Natural Perturbed Training for General Robustness of Neural Network Classifiers

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Abstract

We focus on the robustness of neural networks for classification. To permit a fair comparison between methods to achieve robustness, we first introduce a standard based on the mensuration of a classifier’s degradation. Then, we propose natural perturbed training to robustify the network. Natural perturbations will be encountered in practice: the difference of two images of the same object may be approximated by an elastic deformation (when they have slightly different viewing angles), by occlusions (when they hide differently behind objects) or by saturation, Gaussian noise etc. Training some fraction of the epochs on random versions of such variations will help the classifier to learn better. We conduct extensive experiments on six datasets of varying sizes and granularity. Natural perturbed learning show better and much faster performance than adversarial training on clean, adversarial as well as natural perturbed images. It even improves general robustness on perturbations not seen during the training. For Cifar-10 and STL-10 natural perturbed training even improves the accuracy for clean data and reaches the state of the art performance. Ablation studies verify the effectiveness of natural perturbed training.

1. Introduction

Recent research in machine learning and computer vision shows that changes in the inputs of convolutional neural networks like blur or noise can drastically change the class predictions in the real world [5, 1, 25]. Considering the importance of robustness against natural perturbations [13] proposed a benchmark consisting of a subset of ImageNet [4] with corruptions applied to them. Although they introduced five severity levels for each type of perturbations, they do not standardize the effect of the perturbations for a fair, quantitative comparison among the different perturbations. Therefore, in this work instead of qualitative evaluation, we introduce a standardization procedure to permit a quantitative evaluation of robustness among alternative types of perturbations to train a network.

Several methods for the robustness of neural networks against natural perturbations have been proposed in the literature [39, 26, 14]. [39] hypothesized that Gaussian noise and adversarial training help against perturbations in the high frequency domain. [26] showed that by generating properly tuned Gaussian or speckle noise it is possible to generalize a network to unseen perturbations. In order to systematically enhance and study the robustness of neural networks against perturbations in this paper, we introduce a simple yet effective training procedure natural perturbed training: the network is first trained for \( n_1 \) epochs on clean images followed by \( n_2 \) epochs on naturally perturbed versions of the same training images. Unlike previous methods, this method of training does not require architectural changes and it is not computationally expensive, while any type of natural perturbation could be used with it.

Concurrently, training methods have been introduced to achieve robustness against adversarial perturbations [11, 22, 29]. To date, it is an open problem whether adversarial perturbations help making networks robust against natural perturbations and vice versa [41, 7]. [41] showed that adversarial training helps to reduce the texture bias in neural networks, however [7] showed that adversarial perturbations do not generalize to natural transformations like translations and rotations. Therefore, in this work after standardization permits a fair comparison between differently trained networks for robustness, we evaluate whether adversarial perturbations generalize to natural perturbations and the other way around.

There is also an open debate in literature [35, 40, 31] about the trade-off between robustness and accuracy of clean image classifiers when networks are robustified with adversarial training. We found that our natural perturbed training procedure does not lead to the large drop in the performance on clean images as adversarial training does. For Cifar-10 and STL-10 natural perturbation even helps to im-
prove the accuracy to reach the state of the art performance [30], without the high computational costs of adversarial training.

Standardization is also useful in the evaluation of robustified networks for unseen perturbations. In contrast to [13, 19, 26], we learn the quantitative effect of the type of training for robustness also against unseen perturbations.

Our contributions are: (1) Where in literature a qualitative evaluation of robustness is often used, we propose standardization to permit quantitative evaluation for the comparison between two alternative training procedures aimed at achieving robustness. (2) We introduce natural perturbed training which is computationally fast and shows better performance than adversarial training on clean, adversarial as well as natural perturbations. (3) Natural perturbed training is demonstrated to improve the quantitative robustness of perturbations both seen and unseen during the training. (4) Natural perturbed training even improves the performance of classifiers in the absence of perturbations (without using more data and at almost no costs).

2. Related Work

Natural Perturbations and Robustness. In [8, 15] authors showed that neural networks are not even robust to translations and rotations. [10] deduced that the performance of neural networks drops significantly as compared to humans with the increase of the signal-to-noise ratio of images. [5] also concluded that although neural networks are on par in performance with humans, they fail to perform well in the presence of perturbations like Gaussian noise or blur, which are easily handled by humans. Therefore, it is crucial to build robustness against such perturbations into the classification without degrading the performance on clean images, especially in such applications like autonomous driving and health.

To promote the study of robustness against naturally occurring perturbations a few benchmarks have been proposed [13, 12, 10]. Closely related to our work, in [13] the authors have introduced a large benchmark for natural perturbations quite a few of which will be correlated [20]. In our work we selected six more or less independent types of natural perturbations covering the breadth of styles, see Figure 2. In the reference, the authors have gone through the effort of defining five levels of severity for each type of perturbation. These levels are based on the visual effect but not standardized on their effect on the classification. As robustness is primarily aimed at the loss of classification performance, in this work at first we quantitatively standardize the comparison among differently trained networks to analyze the effect on their robustness. Table 1 shows the significance of our standardization method for fair comparison of robustness. When using the mean square error (MSE) between clean and perturbed images for standardization of perturbations, we see that the MSE shows a large variation in classification performance among different types of perturbations. Especially the MSE calculated for adversarial and other natural perturbations show different behavior. This is because adversarial perturbations are generated in order to misclassify an image while keeping the optical difference between clean and adversarial images to a minimum. We start from standardizing according to their effect on classification accuracy. Hence, we drop the accuracy of the network by a constant value for each type of perturbation Table 1. This enables the comparison among different perturbations and the robustness of classifiers.

Simultaneously, to improve the robustness against natural perturbations [26] performed data augmentation by carefully tuning Gaussian or speckle noise. [34] introduced two normalization techniques SelfNorm and CrossNorm to enhance the generalization for out of distribution data. [27] proposed to use batch normalization statistics calculated on corrupted images instead of clean images to enhance the robustness against perturbations. However, all the aforementioned approaches either require an extra network to find the suitable perturbation or a modification in the network. In contrast, in this paper, we introduce a training procedure in which after training on clean images we continue on perturbed versions of the clean inputs and minimize the loss for both of them. This leads to an improvement in the performance on robustness against perturbed images without requiring any architectural changes. Note that our natural perturbed training is different from standard data augmentation. Figure 1 contrasts the performance of clean images when the network is trained with the data augmentation versus when it is trained with natural perturbed training. For Cifar-10, we clearly see that natural perturbed training shows an improvement on clean image classifica-

| Input          | Our standardization | MSE $(\xi^a(x_n), \xi^c(x_n))$ |
|---------------|---------------------|-------------------------------|
| Adversarial   | 10.22               | 0.02                          |
| Elastic       | 10.60               | 54.31                         |
| Occlusion     | 10.24               | 199.73                        |
| Gaussian Noise| 10.10               | 11.79                         |
| Wave          | 10.18               | 602.61                        |
| Saturation    | 10.4                | 269.71                        |
| Blur          | 10.51               | 18.2                          |

Table 1: Significance of our standardization for Cifar-10. Our method is made consistent in the drop of classification performance across perturbations (with an arbitrary small deviation still remaining). The mean square error (MSE) between clean $x_n$ and perturbed $\xi^a(x_n)$ images shows how large perturbations in the image may be before the same degradation in performance is achieved.
Adversarial Perturbations and Robustness. In [33], the authors explored the robustness of neural networks. They showed that by adding small amounts of carefully crafted noise i.e. adversarial perturbations to the images it is possible to change the prediction of the classifier. Since then plenty of research [18, 24, 32, 2, 23] has been performed on finding different types of adversarial perturbations and study the robustification against them [11, 18, 11, 2, 6]. In this work we utilize a strong yet undefended attack basic iterative method [18] for generating adversarial perturbations and projected gradient descent [21] for adversarial training, which is one of the state of the art defense methods, for the comparison with natural perturbed training.

Although adversarial training helps to enhance the performance against adversarial perturbations, [40, 35] showed that with an increased robustness of adverserially trained neural networks in classification with such perturbations, simultaneously the network decreases in accuracy of the classification of clean images. This behavior deviates for our natural perturbed training. Apart from increasing the robustness for classification of perturbed images, the network retains its accuracy for clean images for most datasets, and even enhances its performance on CUB, StanfordCars, Cifar-10 and STL-10 datasets.

[9] established connections between adversarial and natural perturbation robustness, suggesting that neural networks should be robustified against both of them. [26] focused on robustification against adversarial as well as natural perturbations by using properly tuned Gaussian and Speckle noise. In this work, instead of generating tuned noise and then training the network, we refrain from tuning noise during training. We show that our natural perturbed training shows better performance with occlusion, elastic and wave than with Gaussian noise as perturbation.

3. Methods

Given the $n^{th}$ input image $x_n$, and its respective output $y_n$, a classifier $f$ predicts the class $f(x_n) = y_n$. Here we consider the problem of robust classification against artificially created adversarial $\zeta^a$ and natural $\zeta^i$ perturbations as noise, motion blur, difference in viewing angle, color saturation, and occlusion.

3.1. Quantitative Standardization

As the evaluation metric for classification is accuracy, we propose to add perturbations in the input images such that the performance drop $\rho$ in classification accuracy is equal for all perturbations under consideration as shown in the Table 1. It is given as:

$$\rho = \frac{1}{n} \sum_{n=1}^{N} \mathbb{1}(f(x_n) = y_n) - \frac{1}{n} \sum_{n=1}^{N} \mathbb{1}(f(\zeta^i(x_n)) = y_n)$$

where $\mathbb{1}$ is the indicator function. Hence, we set the parameters of each $\zeta^i$ under consideration such that the drop $\rho$ is constant for each type of perturbation.

3.2. Perturbations

Natural Perturbations. We consider a set of natural perturbations $\zeta^i$ with least correlations among them, where $t \in \{E, O, N, W, S, B\}$ represents the type of perturbation operator. We create perturbed images by selecting a perturbation from $t$ and applying it on the image $\zeta^i(x_n)$. This leads to a drop in the performance of the classifier $f(\zeta^i(x_n))$. Samples for the six natural perturbations under consideration are shown in Figure 2.

The first natural perturbation is elastic deformation $\zeta^E$. Elastic deformation usually appears in small variations in the viewing angle of the recording. Similar to [28] we add elastic deformation to the images by applying $\zeta^E = \mathcal{T}(x_n, \alpha x_n \odot N(\mu, \sigma^2))$ on the image. We generate random displacement fields by selecting a random number between $-1$ and $+1$ i.e. $x' \in \text{rand}(-1, +1)$. Then we apply a Gaussian filter by convolving these fields with it i.e. $\alpha x_n \odot N(\mu, \sigma^2)$. Occclusions are created by selecting minimum values from $\zeta^O = \min(x_n, b(x_c, t, r))$, where, $b$ is a matrix of zeros with $x_c$ as its center and $t, r$ being the thickness and radius of the circle respectively. Gaussian noise is introduced by $\zeta^N(x_n = x_n + N(\mu, \sigma^2))$. A wave transform is added by $\zeta^W = x_n \rightarrow (\text{Sin}(2\pi x_n, w))$, where $\rightarrow$ is the roll operator (in numpy) which rolls the original image by $\text{Sin}(2\pi x_n, w)$. Saturation is introduced
by using $\zeta^B = (1 - \alpha)x' + \alpha x_n$, where, $\alpha \in [0, 1]$, $x'$ is the black and white version of $x_n$. Gaussian blur $\zeta^B$ is introduced by convolving a two-dimensional Gaussian function to the image.

The natural perturbations are class agnostic in a stochastic sense. However, they are made image specific by selecting different perturbations for different images. For elastic deformation, we vary the intensity of elasticity for each image such that it leads to a specific drop in accuracy. For occlusion, the position of occlusion is randomly selected for each image, the intensity of Gaussian noise is also randomly uniformly varied. Per image, the wave is scaled uniformly at random, as are the saturation factor and variance of the Gaussian blur filter.

**Adversarial Perturbations.** Adversarial examples are generated while satisfying two properties 1) the class of the adversarial image is different from the class predicted for clean image i.e. $f(\zeta^A(x_n)) \neq f(x_n)$. 2) Perturbed and original images are visually similar and their similarity is determined by the $l_p$-norm. While fulfilling these two properties we use a basic iterative method [18] for generating adversarial examples $\zeta^A(x_n)$. We find the perturbation $\delta_n$ with a small norm $l_\infty$ bounded by $\epsilon$ such that $f(x_n) \neq f(\zeta^A(x_n))$, where $\zeta^A(x_n) = x_n + \delta_n$ and $\delta_n \leq \epsilon$. We solve the following equation:

$$\zeta^A(x_n^0) = x_n + \delta$$

$$\zeta^A(x_n^{k+1}) = \text{Clip}_x(\zeta^A(x_n^k) + \epsilon_s \text{Sign}(\nabla_x \mathcal{L}^\delta(\zeta^A(x_n^k), y_n, \theta)))$$

where $\mathcal{L}^\delta(\zeta^A(x_n^k), y_n, \theta)$ represents the gradient of cost function w.r.t the perturbed image $\zeta^A(x_n^k)$ at step $k$, $\epsilon_s$ determines the step size taken in the direction of sign of the gradient and the result is clipped by $\epsilon$.

Figure 2: Randomly selected sample images for the six natural perturbations under consideration in our experiments.

Figure 3: Our natural perturbed training procedure. We train a network $f$ on clean samples $x_n$ for first $n_1$ epochs. In subsequent $n_2$ epochs we add perturbed versions of input images $\zeta^A(x_n)$ in the training while optimizing the loss for both clean and perturbed samples for the rest of epochs.

3.3. Robustness

The neural network classifier is trained by minimizing the loss function:

$$\mathcal{L}_s = \min_\theta \frac{1}{|S|} \sum_{(x_n, y_n) \in S} \mathcal{L}(f(x_n), y_n)$$

where $S = \{(x_n, y_n)|x_n \in X, y_n \in Y\}$ is the training set, $\theta$ the network parameters and $\mathcal{L}$ the cross-entropy loss. Usually, the data augmentation is performed by adding perturbed versions of the input images. The network is trained by replacing the clean input image $x_n$ with its perturbed version $\zeta^A(x_n)$ in Equation 5.

**Natural Perturbation Robustness.** In order to learn better loss surfaces for clean image classification and robustification against perturbed inputs, in this work we introduce *natural perturbed training* as shown in Figure 3. We start training the classifier with clean images $x_n$ for $n_1$ epochs while optimizing the loss $\mathcal{L}_s$. Then we add their perturbed versions $\zeta^A(x_n)$ besides the clean for the subsequent $n_2$ epochs while minimizing the loss for both of them i.e. $\mathcal{L}_s^A = \frac{\mathcal{L}_s + \mathcal{L}_s^A}{2}$, where $\mathcal{L}_s^A$ is the loss for perturbed samples. The procedure for natural perturbed training is given in the box 1.

**Adversarial Robustness.** For adversarial robustness, we consider adversarial training as described in [11]. The network is trained on adversarial samples besides clean images, while the loss function is optimized for both clean and adversarial samples given by:

$$\mathcal{L}^\delta = \min_\theta \frac{1}{|S|} \sum_{(x_n, y_n) \in S} \mathcal{L}(f(\zeta^A(x_n)), y_n)$$

$$\mathcal{L}^\delta_s = \mathcal{L}_s + \mathcal{L}^\delta$$

where $x_n$ is the clean input image, $\zeta^A(x_n)$ is the perturbed version of the input image.
where $\mathcal{L}_s$ is the loss for clean images and $\mathcal{L}_b$ is the loss for adversarial images.

\section*{Algorithm 1 Natural Perturbed Training for Robustification}

1: Given $S = \{(x_n, y_n) | x_n \in X, y_n \in Y\}$, learning rate $\eta$ and a set of natural perturbations $\zeta^t$.
2: Initialize $\theta$ randomly
3: for epoch = 1 to $n_1 + n_2$ do
4: for minibatch $B \subset |S|$ do
5: $\mathcal{L}_s = \mathcal{L}(f(x_n), y_n, \theta)$
6: if epoch $>$ $n_1$ then
7: $\mathcal{L}_s^t = \mathcal{L}(f(\zeta^t(x_n)), y_n, \theta)$
8: $\mathcal{L}_s^\zeta = \frac{\mathcal{L}_s + \mathcal{L}_s^t}{2}$
9: end if
10: Update $\theta$ with SGD.
11: $\theta = \theta - \eta \nabla_{\theta} \mathcal{L}_s^\zeta$
12: end for
13: end for

\subsection*{3.4. Implementation Details}

\section*{Evaluation Metric.} We use change in the accuracy $\Delta$ as the evaluation metric for the robustness of classifiers. The change is calculated between a standard classifier for clean inputs $f(x_n)$ and a robustified classifier for clean $f_r(x_n)$ or perturbed $f(\zeta^t(x_n))$ inputs. The change in the accuracy is given by:

$$\Delta = \left[ \frac{1}{n} \sum_{n=1}^{N} \mathbb{I}(f(x_n) = y_n) \right] - \left[ \frac{1}{n} \sum_{n=1}^{N} \mathbb{I}(f_r(\zeta^t(x_n)) = y_n) \right]$$

(8)

where $\mathbb{I}$ is the indicator function.

\section*{Standard Network Training and Testing.} We perform classification using Resnet-152. For Cifar-10 we train the networks from scratch. For other datasets networks are pre-trained on Image-net and fine-tuned on the respective datasets. The networks are tested for both clean and perturbed inputs. Natural perturbations are generated using the method described in section 3.2 while keeping the drop $\rho$ from equation 1 the same for all perturbations to ensure standardization. To make the perturbations diverse across each image we select the parameters of perturbations randomly. Adversarial perturbations are created using the basic iterative method with the number of steps $K$ taken as 10 and $\epsilon$ values such that the drop $\rho$ is the same as for other perturbations. The metric of similarity between clean and adversarial samples is $l_{\infty}$ norm.

\section*{Robust Network Training and Testing.} Networks are robustified with natural perturbed training, see the box 1. Each network is robustified with one type of perturbation and the parameters for perturbations are tuned such that they lead to a constant drop $\rho$, see Equation 1. Adversarial training is performed using projected gradient descent (PGD) with $K = 10$ and $\epsilon$ tuned such that it leads to the same drop $\rho$ as the drop of other perturbations. The parameters for the optimizer, learning rate scheduler, and number of epochs are constant across adversarial training and natural perturbed training within a dataset. PGD adversarial training makes $O(KS)$ computational gradient steps in one epoch where $K$ is the number of steps and $S$ is the dataset size. This procedure is $K$ times slower than the standard training $O(S)$ [37] hence, our perturbed natural training is equally faster than adversarial training.

\section*{4. Experiments and Results}

We compare natural perturbed training with adversarial training on clean, natural perturbed and adversarial inputs. In all plots, a symbol represents one run on a trained network with one specifically (perturbed or clean) test set: the symbol represents the test perturbation type while the color represents the training perturbation type.

\section*{Datasets.} Six datasets of varying granularity and size are used in our experiments. Cifar-10 [17] consists of ten coarse-grained classes with 50000 training and 10000 test images. STL-10 [3] contains 5000 training and 8000 test images belonging to ten coarse-grained categories. Different from Cifar-10 the image size is 96 x 96 pixels. The Large attribute dataset (LAD) [42] contains 78017 images with 230 fine-grained classes. We use 11702 training, 9947 validation and 9284 test images for our experiments. Animals with attributes (AwA) [38] consists of 37322 images with 50 fine-grained classes. We use 10450 of them for train-
Figure 5: Comparing the performance of natural perturbed training with adversarial training for clean images, where the cross symbol represents a clean test set and the color of the symbol represents the type of training perturbation. Adversarial training degrades the accuracy in the classification of clean images, but natural perturbed training does not degrade the performance on clean images. It even improves the classifier accuracy for four in six datasets.

4.1. Standardizing Network Robustness

Normalizing Accuracy. We begin by evaluating the performance of a standard neural network classifier for clean images. A standard classifier shows the test accuracy of 93.18 for Cifar-10, 88.60 for STL-10, 87.86 for LAD, 84.79 for AwA, 86.48 for StanfordCars, and 81.20 for CUB dataset. The performance of the standard classifiers for clean images is the reference value of zero, as indicated by the cross symbol, see Figure 4.

Standardization by Calibrating the Drop $\rho$. While considering the standard networks as the baseline, we standardize the comparison among robustness of different networks by setting the desired drop $\rho$ in Equation 1 at 10% for each dataset, shown in Figure 4 at $-10\%$. We succeed in reaching a standardized drop with a maximum deviation of 0.26%. Hence, our standardization enables fair comparison among robustified networks on different types of perturbations.

4.2. Evaluating Robustified Networks on Clean Images

We contrast the performance of adversarial training with natural perturbed training on the clean test set. Figure 5a shows the performance of a network trained with natural perturbed training and tested on clean inputs. Except for Gaussian blur on LAD and Gaussian noise on AwA and CUB, natural perturbed training retains the performance of the classifier on clean images. For CUB, StanfordCars, Cifar-10 and STL-10 datasets training with the perturbed natural images even leads to an improvement in performance as compared to a standard network trained only on clean images. We achieve a maximum of 95.04 for Cifar-10 and 91.81 for STL-10 with our natural perturbed training. Figure 5b shows the performance of adversarially robustified networks on clean images. We see that robustifying networks against adversarial perturbations leads to the drop in the performance on clean images for all datasets except STL-10. Hence, adversarial training shows a trade-off between robustness on adversarial perturbations and clean image accuracy. In contrast, our natural perturbed training does not degrade clean image accuracy but leads to an improvement in the performance.

4.3. Evaluating Robustified Networks on Seen Perturbations

We evaluate the robustness of natural perturbed training on the same type of perturbation e.g. a network trained with elastic perturbed training tested on elastic (seen perturbations) as shown in Figure 6a. Results show that natural perturbed training helps to recover the performance when tested on seen perturbations for both coarse and fine-grained datasets. The recovery is highest for STL-10 and least for Cifar-10. Where Cifar-10 and STL-10 are both coarse-grained, the input size in Cifar-10 is around three times smaller than STL-10. Hence we argue that after introducing natural perturbations, the damage in Cifar-10 is too much to recover from. In general, all datasets show signifi-
Accuracy of a Classifier

(a) Evaluating Natural perturbed training for seen natural perturbations.

(b) Evaluating Adversarial training (AT) for adversarial perturbations.

Figure 6: Comparing the performance of natural perturbed training with adversarial training on seen perturbations. Where the type of the symbol represents the test perturbation type and color of the symbol represents the type of training perturbation. Adversarial training recovers the performance on adversarial images, but the recovery for natural perturbations with natural perturbed training is higher.

Figure 6b shows the results for adversarial images tested on adversarially robustified networks. We observe that adversarial training helps against adversarial perturbations. However, the recovery in the performance of natural perturbations with the natural perturbed training is higher for all datasets except Cifar-10. Hence, our natural perturbed training shows better generalization on perturbation in images seen during training as compared to adversarial training on seen adversarial perturbations.

4.4. General Robustness: Evaluating Robustified Networks on Unseen Perturbations

In Figure 7 we contrast the general robustness of natural perturbed training with adversarial training by testing them for unseen perturbations i.e. perturbations not seen during the training.

Effectiveness of Natural Perturbed Training on Unseen Perturbations. Figure 7a, 7b shows the performance of elastic perturbed training and occlusion perturbed training tested on unseen adversarial and natural perturbations respectively. Results show that robustification with both elastic and occlusion perturbations recover the drop due to adversarial perturbations (plus symbol). We observe that natural perturbed training generalizes to other natural perturbations, except for elastic perturbed training on Gaussian noise for StanfordCars, AwA and LAD (red star symbol). Coarse grained Cifar-10 and STL-10 show the highest recovery on unseen natural perturbations. Hence, our natural perturbed training shows general robustness over adversarial as well as natural perturbations, while being even remarkable for coarse-grained datasets.

Ineffectiveness of Adversarial Training on Unseen Perturbations. Figure 7c shows the results for an adversarially trained network (depicted by yellow symbols) and tested on unseen natural perturbations elastic (circle symbol) and occlusion (square symbol). Adversarial training does not generalize to unseen natural perturbations for fine grained datasets. It even leads to a further drop in the performance for them. For CUB and LAD, the drop almost doubles. For the coarse grained Cifar-10 dataset it helps against occlusion perturbation and for STL-10 it helps for all perturbations. However, the recovery is smaller than with the natural perturbed training. Hence, natural perturbed training shows better generalization than adversarial training for unseen perturbations.

4.5. Ablation Studies

We perform ablation studies in Figure 8 on Cifar-10 by varying the parameters of the natural perturbed training. In Figure 8a we compare a standard network trained for 200 epochs on clean images with natural perturbed training by 100 clean and 50 perturbed epochs. Results show that natural perturbed training with a smaller number of epochs achieves better performance for clean images than a standard network with a larger number of epochs.

In Figure 8b we vary the number of perturbed epochs $n_2$ and test the performance of networks for clean images. Results depict that perturbed training with an average number of 50 epochs performs best. Figure 8c compares the performance of networks trained with different perturbation levels leading to drops of 5%, 10% and 20%. Results show that a moderate drop of 10% leads to the best performance on clean images.

Finally, in Table 2 we evaluate the robustness of a net-
Figure 7: Comparing the performance of Natural perturbed training with Adversarial training on unseen perturbations. The type of symbol represents test perturbation and color of the symbol represents the type of training perturbation. Adversarial training shows some general robustness on coarse-grained datasets but for fine-grained datasets it fails to generalize. Natural perturbed training generalizes to adversarial perturbations and other natural perturbations.

Figure 8: Ablation on Cifar-10 clean: Figure 8a shows training with perturbed images for a small number of epochs performs better than training with clean for a large number of epochs. Figure 8b shows perturbed training with an average number of epochs performs best. Figure 8c shows a moderate drop of 10% leads to the best performance on clean images.

Table 2: Multiple perturbations training. △ shows the change in the accuracy between a standard network and robustified one. Numbers in positive show an improvement in performance, negative show the drop not recovered from the initial 10% drop. In contrast with the Cifar-10 results in Figure 6a, 7a and 7b we observe a better generalization with multiple perturbations training, while being computationally fast, also shows better generalization on adversarial and natural perturbations than adversarial training. Moreover, it improves the classifier accuracy on clean images for the fine-grained CUB and StanfordCars, while for coarse-grained Cifar-10 and STL-10 improving the state of the art. [30].
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6. Supplementary Material

6.1. General Robustness of Wave and Gaussian Perturbations: Evaluating Robustified Networks on Unseen Perturbations

In Figure 9 we contrast the general robustness of natural perturbed training with adversarial training by testing them for unseen perturbations i.e. perturbations not seen during the training. Here, we present the results for wave and Gaussian noise.

Effectiveness of Natural Perturbed Training on Unseen Perturbations. Figure 9a, 9b shows the performance of wave perturbed training and Gaussian perturbed training tested on unseen adversarial and natural perturbations respectively. Results show that robustification with both wave and Gaussian perturbations recover the drop due to adversarial perturbations (plus symbol). We observe that natural perturbed training especially wave perturbed training generalizes to other natural perturbations too. Gaussian perturbed training also generalizes to other natural perturbations except for AwA and LAD datasets. Coarse grained Cifar-10 and STL-10 show the highest recovery on unseen natural perturbations. The recovery for coarse grained datasets with wave perturbations is better than the Gaussian noise. Hence, our natural perturbed training shows general robustness over adversarial as well as natural perturbations, while being even remarkable for coarse-grained datasets.

Ineffectiveness of Adversarial Training on Unseen Wave and Gaussian Perturbations. Figure 9c shows the results for an adversarially trained network (depicted by yellow symbols) and tested on unseen natural perturbations wave (triangle symbol) and Gaussian (star symbol). Adversarial training does not generalize to unseen natural perturbations for fine grained datasets. It even leads to a further drop in the performance for them. For CUB and LAD, the drop almost triples. For the coarse grained Cifar-10 dataset it helps against Gaussian perturbation and for STL-10 it helps for both perturbations. However, the recovery is smaller than with the natural perturbed training. Hence, natural perturbed training shows better generalization than adversarial training for unseen perturbations.

6.2. General Robustness of Saturation and Gaussian Blur Perturbations: Evaluating Robustified Networks on Unseen Perturbations

In Figure 10 we compare the general robustness of natural perturbed training with adversarial training by testing them for unseen perturbations i.e. perturbations not seen during the training. Here, we present results for saturation and Gaussian blur.

Effectiveness of Natural Perturbed Training on Unseen Perturbations. Figure 10a, 10b shows the performance of saturation perturbed training and Gaussian blur perturbed training tested on unseen adversarial and natural perturbations respectively. Results show that robustification with both saturation and Gaussian blur perturbations recover the drop due to adversarial perturbations (plus symbol). We observe that natural perturbed training generalizes to other natural perturbations too. Except for saturation perturbed on AwA and LAD datasets. Coarse grained Cifar-10 and STL-10 show the highest recovery on unseen natural perturbations. Hence, our natural perturbed training shows general robustness over adversarial as well as natural perturbations, while being even noteworthy for coarse-grained datasets.

Ineffectiveness of Adversarial Training on Unseen Wave and Gaussian Perturbations. Figure 10c shows the results for an adversarially trained network (depicted by yellow symbols) and tested on unseen natural perturbations saturation (five pointed star symbol) and Gaussian blur (triangle down symbol). Adversarial training does not generalize to unseen natural perturbations for fine grained datasets. It even leads to a further drop in the performance for them. For CUB, LAD and Cifar-10 Gaussian blur test set the drop almost doubles. For coarse grained Cifar-10 saturation test it neither helps nor degrades the performance. For STL-10 it helps for both perturbations. However, the recovery is smaller than with the natural perturbed training. Hence, natural perturbed training shows better generalization than adversarial training for unseen perturbations.
Figure 9: Comparing the performance of Natural perturbed (wave, Gaussian) training with Adversarial training on unseen perturbations. The type of symbol represents test perturbation and color of the symbol represents the type of training perturbation. Adversarial training shows some general robustness on coarse-grained datasets but for fine-grained datasets it fails to generalize. Natural perturbed training generalizes to adversarial perturbations (plus symbol) and other natural perturbations.

Figure 10: Comparing the performance of Natural perturbed (saturation, Gaussian blur) training with Adversarial training on unseen perturbations. The type of symbol represents test perturbation and color of the symbol represents the type of training perturbation. Adversarial training shows some general robustness on coarse-grained datasets but for fine-grained datasets it fails to generalize. Natural perturbed training generalizes to adversarial perturbations (plus symbol) and other natural perturbations.