Analyzing the Stability of Convolutional Neural Networks against Image Degradation

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Abstract: Understanding the underlying process of Convolutional Neural Networks (ConvNets) is usually done through visualization techniques. However, these techniques do not provide accurate information about the stability of ConvNets. In this paper, our aim is to analyze the stability of ConvNets through different techniques. First, we propose a new method for finding the minimum noisy image which is located in the minimum distance from the decision boundary but it is misclassified by its ConvNet. Second, we exploratorly and quanitatively analyze the stability of the ConvNets trained on the CIFAR10, the MNIST and the GTSRB datasets. We observe that the ConvNets might make mistakes by adding a Gaussian noise with $\sigma = 1$ (barely perceivable by human eyes) to the clean image. This suggests that the inter-class margin of the feature space obtained from a ConvNet is slim. Our second founding is that augmenting the clean dataset with many noisy images does not increase the inter-class margin. Consequently, a ConvNet trained on a dataset augmented with noisy images might incorrectly classify the images degraded with a low magnitude noise. The third founding reveals that even though an ensemble improves the stability, its performance is considerably reduced by a noisy dataset.

1 INTRODUCTION

The common pipeline in recognizing objects is to extract some features for each object and train a model to classify the objects using the extracted features. Conventionally, features are extracted using hand-crafted methods such as HOG, SIFT, BoW, Gabor, LBP and Fisher Vectors. These methods transform an image into another space where classes of objects are separable. In large-scale object recognition tasks, objects are likely to be non-linearly separable using these feature extraction methods. As the result, a non-linear model such as SVM, Random Forest or Gaussian Process is required to learn the non-linear decision boundaries in this space.

One problem with the hand-crafted features is their limited representation power. This causes that some classes of objects overlap with other classes which adversely affect the classification performance. Two common approaches for partially alleviating this problem are to develop a new feature extraction algorithm and to combine various methods. The problems with these approaches are that devising a new hand-crafted feature extraction method is not trivial and combining different methods might not separate the overlapping classes.

Another solution is to automatically learn a function to transform the image into a feature space in which classes are linearly separable. A Convolutional Neural Network (ConvNet) is a highly non-linear function which learns to extract these kinds of features. Krizhevsky *et al.* (Krizhevsky et al., 2012) developed a ConvNet to classify 1000 classes inside the ImageNet dataset that was more accurate than the methods based on hand-crafted features. More recently, He *et al.* (He et al.,) designed a ConvNet which surpassed the human performance on classification of objects in the ImageNet dataset. Similarly, Jin *et al.* (Jin et al., 2014), Ciresan *et al.* (Cirean et al., 2012), Aghdam *et al.*(Aghdam et al., 2015) and Sermanet and Le Cunn (Sermanet and Lecun, 2011) utilized ConvNets with different architectures to classify 43 traffic signs and obtained considerably higher classification accuracy compared with hand-crafted features. In fact, the first three ConvNets beat the human performance in recognizing traffic signs.

ConvNets are multi-layer feed forwards networks consisting mainly of convolution, activation, pooling, dropout, fully-connected and loss layers that are trained using the Stochastic Gradient Descent (SGD) method. In contrast to hand-crafted features, it is hard to explain behaviour of a ConvNet under different cir-

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cumstances without plugging data and analyzing the output of each layer.

From optimization perspective, Glorot and Bengio (Glorot and Bengio, 2010) investigated the problem of SGD and its sensitivity to the initialization. They showed that logistic sigmoid activation can derive the top layers to saturation. Sutskever *et al.* (Sutskever et al., 2013) investigated the importance of initialization and momentum and showed that a ConvNet can fail with a poor initialization or inappropriate tuning of momentum.

Yosinski *et al.* (Yosinski et al., 2014) studied the degree of which a ConvNet is able to transfer its knowledge to a new problem. They mentioned that the bottom layers of a ConvNet are more generalized and they become more class specific in the top layers. Goodfellow *et al.* (Goodfellow et al., 2013) empirically analyzed the forgetting problem of the SGD when they are first utilized to train on one task and then used to train on a second task. They found that including a dropout layer in the network helps the SGD method to remember the first task while it is running on the second task. Besides, other aspects of ConvNets such as the size of the receptive field (Coates and Ng, 2011) and finding a shallow architecture corresponding to a deep architecture (Ba and Caurana, 2013) are examined.

Notwithstanding, one of the important aspects of ConvNets which is not adequately studied is their stability against image degradation. To be more specific, noise is a very common degradation that usually occurs during image acquisition specially in insufficiently illuminated environment. For instance, a traffic sign recognition system must be able to recognize signs during day, at night and under different weather conditions.

Contribution: In this paper, we aim to inspect the behaviour of ConvNets when they are plugged with noisy images. To this end, we first propose a new method for finding the minimum additive noise which causes the clean image to be incorrectly classified with a minimum score margin between the actual class and predicted incorrect class (Section 3). We apply our method on different ConvNets trained on various datasets and show that although the minimum noise is hardly perceivable for human eyes, but it easily tricks a ConvNet (Section 4). Then, we empirically study the behavior of these ConvNets under various levels of noise and illustrate that ConvNets are not stable against noise. Next, we inspect what happens if we augment our dataset using many noisy versions of each image with various levels of noise and noise configurations. Finally, we study the stability of ensemble of ConvNets and conclude that an ensemble of ConvNets is more stable but it is as prone as a single ConvNet to low level noise.

2 RELATED WORK

In contrast to hand-crafted features that their internal process is easily explained, ConvNets are still a mystery for machine learning experts. There is a large body of work on understanding the internal process of ConvNets through visualization of hidden units. Zeiler and Fergus (Zeiler and Fergus, 2013) visualize the hidden units using Deconvolutional Networks. To be more specific, they reconstruct the images which have highly activated each unit. By this way, we can assess how each unit see the world and which parts of objects activate each neuron more. Simonyan *et al.* (Simonyan et al., 2013) find a L_2-regularized image for each class by maximizing the class specific score. They also compute a class saliency map for the input image.

Girshick *et al.* (Girshick et al., 2014) keep record of activations for a specific unit by entering many images to ConvNet and calculating their activations on the unit. Then, the images are sorted according to their activation on this particular unit and illustrated. Taking into account the fact that each unit in top layers has a corresponding receptive field on the image, it is possible to see which parts are important for each unit.

Mahendran and Vedaldi (Mahendran and Vedaldi, 2014) invert the d-dimensional representation of an image computed by function $\Theta : \mathbb{R}^{H\times W\times C} \longrightarrow \mathbb{R}^d$. This approach tells us that to which extend it is possible to reconstruct the image using the representation function Θ. By applying this method on each layer of the network we can understand which information is preserved by each layer. Similarly, Dosovitskiy and Brox (Dosovitskiy and Brox, 2015) reconstructed the image by minimizing the squared Euclidean between the downsampled image and reconstructed image. Recently, Nguyen *et al.* (Nguyen et al., 2015) developed an evolutionary algorithm for generating images that do not look like to any of objects in the database but are classified with high score by ConvNet into one of object classes.

Even though the visualization approaches help us to better understand the internal process of ConvNets, they do not provide a tool for assessing the stability of the network against noise. To address this problem, Szegedy *et al.* (Szegedy et al., 2013) proposed a method for finding the L_2 regularized noise which minimizes the score of a specific class. To our knowledge, this is the only published work which has stud-

ied the stability of ConvNets. As we will discuss shortly, their objective function has a problem which might not generate the optimal results. Furthermore, they have not thoroughly studied different aspects related to the performance of ConvNets that we discussed in the last part of Section 1.

3 ANALYZING STABILITY

A ConvNet is a non-linear vector function that transforms a D-dimensional input vector into a M-dimensional vector in the layer before the classification layer. Ideally, small changes in the input should produce small changes in the output. In other words, if the classification score of the input image $\mathcal{X} \in \mathbb{R}^{M\times N}$ computed by ConvNet for class c is $s_c(\mathcal{X}) = z$, then, the score of image $\mathcal{X}_{noisy} = \mathcal{X} + r$ obtained by adding a small degradation $r \in \mathbb{R}^{M\times N}$ to $\mathcal{X}$ must also be $s_c(\mathcal{X}) = z \pm \varepsilon$. Note that c is the class with the highest score when $\mathcal{X}$ is plugged into ConvNet.

However, f is strongly degraded as $\|r\|$ increases. Therefore, at a certain point, the degraded image $\mathcal{X}_{noisy}$ is no longer recognizable. We are interested in finding r with minimum $\|r\|$ that causes the $\mathcal{X}_{noisy}$ and the $\mathcal{X}$ are classified differently. Szegedy *et al.* (Szegedy et al., 2013) investigated this problem and they proposed to minimize the following objective function with respect to r:

$$\begin{aligned} &minimize \;\; \lambda|r| + loss(\mathcal{X}+r, c) \\ &s.t \quad \mathcal{X}+r \in [0,1]^{M\times N} \end{aligned} \tag{1}$$

where c is the actual class label, λ is the regularizing weight and $loss(\mathcal{X}+r,c)$ returns the loss of the degraded image $\mathcal{X}+r$ given the actual class of image $\mathcal{X}$. It is worth mentioning that loss is a vector that shows the classification score of the input image for each class.

Denoting the loss vector by $\mathcal{L} \in [0,1]^K$ where K is the total number of the classes, $\mathcal{L}[k]$ returns the score of the predicted class where $k = \arg\max \mathcal{L}$. The image is classified correctly if $k = c$. If $max(\mathcal{L}) = 0.9$, the ConvNet is 90% confident that the input image belongs to class k. However, there might be another image where $max(\mathcal{L}) = 0.3$. This means that the image belongs to class k with probability 0.3.

Conversely, assume two images that are misclassified by ConvNet. In the first image, $\mathcal{L}[k] = 0.9$ and $\mathcal{L}[c] = 0.1$ meaning that the network believes the input image belongs to class k with probability 0.9 but it belongs to class c with probability 0.1. In the second image, the beliefs of ConvNet are $\mathcal{L}[k] = 0.51$ and $\mathcal{L}[c] = 0.49$. Even tough in both cases the images are misclassified, however, the degrees of misclassification are different.

One problem with the objective function (1) is that it tends to find r such that $loss(\mathcal{X}+r,c)$ approaches to zero. In other words, it tries to find r such that $\mathcal{L}[c] = \varepsilon$ and $\mathcal{L}[k] = 1-\varepsilon$. Assume a r such that $loss(\mathcal{X}+r,c) = 0.3$ and $\mathcal{L}[k] = 0.7$. In other words, the input image $\mathcal{X}$ is misclassified using the current degradation r. Yet, the goal of the objective function (1) is to settle in a point where $loss(\mathcal{X}+r,c) = \varepsilon$. As the result, it might change r which results in a greater $\|r\|$. Consequently, the degradation found by minimizing the objective function (1) might not be optimal. To address this problem, we propose the following objective function to find the degradation r:

$$r^* = \arg\min_r \;\; \psi(loss(\mathcal{X}+r), c) + \lambda\|r\|_2 \tag{2}$$

$$\psi(\mathcal{L}, c) = \begin{cases} \beta \times \mathcal{L}[c] & \arg\max \mathcal{L} = c \\ \mathcal{L}[k] - \mathcal{L}[c] & otherwise \end{cases} \tag{3}$$

where λ is the regularizing weight, β is a multiplier to penalize those values of r that do not properly degrade the image so it is not misclassified by ConvNet. The above objective function finds the value r such that degrading the input image $\mathcal{X}$ using r causes the image to be classified incorrectly and the difference between the highest score in $\mathcal{L}$ and the true label of $\mathcal{X}$ is minimum. This guarantees that $\mathcal{X}+r$ will be outside the decision boundary of actual class l but it will be as close as possible to the decision boundary.

Our proposed objective function has an important property. It finds the degradation r that causes the image to be misclassified with a slim margin compared with the actual class. In other words, the degraded image lies very close to the decision boundary in the feature space computed by the layer just before the classification layer. This quantitatively shows the margin between two classes.

Minimizing (2) using gradient descent method is not trivial. For this reason, we minimize the objective function (2) using *evolutionary algorithms*. To this end, we use real-value encoding scheme for representing the population. The size of each chromosome in the population is equal to the number of the elements in r. Each chromosome represents a solution for r. We use *tournament* method with tour size 5 for selecting the offspring. Then, a new offspring is generated using *arithmetic*, *intermediate* or *uniform* crossover operators. Finally, the offspring is mutated by adding a small number in range $[-10, 10]$ on some of the genes in the population. Finally, we use *elitism* to always keep the best solution in the population. The algorithm is terminated when the maximum number of iterations reach or the solution is not improved in the last 50 iterations.

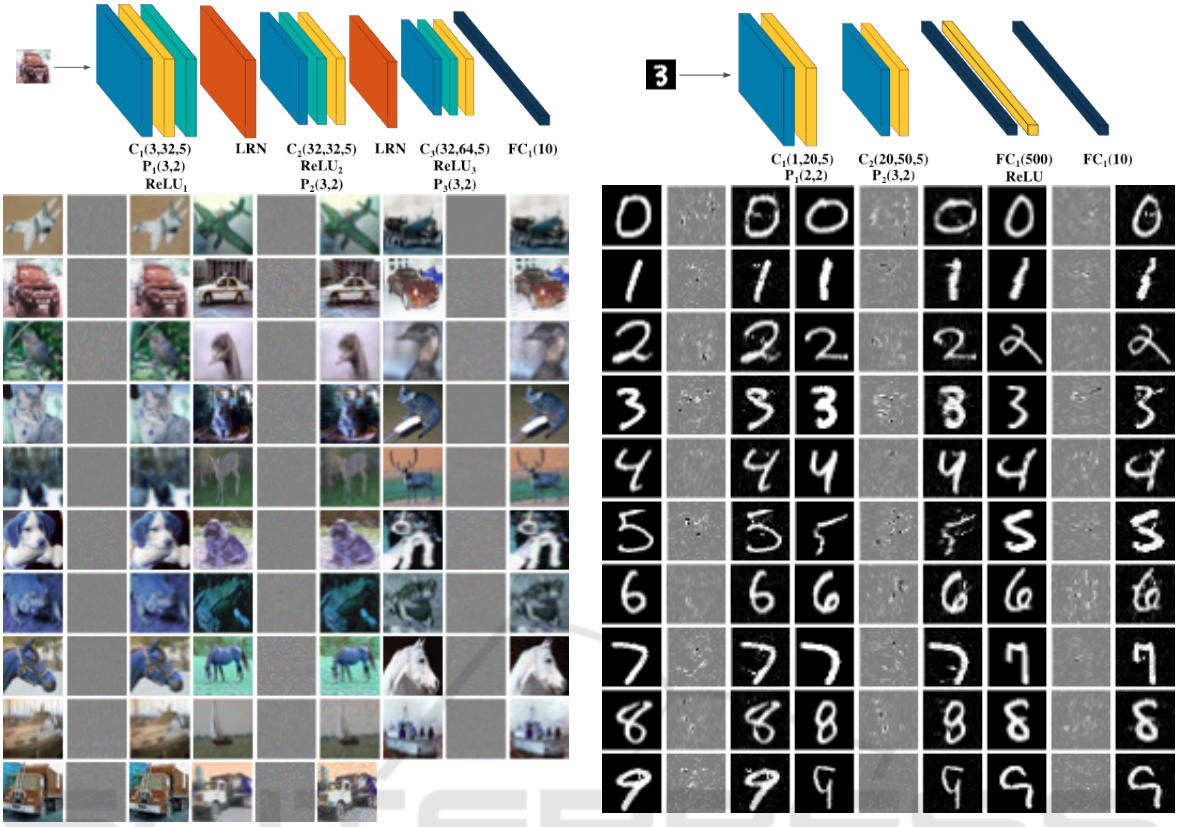


Figure 1: Minimum additive noise, found by optimizing (2), which causes test images in the CIFAR10 (left) and the MNIST (right) datasets are misclassified. $C_i(c,k,w)$ shows a convolution layer with k filters of size $w \times w$ applied on the input with c channels. $P(m,n)$ indicates a MAX pooling layer with kernel size $m \times m$ and stride n. Finally, $FC(x)$ depicts a fully connected layer with x neurons. In the case of CIFAR10, the feature maps are padded with border size 2 before applying the convolution filters (best viewed in color and electronically).

We applied the above optimization procedure on the ConvNets trained using the CIFAR10 (Krizhevsky, 2009), the MNIST (LeCun et al., 1998) and the GTSRB (Stallkamp et al., 2012) datasets. Figure 1 and Figure 2 illustrate the architecture of the utilized ConvNets and additive noise r obtained for a few samples from these datasets.

Inspecting all the images in these figures, we realize that the ConvNets can easily make mistakes even for the noises which are not perceivable by human eyes. In addition, taking into account the fact that our proposed objective function results noisy images which are very close to the decision boundary of each class, we observe that the margin between the classes are very slim since adding a noise with a high signal-to-noise ratio (*i.e.* low-power noise) can alter the classification score drastically.

Furthermore, these results suggests that the function presenting by a ConvNet is highly non-linear where small changes in the input may cause a significant change in the output. In other words, the magnitude of gradient of the ConvNets in the last feature extract layer are large. When the output changes dramatically, it might fall into a wrong class in the feature space. Hence, the image is incorrectly classified. Note that because of our proposed objective function, the difference between the wrongly predicted class and the true class is positive but it is very close to zero.

To further investigate the stability of ConvNets against noise, we carry out several experiments in the next Section to analyze different aspects of ConvNets.

4 EXPERIMENTS

We trained the ConvNets shown in Figure 1 and Figure 2 on the clean datasets. In the case of the GTSRB dataset, we augmented the dataset following the same procedure in (Aghdam et al., 2015). Beside the single ConvNet, we also created an ensemble of ConvNets for the GTSRB dataset. The classification performance of the CIFAR10 and the MNIST

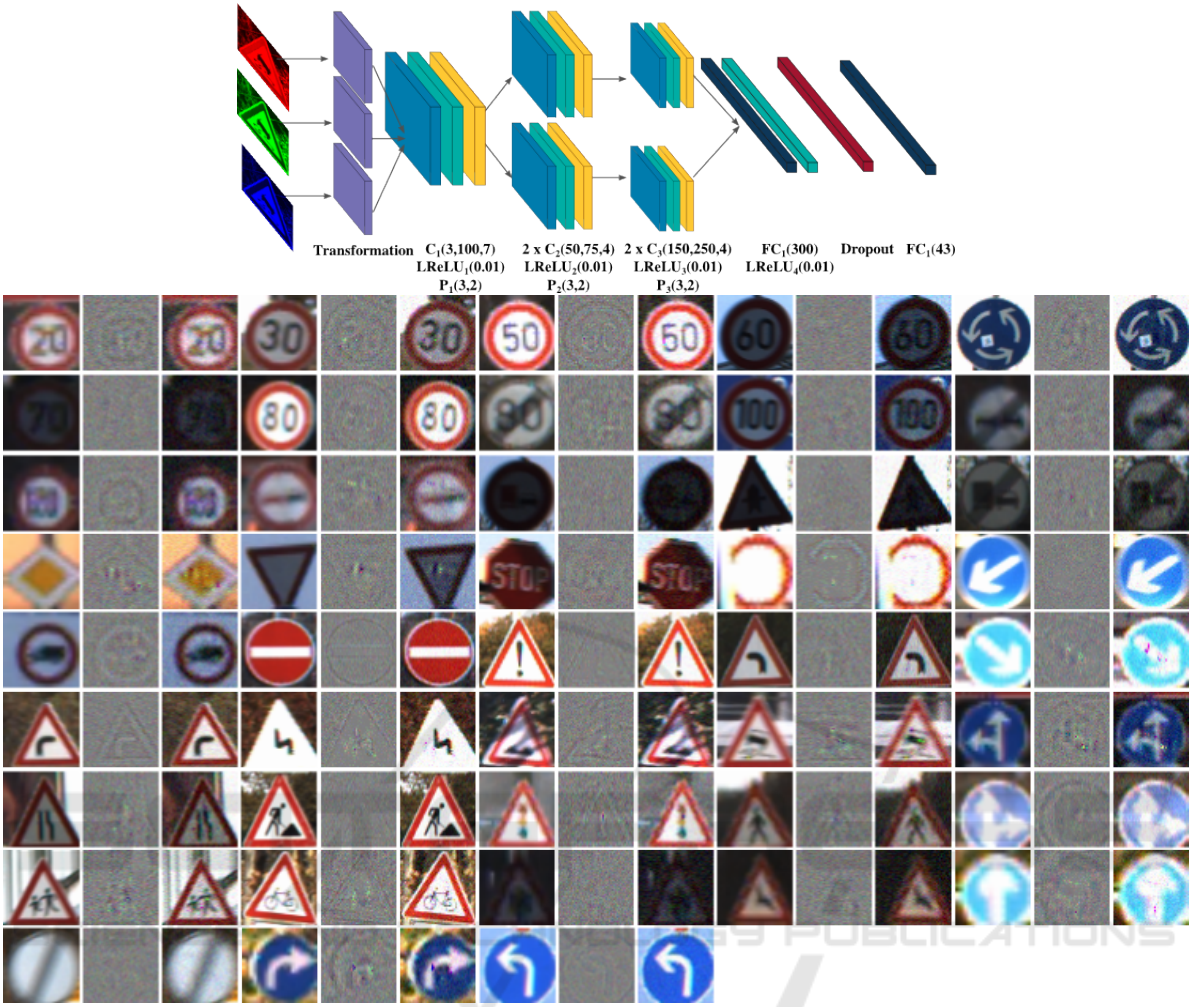


Figure 2: Minimum additive noise, found by optimizing (2), which causes the test images in the GTSRB dataset are misclassified. The network architecture is taken from (Aghdam et al., 2015) (best viewed in color and electronically).

ConvNets on the clean test set is shown in Table 1. In addition, the performance of the ConvNet trained on GTSRB dataset is available in (Aghdam et al., 2015). **Tolerance against Noise:** Having the ConvNets trained, we assess their stability under degradation by additive noise. To this end, we degrade each sample in the test set using the Gaussian noise with $\sigma \in \{1,2,4,8,10,14,18,20,25,30,35,40\}$ and for each value of sigma, we generate 150 noisy images. By this way, 1800 degraded images are generated for each clean sample in the test set. Then, the ConvNets are evaluated using the noisy test sets. We performed this procedure on the CIFAR10, the MNIST and the GTSRB datasets. Figure 3, Figure 4 and Figure 5 to Figure 7 show the results.

Each chart illustrates per class scatter plot of the **peak signal-to-noise ratio** (PSNR), calculated using the noisy images and the clean images, against the classification score of each sample. A high PSNR value corresponds to a small value of σ in the Gaussian noise. As the result, all images with $PSNR \approx 50$ are degraded using a Gaussian noise with $\sigma = 1$ and those with $PSNR \approx 15$ are degraded using a Gaussian noise with $\sigma = 40$. The red points are related to the misclassified samples and the gray points depict the correctly classified samples.

We observe that there are many noisy images which are misclassified by the ConvNets trained on the CIFAR10 dataset regardless of the their PSNR. Note that, the Gaussian noise with $\sigma = 1$ is not easily perceivable for a human eye. However, we see that this low magnitude noise might change the classification result. This is due to the fact that, the CIFAR10 dataset contains complex objects stored in very small images. A small change in the image, may alter the geometry and appearance of the object. Although small changes might not be perceivable by human eyes, they numerically change the appearance and

Table 1: Class specific precision and recall computed on the original CIFAR10 (left) and the MNIST (right) datasets.

CIFAR10					
cls	precision	recall	cls	precision	recall
1	0.81	0.82	6	0.63	0.77
2	0.89	0.89	7	0.87	0.83
3	0.71	0.73	8	0.80	0.86
4	0.64	0.58	9	0.90	0.88
5	0.79	0.75	10	0.91	0.80
accuracy (top-1):			78.95%		

MNIST					
cls	precision	recall	cls	precision	recall
1	0.99	0.99	6	0.99	0.99
2	1.00	0.99	7	0.99	0.99
3	0.99	0.99	8	0.99	0.98
4	0.98	1.00	9	0.99	0.99
5	0.99	0.99	10	0.99	0.99
accuracy (top-1):			98.98%		

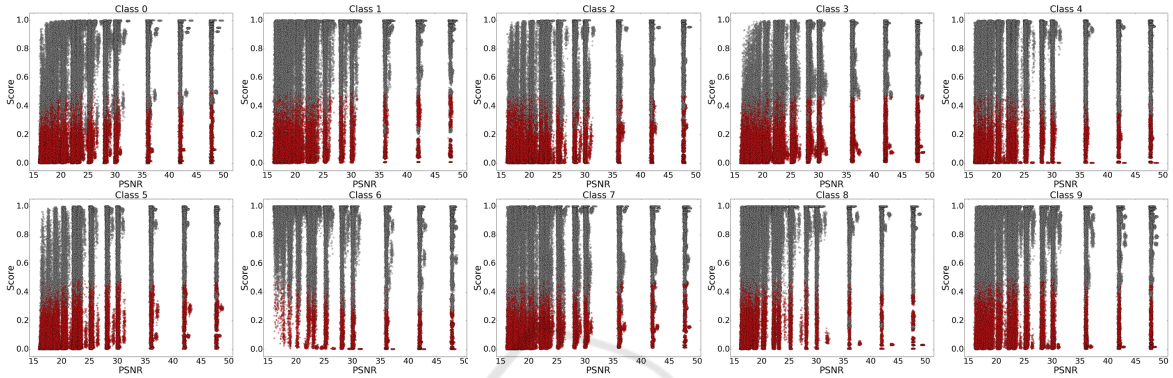


Figure 3: Evaluating the ConvNet trained on the CIFAR10 dataset by creating a noisy test set (see the text). Red and Gray points illustrate misclassified and correctly classified samples, respectively. High resolution images are available at deim.urv.cat/ rivi/cnn-noise-tolerance/.

shape pattern. For this reason, the ConvNet makes mistakes with little degradations in the input image.

Inspecting the results obtained from the ConvNet trained on the MNIST dataset shows that despite the simplicity of the objects in this dataset, the MNIST ConvNet is also vulnerable to noise and it makes mistakes even with a low magnitude degradation. In addition, the scatter plots illustrate that the ConvNet makes mistakes regardless of the object classes. This is due to the fact that images in the MNIST dataset do not have any texture and they can be considered as binary images. Consequently, the network learns edges and edgelets to recognize the digits. However, when the image is degraded using a Guassian noise, it changes the edge patterns dramatically. As the result, the degraded image is misclassified.

The ConvNet trained on the GTSRB dataset utilizes 48×48 images. In addition, the appearance and perspective of the objects in this dataset do not vary significantly. Hence, the ConvNet learns parts and patterns with higher abstraction level compared with the two other ConvNets. For this reason, small degradation of the image does not significantly alter the representation vector computed by the ConvNet and it is classified correctly in most of the cases. However, we observe that the ConvNet makes more mistakes starting from $\sigma = 8 (PSNR \simeq 30)$.

Result: The above results reveal that ConvNets are not noise-tolerant and their classification score might negatively alter with a small change in the input. This is due to the fact that a ConvNet is a highly non-linear function. Therefore, a slight change in the input causes a great change in the output. From another perspective, these results show that the margin between two classes are very small in which a small variation in the input moves the sample to another class.

Beside the exploratory analysis, we conducted a quantitative analysis as well. To be more specific, we evaluated the performance of the ConvNets on the noisy datasets in terms of precision and recall. Table 2 and Table 3 show the results. Comparing the results with Table 1 and (Aghdam et al., 2015) we see a drastic performance reduction in all three ConvNets. This is more obvious in the case of the MNIST dataset for the same reason we mentioned earlier.

Effect of Ensemble: It is shown that ensemble of ConvNets can increase the classification performance (Aghdam et al., 2015; Jin et al., 2014; Cirean et al., 2012). To see if the ensemble makes the classification more robust against noise, we created an ensemble for each of the datasets. Each ensemble contains 5 ConvNets initialized and trained separately. We evaluated the ensembles using the same noisy test sets. Table 4 and Table 5 show the results.

Result: We observe that the ensembles of the CIFAR10 and the GTSRB ConvNets produce more accurate results compared with the corresponding single

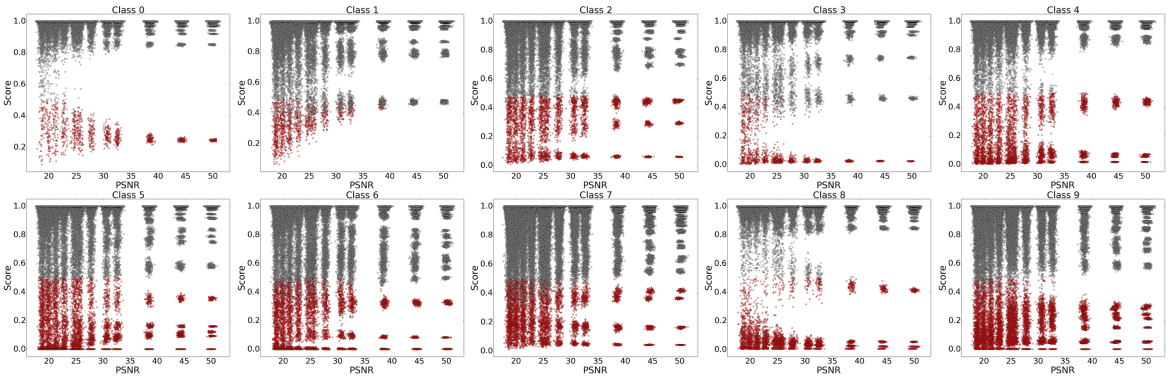


Figure 4: Evaluating the ConvNet trained on the MNIST dataset by creating a noisy test set (see the text). Red and Gray points illustrate misclassified and correctly classified samples, respectively. High resolution images are available at deim.urv.cat/ rivi/cnn-noise-tolerance/.

Table 2: Class specific precision and recall computed on the noisy version of the GTSRB dataset (refer to the text).

Class	precision	recall	class	precision	recall	class	precision	recall	class	precision	recall
0	0.9198	0.9997	11	0.9626	0.9470	22	0.9988	0.9758	33	0.9865	0.9977
1	0.8993	0.9874	12	0.9565	0.9654	23	0.8392	0.8911	34	0.9866	0.9973
2	0.8808	0.9525	13	0.9811	0.9902	24	0.9178	0.9098	35	0.9933	0.9382
3	0.8524	0.8744	14	0.9721	0.9969	25	0.9288	0.9700	36	0.9849	0.9928
4	0.9707	0.8651	15	0.9898	0.9578	26	0.9105	0.9592	37	0.9507	0.9875
5	0.8387	0.9015	16	0.9993	0.9319	27	0.9470	0.9891	38	0.9651	0.9792
6	0.9324	0.7122	17	0.9911	0.9911	28	0.9777	0.9915	39	0.9724	0.9100
7	0.9377	0.8698	18	0.9682	0.8998	29	0.8453	0.9966	40	0.9061	0.9629
8	0.8324	0.9039	19	0.6640	0.7462	30	0.8102	0.7670	41	0.9508	0.9268
9	0.9606	0.9453	20	0.8314	0.9997	31	0.9666	0.8699	42	0.9082	0.9126
10	0.9864	0.8797	21	0.8995	0.9997	32	0.9773	0.8472			
					accuracy (top-1):		93.23%				

Table 3: Class specific precision and recall computed on the noisy versions of the CIFAR10 (left) and the MNIST (right) datasets (refer to the text).

CIFAR10					
cls	precision	recall	cls	precision	recall
1	0.86	0.54	6	0.68	0.49
2	0.89	0.72	7	0.37	0.92
3	0.69	0.48	8	0.82	0.71
4	0.60	0.39	9	0.78	0.80
5	0.59	0.66	10	0.75	0.76
accuracy (top-1):			64.36%		

MNIST					
cls	precision	recall	cls	precision	recall
1	0.98	0.99	6	0.98	0.97
2	0.99	0.99	7	0.99	0.98
3	0.98	0.98	8	0.99	0.98
4	0.96	0.99	9	0.98	0.98
5	0.99	0.98	10	0.98	0.97
accuracy (top-1):			98.51%		

ConvNets when they are applied on the noisy test sets. However, the fact remains that the performance of the ensemble is significantly lower than the performance of the ConvNets on the clean datasets. This founding shows that an ensemble is not able to tackle the instability problem of the ConvNets against noisy images. This is shown in the scatter plots beside Table 4 in which images are still incorrectly classified using the ensemble by adding a Gaussian noise with $\sigma = 1$.

Augmenting Noisy Images: It is a common practice to create a jittery dataset by applying simple transformations such as cropping, contrast adjustment and blurring on the original training dataset in order to train a more accurate ConvNet. In this section, our goal is to find out if augmenting the training dataset with many noisy images improve the stability of the

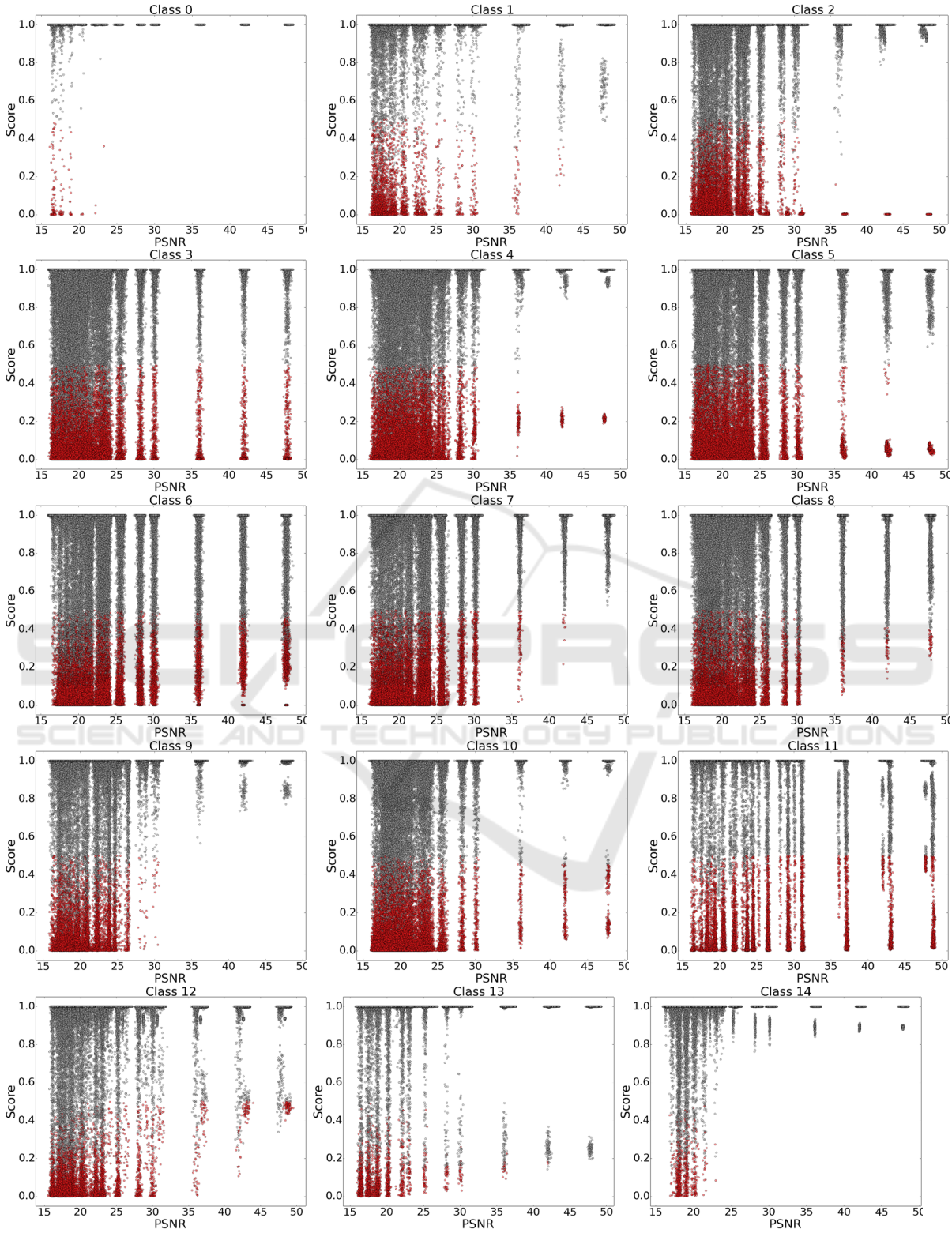


Figure 5: Evaluating the ConvNet trained on the GTSRB dataset (class 0 to class 14) by creating a noisy test set (see the text). Red and Gray points illustrate misclassified and correctly classified samples, respectively. High resolution images are available at deim.urv.cat/ rivi/cnn-noise-tolerance/.

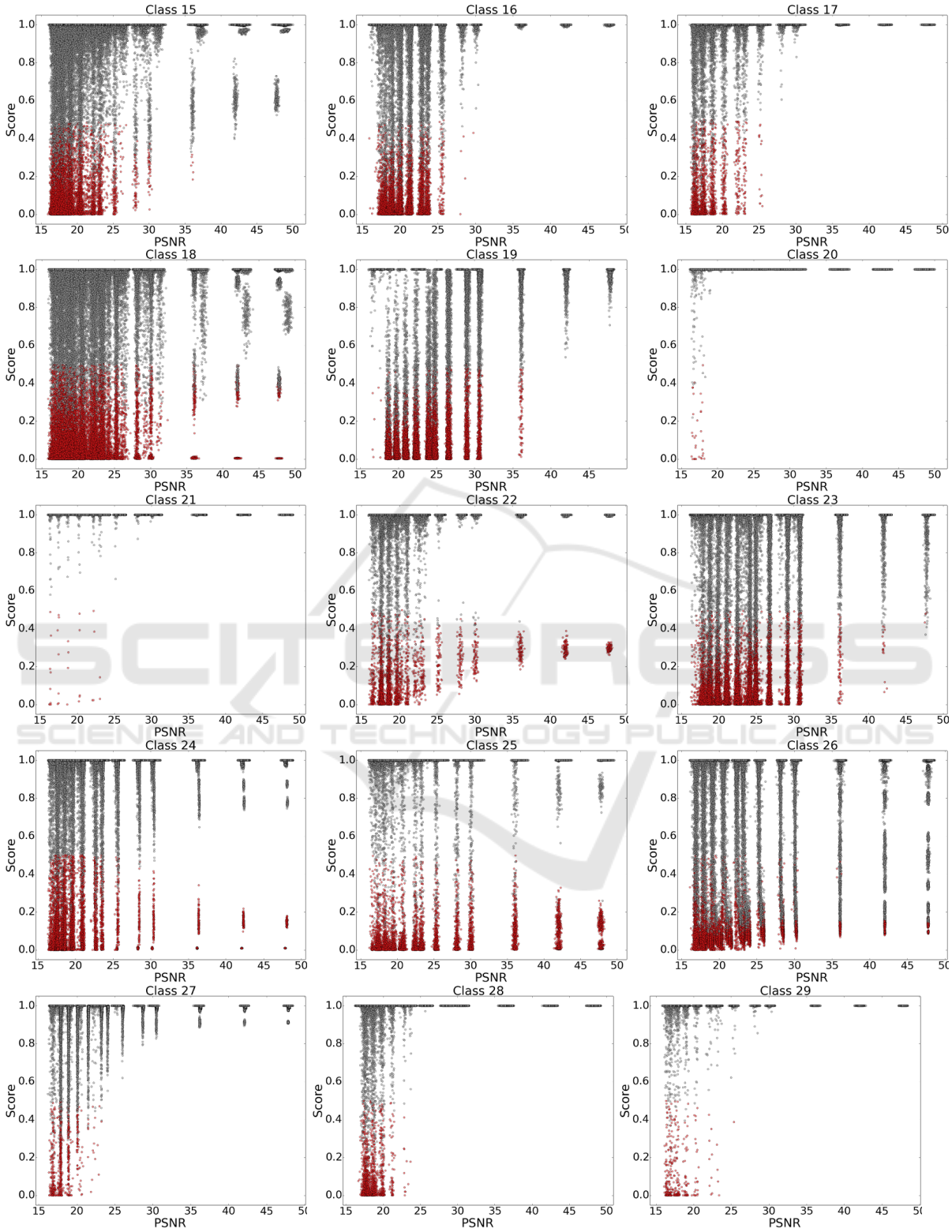


Figure 6: Evaluating the ConvNet trained on the GTSRB dataset (class 15 to class 29) by creating a noisy test set (see the text). Red and Gray points illustrate misclassified and correctly classified samples, respectively. High resolution images are available at deim.urv.cat/ rivi/cnn-noise-tolerance/.

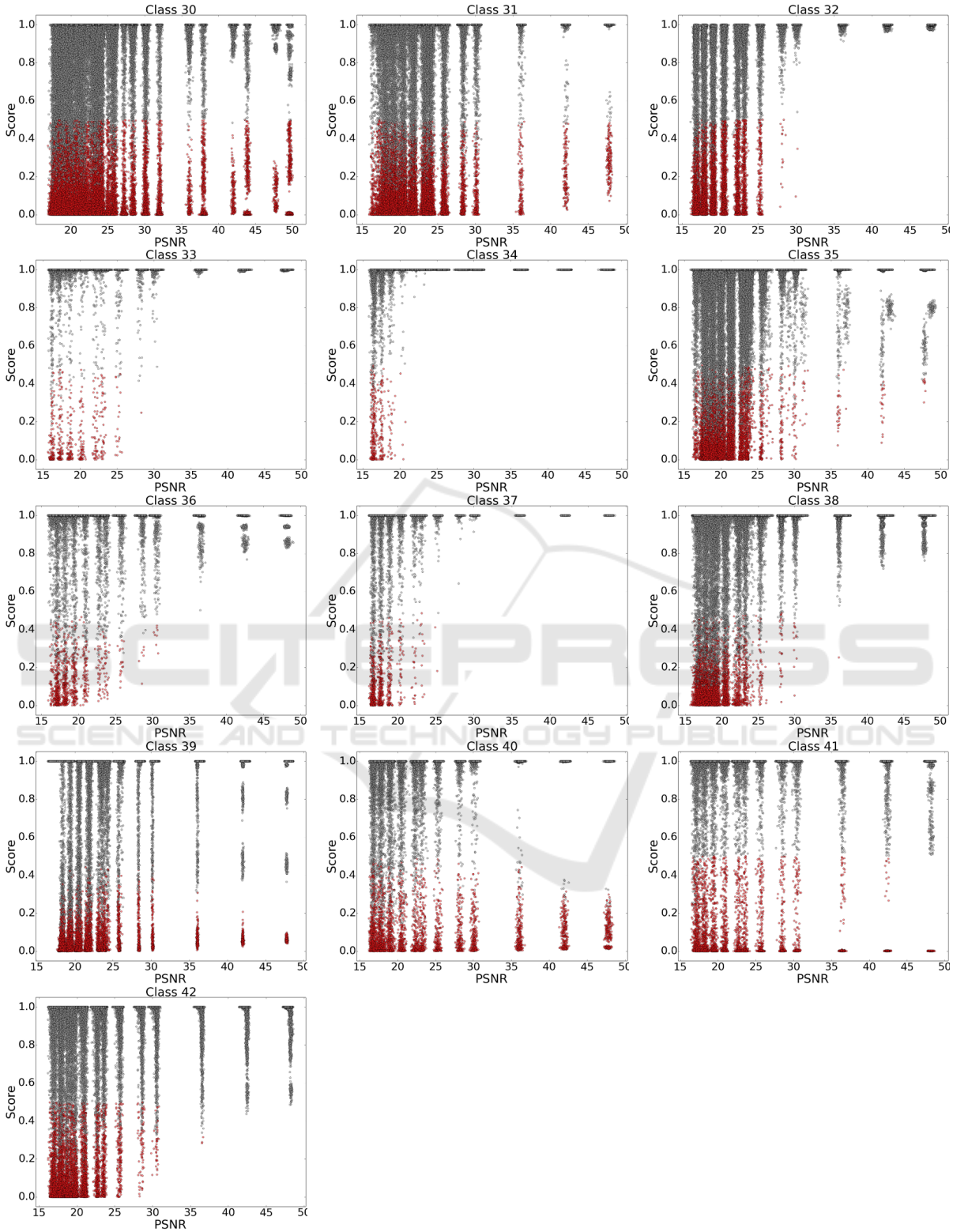


Figure 7: Evaluating the ConvNet trained on the GTSRB dataset (class 30 to class 42) by creating a noisy test set (see the text). Red and Gray points illustrate misclassified and correctly classified samples, respectively. High resolution images are available at deim.urv.cat/ rivi/cnn-noise-tolerance/.

Table 4: Class specific precision and recall computed using the ensemble of 5 ConvNets on the noisy version of the GTSRB dataset.

Class	precision	recall	class	precision	recall	class	precision	recall
0	0.9547	0.9970	15	0.9894	0.9762	30	0.8775	0.8524
1	0.9126	0.9917	16	0.9994	0.9585	31	0.9789	0.9101
2	0.8848	0.9667	17	0.9929	0.9947	32	0.9939	0.8542
3	0.9093	0.8982	18	0.9859	0.9030	33	0.9971	0.9982
4	0.9859	0.8896	19	0.8710	0.7784	34	0.9955	0.9995
5	0.8469	0.9429	20	0.9061	0.9996	35	0.9926	0.9678
6	0.9401	0.7909	21	0.9398	0.9993	36	0.9820	0.9984
7	0.9612	0.8853	22	0.9994	0.9788	37	0.9743	0.9956
8	0.8872	0.9279	23	0.9372	0.8838	38	0.9883	0.9832
9	0.9875	0.9653	24	0.9383	0.9024	39	0.9753	0.9266
10	0.9855	0.9311	25	0.9548	0.9872	40	0.8843	0.9732
11	0.9513	0.9786	26	0.9131	0.9877	41	0.9832	0.9909
12	0.9378	0.9791	27	0.9605	0.9953	42	0.9328	0.9631
13	0.9876	0.9919	28	0.9726	0.9912			
14	0.9699	0.9991	29	0.8925	0.9985			
accuracy (top-1):				95.15%				

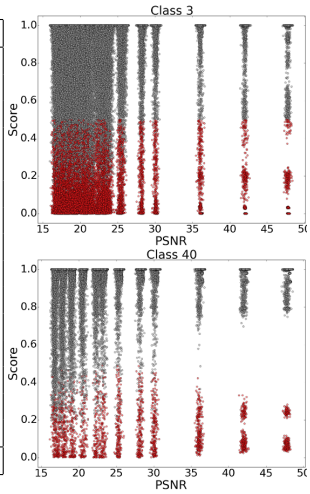


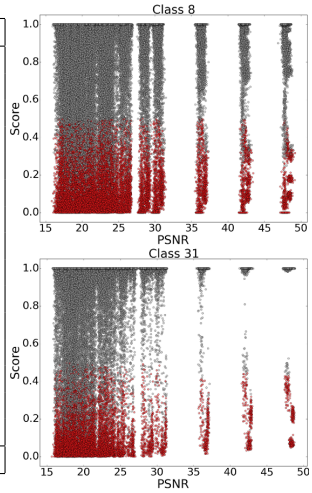
Table 5: Class specific precision and recall computed using two separate ensembles of 5 ConvNets on the noisy version of the CIFAR10 (left) and MNIST (right) datasets.

CIFAR10					
cls	precision	recall	cls	precision	recall
1	0.88	0.57	6	0.74	0.52
2	0.91	0.78	7	0.39	0.94
3	0.73	0.53	8	0.88	0.72
4	0.67	0.42	9	0.82	0.81
5	0.70	0.63	10	0.65	0.86
accuracy (top-1):			67.88%		

MNIST					
cls	precision	recall	cls	precision	recall
1	0.98	0.99	6	0.98	0.98
2	0.98	1.00	7	0.99	0.98
3	0.99	0.99	8	1.00	0.98
4	0.97	0.99	9	0.99	0.98
5	0.99	0.99	10	0.99	0.97
accuracy (top-1):			98.69%		

Table 6: Class specific precision and recall computed using the ConvNet train on a training dataset augmented with noisy images on the noisy version of the GTSRB dataset.

Class	precision	recall	Class	precision	recall	Class	precision	recall
0	0.9970	0.9906	15	0.9812	0.9750	30	0.9496	0.9448
1	0.9503	0.9728	16	0.9951	0.9728	31	0.9486	0.9466
2	0.9281	0.9586	17	0.9911	0.9884	32	0.9859	0.9393
3	0.9170	0.9004	18	0.9325	0.9723	33	0.9931	0.9733
4	0.9205	0.9242	19	0.9386	0.9417	34	0.9905	0.9833
5	0.8263	0.8987	20	0.9624	0.9451	35	0.9820	0.9815
6	0.9506	0.9386	21	0.9872	0.9805	36	0.9851	0.9786
7	0.9173	0.8734	22	0.9982	0.9962	37	0.9948	0.9825
8	0.8823	0.8834	23	0.9840	0.9485	38	0.9575	0.9761
9	0.9648	0.9558	24	0.9877	0.9663	39	0.9491	0.9753
10	0.9336	0.9596	25	0.9687	0.9710	40	0.9917	0.9613
11	0.9519	0.9678	26	0.9556	0.9631	41	0.9834	0.9684
12	0.9019	0.9960	27	0.9965	0.9831	42	0.9845	0.9400
13	0.9451	0.9852	28	0.9935	0.9695			
14	0.9933	0.9956	29	0.9976	0.9913			
accuracy (top-1):				96.08%				



network. To this end, we generated 15 noisy images for each image in the training set with different *signal-to-noise* ratios. Then, the ConvNets are trained using the new noisy training sets. Finally, we evaluate the ConvNets using the noisy test sets. Table 6 illustrates the result. Because of space limitation we could not include the results from the CIFAR10 and the MNIST datasets. However, the complete results are available at *deim.urv.cat/ rivi/cnn-noise-tolerance/*.

Result: While augmenting the training set with noisy images improves the performance, however, we observe that the ConvNets are still sensitive to noise. For instance, the scatter plots beside Table 6 shows that even after training with noisy training set, it is still possible to generate a Gaussian noise with $\sigma = 1$ in order to incorrectly classify the images.

5 CONCLUSIONS

In this paper we studied the degree of which ConvNets are tolerant against noise. For this purpose, we first proposed a method for finding the minimum noisy image close to the decision boundary that is misclassified by the ConvNet. We applied our method on the ConvNets trained on the CIFAR10, the MNIST and the GTSRB datasets and showed that it is possible to generate low magnitude noises which are hardly perceivable by human eyes but they alter the classification score of the ConvNets. Then, we carried out several experiments to study different aspects of stability. First, we randomly generated many noisy images with various signal-to-noise ratios and classified them using the three ConvNets. We found out that the three ConvNets makes mistakes even with very low magnitude noisy images. This can be explained by the fact that the inter-class margin of the feature vectors computed by ConvNets might be very small. Another possibility is that because ConvNets are highly non-linear functions, a small change in the input causes a significant change in the output. For these two reasons, images may fall into wrong classes when they are degraded by a low magnitude noise. Second, we examined the effect of ensemble of ConvNets and found that although ensembles improve the classification accuracy but they are still very vulnerable to low magnitude noises. Third, we investigated the effect of augmenting the training datasets with many noisy images on the stability. Results reveal that even ConvNets trained on noisy datasets are not stable against noise and they easily make mistakes by low magnitude noises.

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