leads to many smaller values within the histogram.

To overcome the limitations of a non-adaptive blur, we hypothesize that an edge-aware adaptive blur can help both preserve pertinent edge features while smoothing over the noisy signal before sending it into the color reduction process. Because image pixels tend to have high spatial correlation with nearby pixels, this process biases pixels back towards their original color. We can also use this process to eliminate the adversary’s ability to add edges in flat regions of the same color by enforcing that the largest blur be applied to areas where the only edges are as weak as the adversary’s edge creation ability. Take Fig. 4 as an example where an adversary has added edges by shifting some pixels down 0.05 and added 0.05 to others. If we set the parameters of the adaptive blur to blur with larger kernels (such as a kernel of size 5 for example) everywhere but around the original square’s border (the strongest edges), we can significantly suppress the perturbation without removing the original border as in Fig. 6. As shown in the figure, adaptive blur allows us to coalesce nearby pixel values in the histogram, while removing the mixing of color clusters (background and foreground).

Essentially, we would like to just to apply blur within the pre-existing shapes and strong edges of the original, unattacked image. This becomes even more important where more complex datasets enforce additional clusters that may be slightly closer to each other than the simple example in Fig. 2.

To finish off the motivation, we can then run a color reduction algorithm (e.g., K-means to recluster pixels). In Fig. 7 we show the example from the result of adaptive blurring with
color reduction applied. The result is essentially the same as the original in Fig. 2.

This result of this is that applying these ideas limits the adversary’s ability to influence the palette - now, the adversary must shift large portions of the image in a similar direction or target changes on the strong, existing edges. An example of this is shown in Fig. 8. Here the adversary needs to either shift large clusters a little bit, or rely on the features (edges) to make smaller adjustments, all of which more strongly constrain the adversary.

D. Summary and Design Considerations

In summary, we derive a two phase transformation: 1) apply adaptive blurring, which uses spatial correlation to limit the effects of isolated perturbation signals and 2) apply an adaptive color reduction process, which limits the attack to a set of separable color clusters on a per-image basis.

Note that this transform is designed to take advantage of the content and simplify the representation. Due to the use of blurring and color reduction, this transformation is designed best for datasets with a high resolution to detail ratio where the assumption that blurring in areas without strong edges largely consist of the same color holds. If we are working with a low resolution dataset, it may help to only apply adaptive color reduction. Additionally, if the dataset is low in resolution, color reduction can remove some of the subtle detail created by edges of similar colors. Both concerns are less of a problem in larger resolution datasets such as ImageNet, but adversarially retraining on ImageNet is difficult and there is a lack of standard datasets in between CIFAR-10 and ImageNet.

The examples show cases where certain transformations fail or succeed. While an adversary is not limited to such examples, they paint of picture of the general attack vectors that are present to adversary’s before and after applying per-image transformations such as Essential Features.

IV. APPROACH

As described in Section III Essential Features aims to cut down the attack surface available to adversaries with two primary components:

- Adaptive blurring: The purpose of adaptive blurring is to clean up the (potentially) noisy adversarial signal and use spatial correlation to give a more accurate representation for color reduction to be applied to. By applying an adaptive Gaussian blurring process to preserve edges, we are able to effectively apply a higher level of blurring in the middle of an object than we would with regular Gaussian blurring. This eliminates the adversary’s ability to add edges in a flat region of a singular color while also preserving necessary natural edge features for classification.

- Adaptive color reduction: Rather than having 256^3 possible colors for each pixel independently, we limit the attacker’s space by reducing each image at evaluation time to k representative colors. We modify k-means so as to have high representation and separability. The goal of this component is to force colors that are similar to a single color, removing the ability of adversaries to subtly perurb pixel values.

A. Adaptive Gaussian Blurring

Applying Gaussian blurring removes high frequency changes an adversary may attempt to add but may additionally blur edges that make up the shape of the object in question or other fine details. Thus, we propose an adaptive Gaussian blurring approach, which attempts to preserve pertinent edges by selecting smaller kernels in areas with a high edge map response and selecting larger kernels in large patches of roughly the same color. We set thresholds to determine the level of the blur based on the desired threat model to defend against - we set the threshold such that even if an adversary adds a maximal edge under their budget to a flat colored region, we still blur it.

1) Computing Edges: We compute an edge response map by taking the gradient magnitude of the standard Sobel filters in the x and y directions. We compute the Sobel edge response maps on each color channel separately.

We choose Sobel edge response maps over the use of Canny Edge Detection for two reasons. First, we want more control over the ability to respond differently to weak edges such as textures in a patch of grass that may be picked up versus the pertinent edges that make up the outline of the main object against the background. Second, we want an efficient computation that we could use in adversarial training.

2) Adaptive Kernel Thresholding: Once an edge response map has been computed, we then adaptively blur the image with different Gaussian kernels based on the edge response in that area. To preserve the edges, we want to apply little blur on strong edge pixels and lots of blur on pixels in the middle of an object. Furthermore, pixels near edges cannot use too large of a kernel, otherwise it risks somewhat blurring the edge still.

We then adaptively blur the image itself. We choose a predetermined, fixed set of kernels to choose from. Then, starting from the largest such kernel, we apply a series of thresholds, where each threshold met decreases the size of the kernel. These thresholds are set based on a selected threat model to use the highest blur on edges less than or equal to the strength of edge increase allowed by the threat model; to have some protection on small edges that the adversary amplified, we double that threshold to set the range of edges that use the
middle blur. More details are specified in Section V-A for our experiments.

Thus, in an area with no edges, we apply the most blur, and then for stronger and stronger edges, we apply less and less blur. This process is applied on each color channel separately. An example of this blurring is shown in Figure 9. In this figure, we have shown only the bottom half of the image for easier visual inspection. We note that there are very strong edges near the plane, weak edges in the details on the right, and no edges in the middle. As shown in the figure, the resulting image on the lower right consists of pixels that come from one of the three different blurred images; the areas between the planes do not have any edge information and derive their values from the blur=13 image, while pixels near the edges of the plane derive their pixel values from the blur=3 image.

B. Adaptive Color Reduction

Once the adaptive Gaussian blurring has been completed, we apply an adaptive per-image color reduction transform. We modify the “Fast” \(k\)-means color reduction process seen in Jalalpour et al. [17], where \(k\)-means clustering is run on a thumbnail version of the image. \(k\)-means clustering finds centers of \(k\) clusters such that replacing each pixel in the image with the closest color in the set by Euclidean distance has a minimal reconstruction error.

We modify \(k\)-means to select \(k\) adaptively based on the content of the image and to enforce a minimum separability between clusters. We first change the initialization of clusters; rather than using random initialization from initial points like the original algorithm, we bin up the color space and initialize a cluster in the center of each cube that is represented in the image at hand. This allows for good initial representation. Then, to enforce separability, we add a final stage after the clustering to weed down the cluster list. To do this, we greedily iterate over the cluster list, accepting colors if they are sufficiently far from all other previously accepted colors and removing colors otherwise.

The effect of the adaptive color reduction is that it makes it harder for an adversary to add a lot of new colors, as this transformation will attempt to simplify the color palette to just the most representative colors. Compared with Jalalpour et al. [17] where the \(k\)-means step follows Gaussian blurring, we preserve more of the object edge features for the network to utilize when making its decision. We also select \(k\) adaptively per image, as some images in a dataset may require more or fewer colors than others (as an example, “meadow” in RESISC45 requires much fewer colors than a “palace” on average). As such, we aim to preserve edges, which we presume to be important features that make up an object, as well as capturing the rough color of each part of the image, without allowing many different tuples of perceptually similar colors that could be impacted with small adversarial noise.

C. Adaptive Attacks and Adversarial Training

With existing image preprocessing defenses being breakable under adaptive attacks, a research question is whether Essential Features can survive adaptive attacks, where an adversary knows our preprocessing strategy. Our strategy for generating strong adaptive attacks for Essential Features is to apply the backwards pass differentiable approximation (BPDA) \(^3\) approach since the Essential Features preprocessing algorithm is non-differentiable. We try two different approaches for the approximation function \(g(x)\) of BPDA \(^3\) to overcome this non-differentiability. The first is to set \(g(x)\) to the identity function for the entire preprocessing transform. As the transform aims to preserve the overall structure of the image and instead aims to clean up redundant and added noise to the image, an identity function is arguably a reasonable approximation function. The second is to approximate only the \(k\)-means step in the transform with the identity function but then take derivatives through the adaptive blurring step. Concretely, for each possible blur kernel size \(s\) we take the pixels where \(s\) was chosen and backpropagate them through the differentiable Gaussian blur function. We then sum all of these gradients together and take this as the final gradient.
We find that this second approach results in more effective attacks than the first approach and refer to this approach as BPDA+AG (where AG stands for Adaptive Gaussian).

We explored a few other adaptive white-box attack strategies but they were no better than the BPDA+AG attack. The first alternative attack tried adding an additional term to the attack objective function to maximize the average Sobel map response to encourage the adversary to add edges. We note that due to edge thresholding in the adaptive kernel selection (Section IV-A2) the attacker is not able to add very much to the edge response within small $L_\infty$ ball limits, which limits the ability to attack the image by adding lots of strong edges. The second alternative attack tried to add a Non Printability Score [29] to encourage the attack to use very few colors. We tried using the set of colors used in [13] and from the palette generated by k-means on the original input image, but neither improved the attack success rate. Third, for the color reduction stage, we tried using the same approximation as Chen et al. [9] for the currently selected cluster at each step. However, initial testing found this to be less effective than the identity function, so we focus our evaluations with the identity function at the color reduction stage.

We also, to sanity check our white-box gradient masking, test on Square Attack [1], a score-based attack that does not require differentiability and has been shown in some case to outperform SOTA white-box attacks.

V. EXPERIMENTS

We test our Essential Features approach against other adversarial training baselines and test on a variety of attacks, including adaptive PGD [24] and black-box [1] attacks. We train Essential Features with ATTA-10 [43] training and compare against undefended, Madry adversarially trained networks, and vanilla ATTA-10 training.

A. Experimental Setup

Datasets and Models: We test our Essential Features approach against the MNIST [22], Fashion-MNIST [38], CIFAR-10 [13], GTSRB [30], RESISC45 [10], and ImageNet datasets [27]. For ImageNet, we used the subset of ImageNet used by the NIPS Adversarial Attacks & Defenses Challenge [21] as in prior work [9]. Likewise, we also removed all images with an average intensity of 50 from GTSRB [9]. We use both Madry Adversarial Training (MAT) [24] and ATTA [43] for training techniques and compare against vanilla MAT and ATTA models. We also chose RESISC45 as a good test case because it is a larger, 256x256 resolution dataset as compared to 32x32 resolution in CIFAR-10 but is also possible to adversarially train in a reasonable time. The types of images in RESISC45 are also very different (remote sensing with 45 classes) than in CIFAR-10 (10 classes of animals and objects).

For MNIST and Fashion-MNIST, we use the MNIST architecture used in prior work [24]. For CIFAR-10 and GTSRB, we use the Wide ResNet 34-10 [40] architecture commonly used in adversarial training techniques [24], [42], [43]. For RESISC45, we use the ResNet-34 [16] architecture. We do not retrain ImageNet models and simply use PyTorch ports of Tensorflow models from [36] because of computation cost, although retraining would be ideal. Following prior work [9], we use an Inception v3 naturally trained model [31] and an Inception v2 adversarially trained model [44]. For all other datasets, we tested six settings, following the descriptions and naming conventions from prior work [9]:

1) nat_pre: no defenses, naturally trained on original data
2) adv_pre: no defenses, adversarially trained on original data (two adv. training methods used: MAT and ATTA)
3) ef_nat_pre: EF transform, naturally trained on original data
4) ef_adv_pre: EF transform, adversarially trained on original data
5) ef_nat re: EF transform, naturally trained on transformed data
6) ef_adv re: EF transform, adversarially trained on transformed data (just ATTA).

We focus our results on ATTA because it was more efficient to train.

Training Details: For CIFAR-10, we train natural models for 40 epochs with SGD at a starting learning rate of 0.1, weight decay of 2e-4, and momentum of 0.9. For the MAT baseline, we train for 105 epochs, starting with a learning rate of 0.1 and dividing by 10 at epochs 75 and 90 [41]. For ATTA based models, we use 38 epochs, starting at a learning rate of 0.1 · 1/64 and dividing by 10 at epochs 30 and 35 and 2e-4 · 64 for weight decay[2]. The training time attacks were PGD-7 with a step size of 2/255 = 0.007 and $\epsilon$ of 8/255 = 0.031. GTSRB uses the exact same settings as CIFAR-10. All other datasets use the same hyperparameters unless otherwise specified below.

For the MNIST and Fashion-MNIST MAT baseline, we use settings as in [42] with 100 epochs and a learning rate division of 10 at epochs 55, 75, and 90. For MNIST, the model did not converge originally so we dropped the starting learning rate from 0.1 to 0.01. For ATTA-based models, we use 60 epochs with a learning rate drop at 55. The training time attacks were PGD-40 with a step size of 0.01 and $\epsilon$ = 0.3 for MNIST and PGD-40 with a step size of 0.01 and $\epsilon$ = 0.1 for Fashion-MNIST, following prior work [9]. For RESISC45, we used PGD-10 attacks for training time attacks. For ATTA-based models, we trained for 40 epochs.

Essential Features Transformation Details: To compute the edge responses we start by taking the gradient magnitude of the standard $3 \times 3$ Sobel filters in the $x$ and $y$ directions. We normalize it by dividing by 1140.4 in the image range of [0, 255], which is the maximal attainable Sobel magnitude.

To get the kernel decisions, we use three possible blur kernels of different widths from OpenCV (cv2), with the default standard deviation chosen for each kernel width. Let $\epsilon_1$ and $\epsilon_2$ indicate that it is Inception v3 used to generate the numbers in the paper.

1Although the original paper says they use an Inception v2 network here, the authors’ code and our independent verification tests running their code indicate that it is Inception v3 used to generate the numbers in the paper.

2We confirmed through correspondence with the original authors that an additional batch size division in the code makes these the correct learning rate and weight decay values for replication.
the default blur be the largest of the three and then let there be thresholds \( t_1 \) and \( t_2 \) such that edges of strength between \( t_1 \) and \( t_2 \) causes the algorithm to use the middle sized kernel and edges of strength \( t_2 \) or greater means we use the smallest kernel. In the range of \([0-255]\), we set \( t_1 \) to the first multiple of 5 greater than the strength of edge and adversary could add to eliminate the adversary’s ability to add edges (e.g., if \( \epsilon = 8 \), the adversary could shift adjacent pixels up and down and create an edge of 16, so we set \( t_1 \) to 20). The adversary could also create stronger edges on top of existing edges, so we set \( t_2 = 2 \cdot t_1 \). For MNIST and Fashion-MNIST, since most of the pixels are black or white, we assume that the adversary can only create half as strong of an edge given the budget because pixels can generally only be shifted in one direction.

For MNIST, Fashion-MNIST, CIFAR-10, and GTSRB, the 32 \( \times \) 32 datasets, we use the smallest three possible kernel widths of 1, 3, and 5. For RESISC45, we use kernels of size 3, 7, and 13, which works out to be about 1%, 2.5% and 5% of the 256 \( \times \) 256 images. For simplicity, we use these same RESISC45 kernels for ImageNet.

For our color reduction process, we bin the color space up into 16 \( \times \) 16 \( \times \) 16 cubes when counting representation for cluster initialization. We set 32 \( \times \) 32 to be the thumbnail size for applying the Fast \( k \)-means process \cite{ref}. Then, when coalescing clusters, we enforce a distance that is 3x the size of \( \epsilon \). This way, should an adversary attempt to take two pixels at the center of two clusters and switch them, there are two radii of \( \epsilon \) plus and \( \epsilon \) length of buffer between them, to minimize the number of pixels where the adversary could choose which cluster they belong to.

Note that for MNIST, with an \( \epsilon \) of 0.3, this works out to be 230 / 255. Thus, we tweak the coalescing algorithm to avoid choosing a cluster that would automatically rule out the ability to pick a second cluster. If no such pair of clusters obey this distance, we simply choose the farthest two apart.

Let EF with no subscripts refer to the full Essential Features transform with adaptive blurring and adaptive color reduction. Let EF\(_{\text{AR}}\) refer to Essential Features with just the adaptive blurring and let EF\(_{\text{AC}}\) refer to Essential Features with just the adaptive color reduction.

**Attack Details:** For our \( L_\infty \) PGD-based attacks we follow the process setup by prior work \cite{ref}. Specifically, for MNIST, we use \( \epsilon = 0.3 \) and 100 steps of size 0.01. For Fashion-MNIST, we use \( \epsilon = 0.1 \) and 100 steps of size 0.01. For CIFAR-10, on naturally trained models, we test with \( \epsilon = 2 / 255 \) and 40 steps of size 1 / 255. For adversarially trained models, we test with \( \epsilon = 0.031 \) and 40 steps of size 0.007. For GTSRB and RESISC45, we use \( \epsilon = 0.031 \) and 40 steps of size 0.007. For ImageNet, on naturally trained models, we test with \( \epsilon = 1 / 255 \) and 1 step. For adversarially trained models, we test with \( \epsilon = 4 / 255 \) and 10 steps of size 1 / 255.

For all PGD attacks, we on both adaptive attacks and standard non-adaptive attacks. For adaptive attacks, we evaluate on BPDA attacks with the identity function for the backwards approximation as well as the BPDA+AG attack described in Section IV-C.
Generally, re-training on Essential Features has the highest robustness gains, particularly on RESISC45 which is a higher resolution dataset than the rest. Results from Chen et al. are reported directly from the original paper [9] with the rows being selected on the basis of having the highest robustness floor except for MNIST (marked with *) where we found that PGD attack (non-adaptive to their transform) was more effective. On the various rows, * means that the most successful attack was a PGD attack (non-adaptive to the transform), ** means that the most successful attack was a vanilla BPDA attack. All asterisked lines are on small datasets. Best setting by robustness per dataset is bolded.

| Dataset   | Base Model          | Defense        | Pre-trained Accuracy | Re-trained Accuracy |
|-----------|---------------------|----------------|----------------------|---------------------|
|           |                     |                | Accuracy             | Robustness          | Accuracy             | Robustness          |
|           |                     |                |                      |                     |                      |                     |
| MNIST     | Naturally Trained Model | None           | 99.24%               | 0%                  | N/A                  |                      |
|           | EF - AC Only        | Chen et al. (k=2) | 98.81%               | 75.35%              | 99.15%               | 80.91%              |
|           |                     | EF - AC Only   | 99.12%               | 78.38%              | 99.1%                | 80.89%              |
|           | Adversarially Trained Model (MAT) | None | 99.07%               | 93.23%              | N/A                  |                      |
|           | Chen et al. (k=2)   | EF - AC Only   | 99.07%               | 93.23%              | 99.15%               | 80.91%              |
|           | EF - AC Only        | 98.93%         | 93.83%*              | N/A                 | 98.56%               | 92.80%              |
|           | EF - AC Only        | 98.95%         | 93.86%*              | N/A                 |                      |                     |
|           | Adversarially Trained Model (ATTA) | None | 96.41%               | 86.93%              | N/A                  |                      |
|           | EF - AC Only        | 96.05%         | 90.48%*              | N/A                 | 98.56%               | 91.96%              |
| Fashion-MNIST | Naturally Trained Model | None           | 92.71%               | 1.6%                | N/A                  |                      |
|           | EF (Ours)           | Chen et al. (k=2) | 77.18%               | 38.07%              | 86.74%               | 41.75%              |
|           | EF - AC Only        | 89.96%         | 38.78%               | 90.27%              | 42.21%              |
|           | Adversarially Trained Model (MAT) | None | 87.63%               | 77.99%              | N/A                  |                      |
|           | Chen et al. (k=2)   | EF - AC Only   | 82.68%               | 66.52%              | 86.18%               | 70.05%              |
|           | EF - AC Only        | 87.42%         | 78.82%*              | N/A                 |                      |                     |
|           | Adversarially Trained Model (ATTA) | None | 81.71%               | 70.35%              | N/A                  |                      |
|           | EF - AC Only        | 81.71%         | 72.68%*              | N/A                 | 82.48%               | 71.62%              |
| CIFAR-10  | Naturally Trained Model | None           | 94.75%               | 2.23%               | N/A                  |                      |
|           | EF (Ours)           | Chen et al. (k=2) | 24.20%               | 15.90%              | 68.50%               | 46.70%              |
|           | EF - AC Only        | 76.86%         | 47.36%               | 90.93%              | 70.65%              |
|           | Adversarially Trained Model (MAT) | None | 87.14%               | 49.52%              | N/A                  |                      |
|           | Chen et al. (k=300) | EF (Ours)      | 87.30%               | 46.90%              | 86.80%               | 46.60%              |
|           | EF - AC Only        | 84.53%         | 47.35%               | N/A                 |                      |                     |
|           | Adversarially Trained Model (ATTA) | None | 84.72%               | 52.33%              | N/A                  |                      |
|           | EF (Ours)           | 81.97%         | 51.69%               | 82.5%               | 68.33%**             |
| GTSRB     | Naturally Trained Model | None           | 95.36%               | 13.91%              | N/A                  |                      |
|           | EF (Ours)           | Chen et al. (k=2) | 44.02%               | 23.94%              | 55.39%               | 29.46%              |
|           | EF - AC Only        | 91.57%         | 30.86%               | 94.44%              | 36.64%              |
|           | Adversarially Trained Model (MAT) | None | 93.68%               | 75.62%              | N/A                  |                      |
|           | Chen et al. (k=500) | EF (Ours)      | 93.98%               | 75.54%              | 94.73%               | 76.66%              |
|           | EF - AC Only        | 90.30%         | 72.76%               | N/A                 |                      |                     |
|           | Adversarially Trained Model (ATTA) | None | 93.07%               | 77.71%              | N/A                  |                      |
|           | EF (Ours)           | 89.72%         | 74.39%               | 91.83%              | 78.59%              |
| RESISC45  | Naturally Trained Model | None           | 94.71%               | 26.73%              | N/A                  |                      |
|           | EF (Ours)           | 84.11%         | 40.07%               | 92.13%              | 4.18%               |
|           | EF - AC Only        | 61.76%         | 25.4%                |                      |                     |                     |
|           | Adversarially Trained Model (MAT) | None | 82.0%                | 44.2%               | N/A                  |                      |
|           | EF (Ours)           | 63.33%         | 29.87%               | 88.51%              | 66.73%              |
|           | Adversarially Trained Model (ATTA) | None | 97.3%                | 5.32%               | N/A                  |                      |
|           | EF - AC Only        | 94.80%         | 16.00%               |                      |                     |                     |
| ImageNet  | Naturally Trained Model | None           | 95.53%               | 22.59%              | N/A                  |                      |
|           | EF - AC Only        | 95.53%         | 22.59%               |                      |                     |                     |

For MNIST, we expected a fixed codebook as in Chen et al. [9] to work really well since most images consist of predominantly black and white colors for that dataset. Essential Features’s adaptive codebook provided comparable results. For Fashion-MNIST, which has much more gray colors, Essential Features significantly outperforms a fixed codebook of Chen et al. (78.82% versus 66.52%) as well as standard adversarial training (78.82% versus 77.99%).

To summarize, preprocessing based on an adaptive codebook (combined with adaptive blurring when appropriate), as provided in Essential Features, outperforms in terms of adversarial robustness both a fixed codebook approach [9] and standard adversarial training for existing baselines on several challenging datasets, including Fashion-MNIST, CIFAR-10, GTSRB, RESISC45, and ImageNet. We thus find that pixel discretization can help boost robustness in a broad set of datasets, provided it is adaptive to the input data presented rather than using a dataset-specific codebook. Our key insight is that many datasets may have color separability at the image level, but not at the dataset level, that can provide some oppor-
TABLE II
COMPARISON BETWEEN VARIANTS OF ESSENTIAL FEATURES. ALL MODELS ARE ATTA ADVERSARILY TRAINED ON THE TRANSFORM LISTED EXCEPT FOR IMAGE-NET, WHICH USE A PRE-TRAINED MAT MODEL WITH THE TRANSFORM ADDED AT TEST TIME. * MEANS THAT THE MOST SUCCESSFUL ATTACK WAS A NON-ADAPTIVE PGD ATTACK, ** MEANS THAT THE MOST SUCCESSFUL ATTACK WAS A VANILLA BPDA ATTACK. BLACK-BOX NUMBERS ARE WITH SQUARE ATTACK.

| Dataset      | Defense        | Accuracy | Robustness (White-box) | Robustness (Black-box) |
|--------------|----------------|----------|------------------------|------------------------|
| MNIST        | None           | 96.41%   | 86.93%                 | 90.63%                 |
|              | EF - Full      | 97.49%   | 71.2%                  | 75.91%                 |
|              | EF - AB Only   | 95.83%   | 65.94%                 | 81.48%                 |
|              | EF - AC Only   | 98.56%   | 91.96%                 | 95.35%                 |
|              | EF - Gauss + AC| 98.13%   | 69.13%**               | 76.48%                 |
| Fashion-MNIST| None           | 81.71%   | 70.35%                 | 75.63%                 |
|              | EF - Full      | 82.27%   | 70.57%                 | 71.59%                 |
|              | EF - AB Only   | 80.45%   | 67.44%                 | 72.82%                 |
|              | EF - AC Only   | 82.48%   | 71.62%*                | 72.87%                 |
|              | EF - Gauss + AC| 80.04%   | 64.68%**               | 67.22%                 |
| CIFAR-10     | None           | 84.72%   | 52.33%                 | 97.78%                 |
|              | EF - Full      | 82.5%    | 68.33%**               | 49.5%                  |
|              | EF - Full, FT  | 79.44%   | 63.14%**               | 57.47%                 |
|              | EF - AB Only   | 85.88%   | 52.86%                 | 80.92%                 |
|              | EF - AC Only   | 86.06%   | 53.18%*                | 79.85%                 |
|              | EF - Gauss + AC| 86.98%   | 31.4%**                | 68.31%                 |
| GTSRB        | None           | 93.07%   | 77.71%                 | 90.44%                 |
|              | EF - Full      | 91.83%   | 78.59%                 | 87.16%                 |
|              | EF - AB Only   | 92.92%   | 78.33%                 | 90.79%                 |
|              | EF - AC Only   | 92.19%   | 78.23%                 | 88.48%                 |
|              | EF - Gauss + AC| 92.12%   | 70.59%**               | 84.84%                 |
| RESISC45     | None           | 82.0%    | 44.2%                  | 56.27%                 |
|              | EF - Full      | 88.51%   | 66.73%                 | 73.02%                 |
|              | EF - AB Only   | 85.93%   | 41.8%                  | 90.30%                 |
|              | EF - AC Only   | 83.49%   | 47.04%                 | 76.69%                 |
|              | EF - Gauss + AC| 89.18%   | 63.56%                 | 77.58%                 |
| ImageNet     | None           | 97.33%   | 52.32%                 | 97.72%                 |
|              | EF - Full      | 89.47%   | 18.49%                 | 94.64%                 |
|              | EF - AB Only   | 93.55%   | 8.60%                  | 93.60%                 |
|              | EF - AC Only   | 95.53%   | 22.59%                 | 95.59%                 |
|              | EF - Gauss + AC| 86.07%   | 22.24%                 | 86.27%                 |

Black-box numbers are with Square attack. Although the full transform helps too. This is likely due to the fact that we could not retrain the ImageNet model to rely less on texture and rely more on the essential features preserved in the transformed space.

CIFAR-10 also performs best with the full transform, but there was a interesting discovery we found, explained, and then corrected for as described in the next section.

D. Black-box Robustness

We found in prior sections that the adaptive attack described in Section III-C tends to be the most effective attack in most settings, with most of the exceptions occurring on the smaller / simpler datasets. We now further explore the possibility of gradient masking by testing on Square Attack [11], a black-box score-based attack.

The results are also shown in Table II. In every case except for CIFAR-10 with the full EF transformation, our models are more robust to Square Attack, suggesting that the adaptive attack approximates the gradient well. As it turns out, this one exception on CIFAR-10 with the full EF can be explained as a case of overfitting to the adaptive attack.

The formulation in the original MAT paper [24] designs a min max problem wherein the model is trained on the strongest attacks throughout. However, for this particular case, this turns out to longer be the case past epoch 30. To show this, we plot the robustness numbers for the adaptive attack, vanilla BPDA, and Square attacks over multiple checkpoints along the training process in Fig. 10. The adaptive attack is the most successful attack for each tested checkpoint until 30, when the trends of attack strength flip as the learning rate is dropped for the first time. To address this, we take the model at epoch 29 and then drop the learning rate by a factor of 100 to train for one final epoch, creating the EF - Full, FT row in Table II. While we still find that it overfits a bit to the adaptive attack and that Square attack is more successful, the robustness floor is now higher than all of the other models. Across all attacks, we now raise the robustness floor to 57.47% as opposed to 49.5% on the overfit model. We use this setting for CIFAR-10 EF-Full settings going forward.

E. Final Model $L_{\infty}$ Analysis

In this section we plot robustness over epsilon charts for each of the datasets on each of the six primary settings, taking the best transforms and models for each dataset (i.e., just adaptive color reduction for MNIST and Fashion-MNIST, the finetuned full EF model for CIFAR-10 ATTA retraining on EF, and the default full EF transform models for all other datasets).

The results are shown in Fig. 11. On smaller resolution datasets, Essential Features performs comparably with the other lines with the ATTA retrained versions on the transform generally showing slight improvements, especially towards the higher epsilons. Essential Features performs the best on RESISC45, a higher resolution dataset that we were able to retrain with ATTA on Essential Features. RESISC45 show demonstrable gains in robustness and has higher natural accuracy than other adversarially trained models. ImageNet also....
(a) MNIST $L_\infty$ plot. Adding the adaptive color reduction performs similarly to others with some slight improvement.

(b) Fashion-MNIST $L_\infty$ plot. Adding the adaptive color reduction performs similarly to others with some slight improvement.

(c) CIFAR $L_\infty$ plot. The ATTA retrain on EF line is the fine-tuned model tested on Square Attacks and performs better than other models at $\epsilon = 8/255$.

(d) GTSRB $L_\infty$ plot. The ATTA retrain on EF line creates additional robustness at $\epsilon = 8/255$.

(e) RESISC45 $L_\infty$ plot. The best performing dataset on our technique, which when ATTA retrained on the transform demonstrates significant robustness gains compared to all other models. Additionally, its natural accuracy is significantly higher than all other ATTA models.

(f) ImageNet $L_\infty$ plot. Adding Essential Features improves both natural and MAT models. More improvement may be had if training adversarially with ATTA on the transform were more feasible.

Fig. 11. $L_\infty$ robustness vs. epsilon plots. RESISC45, a larger resolution dataset, performs the best, demonstrating significant. ImageNet also shows demonstrable improvement even without retraining. All other datasets perform similarly with some gain at the higher epsilons.
(a) MNIST $L_2$ plot. ATTA retrained on adaptive color reduction performs similarly to the ATTA baseline.

(b) Fashion-MNIST $L_2$ plot. ATTA retrained on adaptive color reduction performs modestly better than the ATTA baseline.

(c) CIFAR-10 $L_2$ plot. ATTA retrained on Essential Features has significant robustness gains at larger epsilons. The retrained numbers are from the finetuned model with Square Attack.

(d) GTSRB $L_2$ plot. ATTA retrained on Essential Features has modest robustness improvements compared to ATTA baseline.

(e) RESISC45 $L_2$ plot. ATTA retrained on Essential Features is has significant robustness gains across all epsilons.

(f) ImageNet $L_2$ plot. Adding Essential Features to the MAT baseline improves robustness by several factors.

Fig. 12. $L_2$ robustness vs. epsilon plots. Retraining on ATTA and Essential Features has significant robustness gains on CIFAR-10, RESISC45, and ImageNet. All $L_2$ bounds are relative to the $[0, 1]$ image scale.
Essential Features and ImageNet, our ATTA retrained relative to the [0-1] image scale. On CIFAR-10, RESISC45, Essential Features why our technique succeeds even more on results in MNIST. We offer the following explanation as to improvements on GTSRB and Fashion-MNIST, with similar are significantly more robust than either the natural or clean models for every other dataset).

and Fashion-MNIST, the finetuned full EF model for CIFAR-

L on

Essential Features has significant improvement, although retraining adversarially on Essential Features would likely be more beneficial.

F. Final Model $L_2$ Analysis

In this section we plot robustness over epsilon charts for each of the datasets on each of the six primary settings on $L_2$ bounded attacks, taking the best transforms and models for each dataset (i.e., just adaptive color reduction for MNIST and Fashion-MNIST, the finetuned full EF model for CIFAR-10 ATTA retraining on EF, and the default full EF transform models for each other dataset).

The results are shown in Fig. 12. All $L_2$ bounds are relative to the [0-1] image scale. On CIFAR-10, RESISC45, and ImageNet, our ATTA retrained Essential Features models are significantly more robust than either the natural or clean models at higher epsilons. Our technique also has smaller improvements on GTSRB and Fashion-MNIST, with similar results in MNIST. We offer the following explanation as to why our technique succeeds even more on $L_2$ attacks. We observe that on images where the ATTA baseline can be attacked but our Essential Features model cannot, the ATTA baseline attacks generate very large perturbations on a couple of isolated pixels. For example, in Fig. 13 the image on the right is a zoomed in view of an attacked version of the image on the left, with an $L_2$ distance of 13.91 (the same distance as setting each value +/- 8/255). The right hand version exhibits several obvious perturbations of black and pink pixels that are of large changes. Statistically, we find that on average 35.36 values are perturbed with noise greater than 8/255. However, these isolated pixels would not survive adaptive blurring. While this technique is useful for attacking the ATTA baseline, it is a less fruitful avenue for attacking the Essential Features model.

VI. CONCLUSION

We propose Essential Features, a content adaptive pixel discretization defense to improve model robustness. We revisit the pixel discretization approach and find that its limitations on more complex datasets can be circumvented with an adaptive, per-image process. To accomplish this, we use an adaptive codebook to select a separable set of colors to reduce to.

We additionally limit the adversary’s influence on the color clusters by using an adaptive blur to simultaneously move pixels closer to their original value while preserving original edge features. We empirically find that our approach improves robustness, especially on larger datasets, and motivates the use of adaptive discretization techniques in future work.

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REFERENCES

[1] Maksym Andriushchenko, Francesco Croce, Nicolas Flammarion, and Matthias Hein. Square attack: a query-efficient black-box adversarial attack via random search. In European Conference on Computer Vision, pages 484–501. Springer, 2020.
[2] Anish Athalye and Nicholas Carlini. On the robustness of the cvpr 2018 white-box adversarial example defenses. arXiv preprint arXiv:1804.03286, 2018.
[3] Anish Athalye, Nicholas Carlini, and David Wagner. Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples. arXiv preprint arXiv:1802.00420, 2018.
[4] Anish Athalye, Logan Engstrom, Andrew Ilyas, and Kevin Kwok. Synthesizing robust adversarial examples. arXiv preprint arXiv:1707.07397, 2017.
[5] Gary Bradski and Adrian Kaehler. Learning OpenCV: Computer vision with the OpenCV library. ” O’Reilly Media, Inc.”, 2008.
[6] John Canny. A computational approach to edge detection. IEEE Transactions on pattern analysis and machine intelligence, (6):679–698, 1986.
[7] Nicholas Carlini, Anish Athalye, Nicolas Papernot, Wieland Brendel, Jonas Rauber, Dimitris Tsipras, Ian Goodfellow, Aleksander Madry, and Alexey Kurakin. On evaluating adversarial robustness. arXiv preprint arXiv:1902.06705, 2019.
[8] Nicholas Carlini and David Wagner. Towards understanding the robustness of neural networks. In 2017 ieee symposium on security and privacy (sp), pages 39–57. IEEE, 2017.
[9] Jiefeng Chen, Xi Wu, Vaibhav Rastogi, Yingya Liang, and Somesh Jha. Towards understanding limitations of pixel discretization against adversarial attacks. In 2019 IEEE European Symposium on Security and Privacy (EuroS&P), pages 480–495. IEEE, 2019.
[10] Gong Cheng, Junwei Han, and Xiaoqiang Lu. Remote sensing image scene classification: Benchmark and state of the art. Proceedings of the IEEE, 105(10):1865–1883, 2017.
[11] Nilaksh Das, Madhuri Shanbhogue, Shang-Tse Chen, Fred Hofman, Li Chen, Michael E Kounavis, and Duen Horng Chau. Keeping the bad guys out: Protecting and vaccinating deep learning with jpeg compression. arXiv preprint arXiv:1705.02900, 2017.
[12] Gintare Karolina Dziugaite, Zoubin Ghahramani, and Daniel M Roy. A study of the effect of jpeg compression on adversarial images. arXiv preprint arXiv:1608.00853, 2016.
[13] Kevin Eykholt, Ivan Evtimov, Earlene Fernandes, Bo Li, Amir Rahmati, Chaowei Xiao, Atul Prakash, Tadayoshi Kohno, and Dawn Song. Robust Physical-World Attacks on Deep Learning Visual Classification. In Computer Vision and Pattern Recognition (CVPR), June 2018.
[14] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572, 2014.
[15] Chuan Guo, Mayank Rana, Moustapha Cisse, and Laurens Van Der Maaten. Countering adversarial images using input transformations. arXiv preprint arXiv:1711.00117, 2017.
Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

Yeganeh Jalalpour, Li-Yun Wang, Ryan Feng, and Wu-chi Feng. Leveraging image processing techniques to thwart adversarial attacks in image classification. In 2019 IEEE International Symposium on Multimedia (ISM), pages 184–187. IEEE, 2019.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial examples in the physical world. arXiv preprint arXiv:1607.02533, 2016.

Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Adversarial machine learning at scale. arXiv preprint arXiv:1611.01236, 2016.

Alexey Kurakin, Ian Goodfellow, and Samy Bengio. Nips 2017: Defense against adversarial attack. https://www.kaggle.com/c/nips-2017-defense-against-adversarial-attack. 2017.

Yann LeCun, Leon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278–2324, 1998.

Bin Liang, Hongcheng Li, Miaoqiang Su, Xirong Li, Wenchang Shi, and Xiaofeng Wang. Detecting adversarial image examples in deep neural networks with adaptive noise reduction. IEEE Transactions on Dependable and Secure Computing, 2018.

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. arXiv preprint arXiv:1706.06083, 2017.

Aadiitya Prakash, Nick Moran, Solomon Garber, Antonella DiLillo, and James Storer. Deflecting adversarial attacks with pixel deflection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 8571–8580, 2018.

Ravi S Raju and Mikko Lipasti. Blurnet: Defense by filtering the feature maps. In 2020 50th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W), pages 38–46. IEEE, 2020.

Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. International journal of computer vision, 115(3):211–252, 2015.

Ali Shafahi, Mahyar Najibi, Mohammad Amin Ghiasi, Zheng Xu, John Dickerson, Christoph Studer, Larry S Davis, Gavin Taylor, and Tom Goldstein. Adversarial training for free! In Advances in Neural Information Processing Systems, pages 3358–3369, 2019.

Mahmood Sharif, Strut Bhagavatula, Lujo Bauer, and Michael K. Reiter. Accessorize to a crime: Real and stealthy attacks on state-of-the-art face recognition. In Proceedings of the 2016 ACM SIGSAC Conference on Computer and Communications Security, CCS ’16, page 1528–1540, 2016.

J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel. Man vs. computer: Benchmarking machine learning algorithms for traffic sign recognition. Neural Networks, (0):–, 2012.

Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alexander A. Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In Thirty-first AAAI conference on artificial intelligence, 2017.

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2818–2826, 2016.

Florian Tramèr, Nicholas Carlini, Wieland Brendel, and Aleksander Madry. On adaptive attacks to adversarial example defenses. arXiv preprint arXiv:2002.08347, 2020.

Florian Tramèr, Alexey Kurakin, Nicolas Papernot, Ian Goodfellow, Dan Boneh, and Patrick McDaniel. Ensemble adversarial training: Attacks and defenses. arXiv preprint arXiv:1705.07204, 2017.

Anne M Treisman and Nancy G Kanwisher. Perceiving visually presented objects: recognition, awareness, and modularity. Current opinion in neurobiology, 8(2):218–226, 1998.

Ross Wightman. Pytorch image models. https://github.com/rwightman/pytorch-image-models. 2019.

Eric Wong, Leslie Rice, and J Zico Kolter. Fast is better than free: Revisiting adversarial training. arXiv preprint arXiv:2001.03994, 2020.

Han Xiao, Kashif Rasul, and Roland Vollgraf. Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms, 2017.

Weilin Xu, David Evans, and Yanjun Qi. Feature squeezing: Detecting adversarial examples in deep neural networks. arXiv preprint arXiv:1704.01155, 2017.

Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. arXiv preprint arXiv:1605.07146, 2016.

Dinghuaui Zhang, Tianyuan Zhang, Yiping Lu, Zhanxing Zhu, and Bin Dong. You only propagate once: Accelerating adversarial training via maximal principle. In Advances in Neural Information Processing Systems, pages 227–238, 2019.

Hongyang Zhang, Yaodong Yu, Jiantao Jiao, Eric P Xing, Laurent El Ghaoui, and Michael I Jordan. Theoretically principled trade-off between robustness and accuracy. arXiv preprint arXiv:1901.08573, 2019.

Haizhong Zheng, Ziqi Zhang, Juncheng Gu, Honglak Lee, and Atul Prakash. Efficient adversarial training with transferable adversarial examples. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1181–1190, 2020.