Benchmarking the Robustness of Semantic Segmentation Models

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Abstract

When designing a semantic segmentation module for a practical application, such as autonomous driving, it is crucial to understand the robustness of the module with respect to a wide range of image corruptions. While there are recent robustness studies for full-image classification, we are the first to present an exhaustive study for semantic segmentation, based on the state-of-the-art model DeepLabv3+. To increase the realism of our study, we utilize almost 200,000 images generated from Cityscapes and PASCAL VOC 2012, and we furthermore present a realistic noise model, imitating HDR camera noise. Based on the benchmark study we gain several new insights. Firstly, model robustness increases with model performance, in most cases. Secondly, some architecture properties affect robustness significantly, such as a Dense Prediction Cell which was designed to maximize performance on clean data only. Thirdly, to achieve good generalization with respect to various types of image noise, it is recommended to train DeepLabv3+ with our realistic noise model.

1. Introduction

In recent years, Deep Convolutional Neural Networks (DCNN) have set the state-of-the-art on a broad range of computer vision tasks [47, 34, 65, 67, 50, 61, 10, 27, 33, 49]. The performance of DCNN models is generally measured using benchmarks of publicly available datasets, which often consist of clean and post-processed images [16, 22]. However, it has been shown that model performance is prone to image corruptions [77, 68, 36, 26, 21, 24, 3], especially image noise decreases the performance significantly.

Image quality depends on environmental factors such as illumination and weather conditions, ambient temperature, and camera motion, since they directly affect the optical and electrical properties of a camera. Image quality is also affected by optical aberrations of the camera lenses, causing for instance image blur. Thus, in safety-critical applications [31, 45, 43], models must be robust towards such inherently present image corruptions.

In this work, we present an extensive evaluation for the robustness of semantic segmentation models towards a broad range of real-world image corruptions. Here, the term robustness refers to training a model on clean data and then validating it on corrupted data. We choose the task of semantic image segmentation for two reasons. Firstly, image segmentation is often applied in safety-critical applications, where robustness is essential. Secondly, a rigorous evaluation for real-world image corruptions has in recent years only been conducted for full-image classification, e.g., most recently [26, 36].

When conducting an evaluation of semantic segmentation models there are, in general, different choices such as: i) comparing different architectures, or ii) performing a detailed ablation study of a state-of-the-art architecture. In contrast to [26, 36], which focused on aspect i), we perform both options. We believe that an ablation study (option ii) is important since knowledge about architectural choices are likely helpful when designing a practical system, where types of image corruptions are known beforehand. For example, [26] showed that ResNet-152 [34] is more robust to image noise than GoogLeNet [67]. Is the latter architecture more prone to noise due to missing skip-connections, shallower architecture or other architectural design choices? When the overarching goal is to develop robust DCNN models, we believe that it is important to learn about robustness capabilities of architectural properties.

We conduct our study on two popular datasets: Cityscapes [16] and PASCAL VOC 2012 [22]. To generate a wide-range of image corruptions we utilize the image transformations presented by Hendrycks et al. [36]. While they give a great selection of image transformations, the level of realism is rather lacking, in our view. Hence we augment their image transformations by additional ones, in particular realistic HDR camera noise, PSF blur, and geometric distortions. In total, we employ 19 different image corruptions from the categories of blur, noise, weather, digital and geometric distortion. We are thus able to validate each DCNN model on almost 200,000 images.

We use the state-of-the-art DeepLabv3+ architecture [13] with multiple network backbones as reference and
Figure 1: Results of our ablation study. Here we train the state-of-the-art semantic segmentation model DeepLabv3+ on clean Cityscapes data and test it on corrupted data. (a) A validation image from Cityscapes, where the left-hand side is corrupted by shot noise and the right-hand side by fog. (b) Prediction of the best-performing model-variant on the corresponding clean image. (c) Prediction of the same architecture on the corrupted image (a). (d) Prediction of an ablated architecture on the corrupted image (a). We clearly see that prediction (d) is superior to (c), hence the corresponding model is more robust with respect to this image corruption. In this work, we present a study of various architectural choices and various realistic image corruptions for two datasets, Cityscapes [16] and PASCAL VOC 2012 [22].

2. Related Work

Robustness studies [77, 68, 36, 26, 20, 21] and robustness enhancement [71, 76, 27, 37, 6, 66] of DCNN architectures [47, 65, 63, 10, 11, 12] have been addressed in various benchmarks [22, 16, 19]. Vasiljevic et al. [68] examined the impact of blur on the tasks of classification and semantic segmentation with VGG-16 [65] architecture. Model performance decreases with an increased degree of blur for both tasks. We also focus in this work on semantic segmentation but evaluate on a much wider range of real-world image corruptions.

Geirhos et al. [26] compared the generalization capabilities of humans and Deep Neural Networks (DNNs). The ImageNet dataset [19] is modified in terms of color variations, noise, blur, and rotation. Interestingly, models which were trained directly on noisy data did not generalize well to other types of noise. In this work, we show that semantic segmentation models generalize considerably well on unseen types of noise when trained on specific noisy data.

Hendrycks et al. [36] introduce the “ImageNet-C dataset”. In this work, the ImageNet dataset is corrupted by 19 different image corruptions. Although the absolute performance scores increase from AlexNet [47] to ResNet [34], the robustness of the respective models does barely change. They further show that Multigrid and DenseNet architectures [46, 40] are less prone to noise corruption than ResNet architectures. In this work, we use most of the proposed im-
age transformations and apply them to Cityscapes and PASCAL VOC 2012 dataset [16, 22].

Geirhos et al. [25] demonstrated that humans and DNNs classify images with different strategies. Unlike humans, DNNs trained on ImageNet seem to rely more on local texture instead of global object shape. The authors then demonstrated that model robustness with respect to image corruptions increases, when CNNs rely more on object shape than on object texture.

Robustness of models with respect to adversarial examples is an active field of research [41, 5, 15, 29, 8, 55, 7]. Arnab et al. [2] evaluate the robustness of semantic segmentation models for adversarial attacks of a wide variety of network architectures (e.g. [75, 4, 59, 74, 73]). In this work we adopt a similar evaluation procedure, but we do not focus on the robustness with respect to adversarial attacks, which are typically not realistic, but rather on physically realistic image corruptions.

Ford et al. [24] connect adversarial robustness and robustness with respect to image corruption of Gaussian noise. The authors showed that training procedures which increase adversarial robustness also improve robustness with respect to many image corruptions.

3. Image Corruption Models

We evaluate the robustness of semantic segmentation models towards a broad range of image corruptions. Besides using image corruptions from the ImageNet-C dataset, we propose new and more realistic image corruptions.

3.1. ImageNet-C

We employ most image corruptions from the ImageNet-C dataset [36]. These consist of several types of blur: motion, defocus, frosted glass and Gaussian; Noise: Gaussian, impulse, shot and speckle; Weather: snow, spatter, fog and frost; and Digital: brightness, contrast, and JPEG compression. Each corruption is parameterized with five severity levels. We refer to the supplemental material for an illustration of these corruptions.

3.2. Additional Realistic Image Corruptions

Realistic HDR Noise Model. DCNNs are prone to noise. Previous noise models are often simplistic, e.g., images are evenly distorted with Gaussian noise. However, real image noise significantly differs from the noise generated by these simple models. Real image noise is a combination of multiple types of noise (e.g., photon noise, kTC noise, dark current noise as described in [35, 72, 54, 52]). For multi-capture HDR cameras, such as the ones used in autonomous [16] and modern photography, the resulting image noise is even more complex [56]. Each capture is affected by noise depending on the exposure time and sensor properties. The captures are then combined and tone-

![Figure 2: A crop of a validation image of Cityscapes corrupted by various noise models. (a) Clean image. (b) Shot noise. (c) Gaussian noise. (d) Our proposed noise model. The amount of noise is low in regions with high pixel intensity. As in real camera noise, darker regions exhibit more noise than brighter ones. Color-noise is transformed to gray-scale noise for saturated pixels in the rear light.](image_url)

mapped into a high dynamic range image. Image noise hence depends on sensor and environmental properties as well as the camera exposure control states and the image reconstruction.

We propose a noise model that mimics the noise behavior of multi-capture HDR cameras. Our noise model consists of two noise components: i) an intensity-level dependent noise component. It is added to the original pixel intensities in linear color space. ii) an exposure-dependent noise component. The linearized pixel intensities are partitioned into multiple segments, each associated with a distinct weight factor. In accordance to image noise observed from real-world multi-capture HDR cameras, pixels with low intensities are noisier than pixels with high intensities and pixels of longer exposures are noisier than pixels of shorter exposures. We model the noisy pixel intensity for a color channel as a random variable $I_{\text{noise},c}$:

$$I_{\text{noise},c} (\Phi_c, N, N_c; w_s, w_{s,e}) = \log_2 ((2^{\Phi_c} + w_s \cdot N) \cdot (1 + w_{s,e} \cdot N_c))$$

where $\Phi_c$ is the normalized pixel intensity of color channel $c$, $N$ and $N_c$ are random variables following a Normal distribution with mean $\mu$ and standard deviation $\sigma$, $w_s$ is a weight factor for the intensity-level dependent noise component, parameterized by severity level $s$, $w_{s,e}$ is a weight factor for the exposure-dependent noise component, parameterized by $s$ and exposure $e$ of the corresponding segment.

For saturated pixels, our image noise model transforms color noise to gray-scale noise. This method is used in modern image signal processing units. If a color-channel saturates, its value is discarded, and an average intensity value of remaining channels is set.

Fig. 2 illustrates noisy variants of a Cityscapes image-crop. In contrast to the other, simpler noise models, the amount of noise generated by our noise model depends significantly on pixel intensity.

\[\text{Note that we are limited with the level of realism of our noise model since publicly available datasets like Cityscapes and PASCAL VOC 2012 are lacking these data, which is necessary for modeling physically correct HDR camera noise.}\]
PSF blur. Every optical system of a camera exhibits aberrations, which mostly result in image blur. A point-spread-function (PSF) aggregates all optical aberrations that result in image blur [44]. We denote this type of corruption as PSF blur. Unlike simple blur models, such as Gaussian blur, real-world PSF functions are spatially varying. We corrupt the Cityscapes dataset with three different PSF functions that we have generated with the optical design program Zemax, for which the amount of blur increases with a larger distance to the image center.

Geometric distortion. Every camera lens exhibits geometric distortions [23]. We applied several radially-symmetric barrel distortions [70] as a polynomial of grade 4 [64] to both the RGB-image and respective ground truth.

4. Models

We employ DeepLabv3+ [13] as the reference architecture. We chose DeepLabv3+ for several reasons. It supports numerous network backbones, ranging from novel state-of-art models (e.g., modified aligned Xception [14, 13, 18], denoted by Xception) and established ones (e.g., ResNets [34]). For semantic segmentation, DeepLabv3+ utilizes popular architectural properties, making it a highly suitable candidate for an ablation study. Please note that the range of network backbones, offered by DeepLabv3+, represents different execution times since different applications have different demands.

4.1. DeepLabv3+

Fig. 3 illustrates important elements of the DeepLabv3+ architecture. A network backbone (ResNet, Xception or MobileNet-V2) processes an input image [34, 62, 39]. Its output is subsequently processed by a multi-scale processing module, extracting dense feature maps. This module is either Dense Prediction Cell [9] (DPC) or Atrous Spatial Pyramid Pooling (ASPP). We consider the variant with ASPP as original DeepLabv3+, i.e., reference architecture. A long-range link concatenates early features of the network backbone with encoder output. Finally, the decoder outputs estimates of semantic labels. Our reference model is shown by normal arrows (i.e. without DPC). The dimension of activation volumes is shown after each block.

Long-range link. A long range link concatenates early features of the encoder with features extracted by the respective multi-scale processing module [30]. In more detail, for Xception (MobileNet-V2) based models, the long-range link connects the output of the second or the third Xception block (inverted residual block) with ASPP or DPC output. Regarding ResNet architectures, the long-range link connects the output of the second residual block with the ASPP or DPC output.

4.2. Architectural Ablations

In the next section, we evaluate various ablations of the DeepLabv3+ reference architecture. In detail, we remove atrous convolutions (AC) from the network backbone by transforming them to regular convolutions. We denote this ablation in remaining sections as w/o AC. We further removed the long-range link (LRL, i.e., w/o LRL) and Atrous Spatial Pyramid Pooling (ASPP) module (w/o ASPP). The removal of ASPP is replaced by Dense Prediction Cell (DPC) and denoted as w/o ASPP+w/DPC.

5. Experiments

We present the experimental setup (sec. 5.1) and then the results of three different experiments. Please note that various experimental details and images are available in the supplement. We firstly benchmark multiple neural network
backbone architectures (sec. 5.2). While this procedure gives an overview of the robustness across several architectures, no conclusions about which architectural properties affect the robustness can be drawn. Hence, we modify multiple architectural properties of DeepLabv3+ (sec. 4.2) and evaluate the robustness for re-trained ablated models w.r.t. to image corruptions (sec. 5.3, 5.4). Our findings show that specific architectural properties can have a substantial impact on the robustness of a semantic segmentation model w.r.t. image corruption. Finally, we trained and validated every model directly on image corruptions (sec. 5.5). We report a detailed evaluation w.r.t. severe image noise and show that DeepLabv3+ generalizes considerably well to various types of image noise (section 3.2) when it is trained on our noise model. However, when trained on clean data, or simple noise models, it struggles most when tested on our noise model. Hence, we recommend the usage of our noise model in future work on robustness w.r.t. image corruptions.

5.1. Experimental Setup

Network backbones. We trained DeepLabv3+ with several network backbones on clean and corrupted data using TensorFlow [1]. We utilized MobileNet-V2, ResNet-50, ResNet-101, Xception-41, Xception-65 and Xception-71 as network backbones. Every model has been trained with batch size 16, crop-size $513 \times 513$, fine-tuning batch normalization parameters [42], initial learning rate 0.01 or 0.007, and random scale data augmentation. We did not apply global average pooling [51].

Datasets. We use PASCAL VOC 2012 and the Cityscapes dataset for training and validation. The training set of PASCAL VOC consists of 1,464 train and 1,449 validation images. We use the high-quality pixel-level annotations of Cityscapes, comprising of 2975 train and 500 validation images. We evaluated all models on original image dimensions.

Evaluation metrics. We apply mean Intersection-over-Union as performance metric (mIoU) for every model and average over severity levels. In addition, we use, and slightly modify, the concept of Corruption Error and relative Corruption Error from [36] as follows.

We use the term Degradation $D$, where $D = 1 - mIoU$ in place of Error. Degradations across severity levels are often aggregated. We divide the degradation $D$ of a trained model $f$ through the degradation of a reference model $ref$. With this the Corruption Degradation (CD) of a trained model is defined as

$$CD^{f}_{c} = \left(\frac{\sum_{s=1}^{5} D^{f}_{s,c}}{\sum_{s=1}^{5} D^{ref}_{s,c}}\right) \quad (2)$$

where $c$ denotes the corruption type (e.g., Gaussian blur) and $s$ its severity level. Please note that for category noise, only the first three severity levels are taken into account. While we predominately use CD for comparing the robustness of model architectures, we also consider the degradation of models relative to clean data, measured by the relative Corruption Degradation (rCD).

$$rCD^{f}_{c} = \left(\frac{\sum_{s=1}^{5} D^{f}_{s,c} - D^{f}_{clean}}{\sum_{s=1}^{5} D^{ref}_{s,c} - D^{ref}_{clean}}\right) \quad (3)$$

5.2. Benchmarking Network Backbones

We trained various network backbones (ResNet, Xception, and MobileNet-V2) on the original, clean training-sets of PASCAL VOC 2012 and the Cityscapes dataset. Table 1 shows the average mIoU for the Cityscapes dataset and each corruption type averaged over all severity levels. As expected, Xception-71 exhibits the best performance for clean data with an mIoU of 77.1\%\textsuperscript{2}. It is followed by Xception-65, Xception-41, ResNet-101, ResNet-50 and MobileNet-V2.

Network backbone performance. Most Xception based models perform significantly better than ResNets and MobileNet-V2.

Performance w.r.t. blur. Interestingly, all models handle PSF blur well, as the respective mIoU decreases only by roughly 2\%. Thus, even a lightweight network backbone such as MobileNet-V2 is hardly vulnerable against this realistic type of blur. The number of both false positive and false negative pixel-level classifications increases, especially far for distant objects. With respect to Cityscapes this means that pedestrians are simply overlooked or confused with similar classes, such as rider. Please find some result images in the Supplemental.

Performance w.r.t. noise. Noise has a very strong impact on model performance. Hence we only averaged over the first three severity levels. Interestingly, Xception-41 and Xception-71 perform similar and Xception-65 oftentimes performs best. MobileNet-V2 is not able to handle corruption of category noise, as mIoU often falls below 10\%.

Performance w.r.t. digital. Most models handle changes in brightness and contrast relatively well, they struggle with saturation and JPEG compression artifacts.

Performance w.r.t. weather. Snow and frost show very strong effects on the performance, causing mIoU of Xception-71 to fall below 20\%.

Performance w.r.t. Geometric distortion. Barrel distortion decreases performance by 6.5\% to 10\%.

To evaluate the robustness w.r.t. image corruptions of proposed network backbones, it is also interesting to consider Corruption Degradation (CD) and relative Corruption Degradation (rCD). Fig. 4 illustrates the CD and

\textsuperscript{2}Note that we were not able to reproduce the results from [13]. We conjecture that this is due to hardware limitations, as we could not set the suggested crop-size of $769 \times 769$ for Cityscapes.
Table 1: Average mIoU for clean and corrupted variants of the Cityscapes validation set for several network backbones of the Deeplabv3+ architecture. Every mIoU is averaged over all available severity levels, except for corruptions of category noise where only the first three severity levels are considered. Xception based network backbones are usually most robust against each corruption. Every model is robust against our realistic PSF blur. Noise has very strong effects on the performance of all models, but especially on MobileNet-V2. Highest mIoU per corruption is bold.

| Architecture   | Clean | Motion | Defocus | Frusted Glass | Gaussian | PSF | Impulse | Shot | Speckle | Realistic |
|----------------|-------|--------|---------|---------------|----------|-----|---------|------|---------|-----------|
| MobileNet-V2   | 72.0  | 53.5   | 49.0    | 45.3          | 49.1     | 70.8| 6.4     | 7.0  | 6.6     | 16.6      |
| ResNet-50      | 75.7  | 55.8   | 52.4    | 45.0          | 54.0     | 72.3| 8.3     | 8.3  | 11.9    | 29.8      |
| ResNet-101     | 76.5  | 57.0   | 52.5    | 45.9          | 53.3     | 72.4| 5.6     | 4.9  | 8.4     | 29.1      |
| Xception-41    | 76.5  | 60.4   | 55.7    | 50.9          | 55.3     | 74.4| 16.7    | 13.6 | 20.6    | 41.5      |
| Xception-65    | 76.8  | 62.4   | 56.0    | 52.6          | 55.1     | 74.6| 17.1    | 14.5 | 22.5    | 44.3      |
| Xception-71    | 77.1  | 62.6   | 58.2    | 54.8          | 57.0     | 75.5| 16.5    | 13.5 | 20.6    | 40.9      |

Table 4: Robustness of Deeplab-v3+ Backbones

5.3. Ablation Study on Cityscapes

Instead of solely comparing robustness across network architecture backbones, we conduct now an extensive ablation study for DeepLabv3+. We employ the state-of-the-art performing Xception-71 (XC-71) and its lightweight counterpart, MobileNet-V2 (MN-V2, width multiplier 1, 224 × 224), as network backbones. Xception-71 is the best performing backbone on clean data, but at the same time computationally most expensive. The efficient MobileNet-V2, on the other hand, requires roughly 10 times less storage space. For both architectures, we ablated the same properties of the DeepLabv3+ model (section 4.2). Each ablated variant has been re-trained on clean data. Table 2 shows the averaged mIoU, evaluated on Cityscapes.

We see that with Dense Prediction Cell (DPC) and Xception-71 we achieve the highest performance followed by the reference model. We also see that removing ASPP reduces the mIoU significantly for both backbones.

In order to better understand the robustness of each ablated model, we illustrate the CD in Fig. 5. Each degradation is aggregated over severity levels and across corruptions of the same category. Please see the Supplemental regarding rCD, which has, in general, a similar tendency as CD.

Effect of ASPP. Removal of ASPP reduces model performance significantly (Table 2 first column). Hence, we refer to the Supplement for a detailed evaluation.

Effect of AC. Atrous convolutions (AC) show a positive effect w.r.t. corruptions of type blur for both network backbones, especially for Xception-71. Without AC, for defocus and Gaussian blur, the average mIoU decreases by 3.4 % (CD = 108 %) and 2.9 % (CD = 107 %), respectively. Blur reduces high-frequency information of an image, leading to...
similar signals stored in consecutive pixels. Hence, applying AC can increase the information amount per convolution filter, by skipping direct neighbors with similar signals. Regarding Xception-71, AC clearly enhance robustness on each type of noise. Removing AC reduces the average mIoU on Gaussian noise by 5.2% (CD = 106%). AC exhibit also a positive effect w.r.t. geometric distortion. For both backbones, the average mIoU reduces by roughly 2% (CD_{Xception-71} = 106%, CD_{MobileNet-V2} = 106%). In general, atrous convolutions increase model robustness against most image corruptions.

Effect of DPC. When employing Dense Prediction Cell (DPC) instead of ASPP, the model becomes clearly vulnerable against corruptions of most categories. While this ablated architecture reaches the highest mIoU on clean data, it is less robust to a broad range of corruptions. For example, CD for defocus blur on MobileNet-V2 is 113%, and average mIoU decreases by 6.8%. With regards to Xception-71, CD for all corruptions of category noise ranges between 107% and 113%. The average mIoU of this ablated variant is least for all, but one, type of noise (Table 2).

DPC has been found by a neural-architecture-search (NAS, e.g., [79, 78, 60]) with the objective to maximize performance on clean data. This result indicates that such architectures tend to over-fit on this objective i.e. clean data. Consequently, performing NAS on corrupted data might deliver interesting findings of robust architectural properties similar as in [17] w.r.t. adversarial examples.

Effect of LRL. Both network backbones are with a without a long-range link (LRL) vulnerable against noise, especially against Gaussian, impulse and shot noise. Regarding Xception-71, the removed LRL shows a positive effect against corruptions which mutate pixel intensities (e.g., brightness, contrast, and fog). Respective CD scores are 97%, 96% and 94%. Performance for fog in terms of mIoU is larger by 2.6% (Fig. 1). However, the model is more vulnerable w.r.t. blur. Regarding MobileNet-V2, the removal of the LRL decreases robustness w.r.t. blur and geometric distortion as average mIoU reduces by 5.1% (CD = 110%) and 4.6% (CD = 113%), respectively.

5.4. Ablation Study on PASCAL VOC 2012

In general, we observe that the effect of the architectural ablations for DeepLabv3+ architecture w.r.t. image corruptions, employing Xception-71 and MobileNet-V2 as network backbones. Bars above 100% represent a decrease in performance compared to the respective reference architecture. Each ablated architecture is re-trained on the original training dataset. Removing ASPP reduces model performance significantly. Atrous convolutions increase robustness against blur. The model becomes vulnerable against most effects when Dense Prediction Cell is used.

Figure 5: CD evaluated on Cityscapes for the proposed ablated variants of the DeepLabv3+ architecture w.r.t. image corruptions, employing Xception-71 and MobileNet-V2 as network backbones. Bars above 100% represent a decrease in performance compared to the respective reference architecture. Each ablated architecture is re-trained on the original training dataset. Removing ASPP reduces model performance significantly. Atrous convolutions increase robustness against blur. The model becomes vulnerable against most effects when Dense Prediction Cell is used.

Table 2: Average mIoU for clean and corrupted variants of the Cityscapes validation dataset for Xception-71, MobileNet-V2, and four corresponding architectural ablations. Based on DeepLabv3++ we evaluate the removal of atrous spatial pyramid pooling (ASPP), atrous convolutions (AC) and long-range link (LRL). We further replaced ASPP by Dense Prediction Cell (DPC). Every mIoU is averaged over all severity levels, except for corruptions of category noise where only the first three severity levels are considered. Highest mIoU per corruption and network backbone are bold.
and Xception-71 w.r.t. geometric distortion. For Xception-41, we see a positive effect of AC against image noise.

**Effect of DPC.** As on Cityscapes, DPC decreases robustness for almost all corruptions. Generally, CD increases from Xception-41 to Xception-71. The impact on Xception-71 is especially strong as indicated by the CD score, averaged over all corruptions, is 107%. A possible explanation might be that the neural-architecture-search (NAS) e.g., [79, 78, 60] has been performed on Xception-71 enhancing the over-fitting effect, as discussed in section 5.3.

**Effect of LRL.** Unlike on Cityscapes, removing LRL increases robustness against noise for Xception-71 and Xception-41. However, this finding does not hold for Xception-65. As reported in section 5.2, on PASCAL VOC 2012 Xception-65 is also the most robust model against noise. Contrary to Cityscapes, the models are vulnerable to brightness, contrast, and fog corruption.

### 5.5. Noise Study on Cityscapes

Since the previous experiments have shown that image noise affects the performance of our models most, we study it in the following in more detail. In particular, we train DeepLabv3+ on corrupted data of Cityscapes, here on the first three intensity levels of speckle noise\footnote{We also add the clean images to the training set and, as suggested in [36], the corrupted images with Gaussian Blur and Saturation.}. Fig. 6 shows the performance of Xception-71, evaluated on noisy variants of Cityscapes. To make noise models mutually comparable, we averaged their Signal-to-Noise ratio (SNR) over the validation-set. Each abscissa represents averaged SNR of an intensity level of the respective noise model. For ease of reference, solely SNR=mIoU data pairs exhibiting an SNR of at least 5 dB are shown.

In contrast to the task of classification, the model is able to generalize quite well to a wide range of noise models. As expected, the model performs best for the noise type it was trained for (i.e., speckle noise). The model even performs quite well for a noise level around 7 dB, i.e. 3 dB less than the highest noise level it was trained for. Note that a decrease of 3 dB corresponds to doubling the amount of noise, which is the case for the third severity level of Gaussian, impulse and shot noise.

Interestingly, the model performs worst for our noise model. This shows that our noise model is more complex than speckle noise. Employing another backbone (MobileNet-V2) and evaluating on another dataset (PASCAL VOC 2012) shows similar outcomes, see supplement. Our final analysis (Fig. 6 bottom) shows the validation performance of Xception-71 when it was trained on our realistic noise model. Surprisingly, the model still performs worse for our noise model, although it was trained for it. The performance for the other noise models is considerably better, and also slightly better, overall, than in Fig. 6 (top).

### 6. Conclusion

We have presented a detailed, large-scale evaluation of state-of-the-art semantic segmentation models with respect to real-world image corruptions. Based on the study we report various findings about the robustness of specific architectural choices. On one hand, these findings are useful for practitioners, to design the right model for their task at hand, where the types of image corruptions are often known. On the other hand, our detailed study may help to improve on the state-of-the-art for robust semantic segmentation models. When designing a semantic segmentation module for a practical application, such as autonomous driving, it is crucial to understand the robustness of the module with respect to a wide range of image corruptions.
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Supplemental Material

We provide further information about the utilized image corruptions and the conducted experiments. In more detail, we show examples of every image corruption, and we give further details of our proposed image corruptions (section A). We provide supplementary information about the experimental setup (section B.1), and we show qualitative results (section B.2). In addition, we report the individual evaluation metric scores (i.e., mIoU, CD, and rCD), especially for PASCAL VOC 2012 (section B.3). Finally, we provide further results for our proposed study on severe noise (section B.6) and, also, on other image corruptions (section B.7).

A. Image Corruption Models

A.1. ImageNet-C

Fig. 7 shows the utilized image corruptions of the categories blur, noise, digital, and weather of ImageNet-C. To make the image corruption clearly visible, we selected each example of severity level three or higher. The Figure is best viewed on a color screen.

A.2. Proposed Realistic Image Corruptions

In this section, we provide more details about PSF blur and geometric distortion. Fig. 9 shows examples of our proposed image corruptions. Please note that we show in this Figure the corresponding full-sized image of the displayed crop of Fig. 2 in the main paper.

PSF blur. Every optical system, e.g., the lens array of a camera, exhibits optical aberrations. Not all, but many of them, cause image blur. Point-spread-functions aggregates every optical aberration that results in blur. The point-spread-functions of an optical system are typically spatially-varying, e.g., the degree of blur is at the image edge more pronounced than, in the center of the image. Fig. 10 illustrates the intensity distribution of a PSF kernel, where most of its energy is punctually centered.

Figure 10: The normalized intensity distribution of a PSF kernel of our proposed PSF blur.

Fig. 8 illustrates the intensity distribution of several PSF kernels utilized in the main paper. Each row corresponds to a specific PSF blur kernel at the respective angle of incidence, i.e., the larger the angle of incidence, the larger the distance to the image center. Note that the PSF kernel varies its shape within a severity level (i.e., column). The intensity of a PSF kernel is spatially more distributed for larger severity levels.

Geometric distortion. We used the command-line tool ImageMagick to apply a radially-symmetric barrel distortion as a polynomial of grade 4 to both the RGB and ground-truth images. It is essential to use the nearest-neighbor filter for color determination of the ground truth, as otherwise the class labels are corrupted.

B. Experiments

This section contains experimental details, a listing of remaining evaluation metric scores, and additional results with respect to the study on severe image noise (section 5.5 in the main paper).

B.1. Experimental Details

Hardware Setup. We trained every model using four GTX 1080 Ti, each having 11 GB of memory. Training the reference model with Xception-71 on Cityscapes required us to decrease of the suggested crop size from 769 to 513. We kept the crop size for a specific dataset consistent and hence used the crop size 513 for every training. We applied the original training protocol of the developers of DeepLabv3+. For example, we use a weight day of 0.00004 for MobileNet-V2 and Xception-based network backbones and 0.0001 for ResNet based network backbones. We applied a polynomial learning rate with an initial learning rate of 0.007 or 0.01.

Training protocol on Cityscapes. We trained every model with a batch size of 16. On clean data, we trained DeepLabv3+ and every ablation for 90,000 iterations (about three days per training). On corrupted data, we trained these models for 250,000 iterations (about eight days per training).

Training protocol on PASCAL VOC 2012. We trained every model also with a batch size of 16. On clean data, we trained DeepLabv3+ and every ablation for 45,000 iterations (about 6 hours per training). On corrupted data, we trained these models for 90,000 iterations (about 12 hours per training).

B.2. Qualitative Results

We provide qualitative results in this section. As mentioned in the main paper, blurred images cause the models to miss-classify pixels of classes covering small image regions, especially when far away. Please see Fig. 11 for an example. (a) shows a blurred validation image of the Cityscapes dataset and the corresponding ground truth in (b). (c) the prediction on the clean image overlaid with the ground truth (b). In this visualization, true-positives are
Figure 7: Illustration of utilized image corruptions of ImageNet-C. First row: Motion blur, defocus blur, frosted glass blur. Second row: Gaussian blur, Gaussian noise, impulse noise. Third row: Shot noise, speckle noise, brightness. Fourth row: Contrast, saturate, JPEG. Fifth row: Snow, spatter, fog. Sixth row: frost.
Figure 8: The intensity distribution of used PSF kernels. The degree of spatial distribution of intensity increases with the severity level. The shape of the PSF kernel depends on the image region, *i.e.*, the angle of incidence.

Figure 9: Illustration of our proposed image corruptions. From left to right: Proposed noise model, PSF blur, and geometric distortion. Best viewed on a color screen.
alpha-blended, and false-positives as well as false-negatives remain unchanged. Hence, wrongly classified pixels can be easier spotted. (d) the prediction on the blurred image overlaid with the ground truth (b). Whereas the riders and pedestrians are mostly correctly classified in (c), riders in (d) are miss-classified as pedestrian, and extensive areas of road are miss-classified as pavement. We used the reference model along with Xception-71 as network backbone to produce these predictions.

We report in the main paper, that image noise affects model performance the most, as pointed out using mIoU scores. To give a visual example, we selected two noisy variants of a validation image of the Cityscapes dataset and show the predictions of the reference architecture using Xception-71 as network backbone in Fig. 12. The mIoU for both predictions is less than 15%.

Finally, we show qualitative results of every ablated architecture for one image corruption of category blur, noise, digital, and weather. Fig. 13 shows a blurred validation image of the Cityscapes dataset and the corresponding predictions. Note that the ablated variants w/o AC and w/ DPC are especially vulnerable. Fig. 14 shows a noisy validation image of the Cityscapes dataset. Note that the ablated variants w/o AC, w/o ASPP and w/ DPC are especially vulnerable. Fig. 15 and Fig. 16 show a validation image of PASCAL VOC 2012, corrupted by brightness and snow, respectively.

B.3. Experimental Results

In this section, we provide individual mIoU, CD and rCD scores for both the Cityscapes dataset and PASCAL VOC 2012. Table 4 contains the average mIoU for clean and corrupted variants of the validation set of PASCAL VOC 2012 for several network backbones of the DeepLabv3+ architecture. In contrast to the model performance evaluated on Cityscapes, corruptions of category noise and weather have less impact. Xception-71 has the highest mIoU for most corruptions. Xception-65 has for most corruptions of category noise a similar performance. Concerning the ablation study of the main paper, Table 5 shows the averaged mIoU for clean and corrupted variants of the validation set of PASCAL VOC 2012. We used Xception-41, Xception-65, and Xception-71 as network backbones. For all backbones, we ablated the same architectural properties of the DeepLabv3+ model. Each ablated variant has been re-trained on clean data. The models perform significantly worse without ASPP. Regarding Xception-41, the ablated variant without long-range link often has the highest mIoU. Regarding Xception-65, the reference architecture often has the highest mIoU. For Xception-41 and Xception-71, the ablated variant without long-range link often has the highest mIoU for image corruptions of category noise.

**Performance of ablated variant w/o ASPP.** The Atrous Spatial Pyramid Pooling (ASPP) module reduces the model performance significantly. On PASCAL VOC 2012, the average mIoU on clean data reduces by 8.6% (Xception-41), 5.9% (Xception-65), and 6.2% (Xception-71) see Tab. 5. On Cityscapes, the average mIoU decreases by 7.1% (Xception-71) and 7.6% (MobileNet-V2) (see Tab. 2 in the main paper). Therefore, the CD score is in general considerably large. On PASCAL VOC 2012, for example, the CD score for the ablated variant w/o ASPP is the largest for every image corruption and for every network backbone (see bold values Tab. 6). Regarding the evaluation on Cityscapes (see Tab. 8), the CD score of the ablated variant w/o ASPP is against image corruptions of category blur the largest for both datasets. However, with respect to corruptions of category noise, other ablated variants, as DPC along with Xception-71, have even larger CD scores. Interestingly, regarding MobileNet-V2, the removal of ASPP increases the robustness against image noise, as the CD scores are below 100%. However, as shown in Tab. 2 in the main paper, the performance of MobileNet-V2 on that type of corruption is drastically poor.

B.4. rCD on Cityscapes

In the main paper, we evaluated ablated variants mainly with the CD score. We now also report the corresponding rCD scores. Recall that the rCD incorporates the degradation on clean data (see Eq. 3 in the main paper). Fig. 17 illustrates the rCD score of each ablated variant across image corruptions of a certain category, evaluated on Cityscapes. Bars above 100% represent lower robustness (in terms of rCD) compared to the respective reference architecture.

**Effect of ASPP.** The rCD score is especially small for corruptions of geometric distortion (62% on Cityscapes, 46% on MobileNet-V2). Regarding MobileNet-V2, the averaged mIoU is even in a comparable range as the other ablated variants (see the last column of Tab. 2 in the main paper). A possible explanation is that models using a multi-scale feature extraction module (as ASPP) learns about the shape and sizes of objects in a scene. These properties are geometrically distorted: the content in and near the image center is enlarged and compressed near the image edges (see the image on the right in Fig. 9). Generally, geometric barrel distortion seems to affect the model performance, in terms of rCD, less than it affects both the reference model and ablated variants.

**Effect of AC.** For both network backbones without atrous convolutions, the rCD with respect to geometric distortion is exceptionally significant. The aiding effect of AC against image blur and noise is in terms of rCD especially present for Xception-71. For this ablated variant, the rCD score shows the same tendency as the CD score illustrated in the main paper.

**Effect of DPC.** The rCD scores for the ablated variant without ASPP and with Dense Prediction Cell, shows the
Figure 11: Prediction of the reference architecture (i.e. original DeepLabv3+) on blurred input, using Xception-71 as network backbone. (a) a blurred validation image of the Cityscapes dataset and corresponding ground truth (b). (c) prediction on the clean image overlaid with the ground truth. True-positives are alpha-blended, false-positives and false-negatives remain unchanged. Hence, wrongly classified pixels can be easier spotted. (d) prediction on the blurred image overlaid with the ground truth (b). Whereas the riders are mostly correctly classified in (c), they are in (d) miss-classified as pedestrian. Extensive areas of road are miss-classified as pavement.

Figure 12: Drastic influence of image noise on model performance. (a) a validation image of Cityscapes is corrupted by the second severity level of Gaussian noise and respective prediction (b). (c) a validation image of Cityscapes is corrupted by the third severity level of Gaussian Noise and respective prediction (d). Predictions are produced by the reference model, using Xception-71 as the backbone.

Figure 13: Predictions of reference architecture and ablations on a blurred image. The ablated variants w/o AC and w/ DPC are especially vulnerable to blur.

Figure 14: Predictions of reference architecture and ablations on a noisy image. The ablated variants w/o AC, ASPP, and w/ DPC are especially vulnerable.
Figure 15: Predictions of reference architecture and ablations on a validation image of PASCAL VOC 2012, corrupted by brightness.

Figure 16: Predictions of reference architecture and ablations on a validation image of PASCAL VOC 2012, corrupted by snow.
Table 4: Average mIoU for clean and corrupted variants of the validation set of PASCAL VOC 2012 for several network backbones of the DeepLabv3+ architecture. Every mIoU is averaged over all available severity levels, except for corruptions of category noise where only the first three severity levels are considered. Highest mIoU per corruption is bold.

| Architecture | Clean | Blur | Noise | Digital | Weather | Geometric Distortion |
|--------------|-------|------|-------|---------|---------|----------------------|
| DeepLabv3+   |       |      |       |         |         |                      |
| Xception-41  | 75.5  | 77.6 | 76.5  | 76.7    | 76.1    |                      |
| w/o ASPP     | 66.9  | 67.2 | 65.6  | 65.2    | 64.8    |                      |
| w/o AC       | 75.0  | 76.5 | 75.3  | 76.0    | 75.4    |                      |
| w/o LRL      | 76.1  | 77.6 | 76.5  | 76.7    | 76.1    |                      |
| Xception-65  | 76.6  | 77.7 | 76.6  | 76.7    | 76.0    |                      |
| w/o ASPP     | 70.6  | 71.5 | 70.3  | 70.4    | 70.0    |                      |
| w/o AC       | 76.4  | 77.4 | 76.3  | 76.4    | 76.0    |                      |
| w/o LRL      | 78.2  | 78.7 | 78.2  | 78.3    | 78.0    |                      |
| Xception-71  | 76.7  | 77.6 | 76.5  | 76.5    | 76.1    |                      |
| w/o ASPP     | 70.5  | 71.4 | 70.3  | 70.4    | 70.0    |                      |
| w/o AC       | 76.3  | 77.3 | 76.2  | 76.3    | 76.0    |                      |
| w/o LRL      | 78.3  | 78.8 | 78.3  | 78.4    | 78.1    |                      |

Table 5: Average mIoU for clean and corrupted variants the validation dataset of PASCAL VOC 2012 for Xception-41, Xception-65, Xception-71, and corresponding architectural ablations. Based on DeepLabv3+ we evaluate the removal of atrous spatial pyramid pooling (ASPP), atrous convolutions (AC) and long-range link (LRL). We further replaced ASPP by Dense Prediction Cell (DPC). Every mIoU is averaged over all severity levels, except for corruptions of category noise where only the first three severity levels are considered. Highest mIoU per corruption and network backbone are bold.

**Effect of LRL.** Contrary to the CD score with respect to geometric distortion on Xception-71, the tendency of the rCD for the ablated variant without LRL is mostly similar. Even though the rCD for geometric distortion is 83 %, the averaged mIoU differs only by 0.5 % and the CD is around 100 %, which qualifies this low rCD score.

**B.5. rCD on PASCAL VOC 2012**

Fig. 18 illustrates the rCD score of each ablated variant across image corruptions of a certain category, evaluated on PASCAL VOC 2012.

**Effect of ASPP.** For geometric distortion, this ablated variant shows a similar tendency as on Cityscapes for every network backbone. The rCD for Xception-41, Xception-65, and Xception-71 are 60 %, 62 %, and 41 %.

**Effect of AC.** As mentioned in the main paper, AC show no positive effect against blur. We explain this with the fundamentally different datasets. On Cityscapes, a model without AC often overlooks classes covering small image-regions, especially when far away. Such images are hardly present in PASCAL VOC 2012. An example for Cityscapes is illustrated in Fig. 11.

**Effect of DPC.** The harming effect of DPC with respect to image corruptions is especially large for Xception-71. As
Figure 18: rCD evaluated on PASCAL VOC 2012 for the proposed ablated variants of the DeepLabv3+ architecture w.r.t. image corruptions, employing Xception-based network backbones. Bars above 100% represent a decrease in performance compared to the respective reference architecture. Each ablated architecture is re-trained on the original training dataset.

mentioned in the main paper, a possible explanation might be that the neural-architecture-search has been performed on Xception-71. The performance on clean data is large for Xception-71 (first column in Tab. 4).

Effect of LRL. Regarding Xception-71, the rCD for this ablated variant is 125%. However, the averaged mIoU differs only by 0.4% (see Tab. 5). Regarding Xception-41 and Xception-71, the removal of LRL has a positive effect against image noise.

Finally, we provide individual CD and rCD scores for all image corruptions and both datasets. The CD and rCD scores, evaluated on PASCAL VOC 2012, are shown in Tab. 6 and Tab. 7, respectively. The CD and rCD scores, evaluated on Cityscapes, are shown in Tab. 8 and Tab. 9, respectively.

B.6. Noise Study

In this section, we provide additional results of our proposed study on severe image noise (section 5.5 in the main paper). We trained DeepLabv3+ on corrupted data of Cityscapes and PASCAL VOC 2012, here on the first three intensity levels of speckle noise, Gaussian blur and saturate. To make noise models mutually comparable, we averaged their Signal-to-Noise ratio over the training-set and validation-set. Table 10 shows the SNR values for various types of image noise as well as the corresponding severity level for the Cityscapes dataset and PASCAL VOC 2012. Note, that the average SNR of training-set and validation-set for a particular severity level and type of noise is very similar. As reported in the main paper, the reference model struggles the most when evaluated on our noise model. In the following, we report that employing other network backbones or evaluating on PASCAL VOC 2012 (instead of Cityscapes), show a similar result. Fig. 19 shows the performance of several network backbones, evaluated on noisy variants of Cityscapes and PASCAL VOC 2012. Each abscissa represents averaged SNR of an intensity level of the respective noise model and the respective validation-set. For ease of reference, solely SNRmIoU data pairs exhibiting an SNR above 5 dB are shown. Fig. 19 (a) shows the performance of MobileNet-V2 on noisy variants on Cityscapes. Note that the model is very vulnerable to image noise when it is trained only on clean data. The model performance on all types of noise enhances significantly when we train the model on speckle noise. Fig. (b – d) show the performance of Xception-based network backbones, evaluated on PASCAL VOC 2012. Compared to the model performance on Cityscapes, the model performs better on all types of noise. This is probably due to the different types of datasets: The combination of i) a larger number of classes in a single image of Cityscapes and ii) classes covering small image regions, cause the mIoU to decrease rapidly fast (when evaluated on Cityscapes). Note that every model performs almost for all severity levels worst on our proposed noise model, especially when trained on speckle noise. The latter result indicates that our noise model is more complex than speckle noise.

B.7. Study on other Corruptions

As we trained the models in addition on a corruption of type blur and digital, we can evaluate the results accordingly to the previous section.

Study on image blur. We use the SNR also for blur to make the image corruptions mutually comparable. Table 13 lists the SNR values for various types of image blur, and the corresponding severity level for the Cityscapes dataset and PASCAL VOC 2012. Again, the SNR values between validation and training set are considerably similar. Note, that the SNR of frosted glass blur is not steadily decreasing for increasing severity levels. When we visually evaluate this type of corruption, no rapid increase in the degree of blur can be observed. However, the shape of the blur appears to be more granular, which is not affecting the SNR. Fig. 20 and Fig 21 shows the performance of several network backbones, evaluated on noisy variants of Cityscapes and PASCAL VOC 2012, respectively. For ease of reference, we excluded frosted glass blur from the Figures and report their mIoU per severity level and SNR in Tab. 11 and Tab. 12. Please note, that we could apply PSF blur only on the Cityscapes dataset. Hence, the corresponding column is not present in evaluations on PASCAL VOC 2012. Each abscissa in Fig. 20 and Fig 21 represents the averaged SNR of an intensity level of both the respective type of blur and the respective validation-set. We trained DeepLabv3+ on the first three intensity levels of Gaussian blur. Compared to the study on noise, the performance gap between the models when trained on clean and corrupted data is less.
### Table 6: CD for corrupted variants of the validation dataset of PASCAL VOC 2012 for Xception-71, Xception-65, Xception-71, and corresponding architectural ablations. Largest CD per backbone (i.e., the ablated variant w/o ASPP) and corruption is bold.

| Blurred/Noisy | Motion | Defocus | Frosted Glass | Gaussian | Impulse | Shot | Speckle | Geometric Distortion |
|---------------|--------|---------|----------------|----------|---------|------|---------|---------------------|
| Xception-71   | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o AC  | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o ASPP | 93     | 104            | 99       | 100     | 100  | 100     | 100                 |
|               | w/o ASPP + w/ DPC | 100  | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |

### Table 7: CD for corrupted variants of the validation dataset of PASCAL VOC 2012 for Xception-41, Xception-65, Xception-71, and corresponding architectural ablations. Largest or smallest CD per backbone and corruption is bold.

| Blurred/Noisy | Motion | Defocus | Frosted Glass | Gaussian | Impulse | Shot | Speckle | Geometric Distortion |
|---------------|--------|---------|----------------|----------|---------|------|---------|---------------------|
| Xception-41   | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o AC  | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o ASPP | 93     | 104            | 99       | 100     | 100  | 100     | 100                 |
|               | w/o ASPP + w/ DPC | 100  | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |

### Table 8: CD for corrupted variants of the Cityscapes dataset for Xception-71, MobileNet-V2 and corresponding architectural ablations. Largest or smallest CD per backbone and corruption is bold.

| Blurred/Noisy | Motion | Defocus | Frosted Glass | Gaussian | Impulse | Shot | Speckle | Geometric Distortion |
|---------------|--------|---------|----------------|----------|---------|------|---------|---------------------|
| Xception-71   | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o AC  | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o ASPP | 93     | 104            | 99       | 100     | 100  | 100     | 100                 |
|               | w/o ASPP + w/ DPC | 100  | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |

### Table 9: CD for corrupted variants of the Cityscapes dataset for Xception-71, MobileNet-V2 and corresponding architectural ablations. Largest or smallest CD per backbone and corruption is bold.

| Blurred/Noisy | Motion | Defocus | Frosted Glass | Gaussian | Impulse | Shot | Speckle | Geometric Distortion |
|---------------|--------|---------|----------------|----------|---------|------|---------|---------------------|
| MobileNet-V2  | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o AC  | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o ASPP | 93     | 104            | 99       | 100     | 100  | 100     | 100                 |
|               | w/o ASPP + w/ DPC | 100  | 100            | 100      | 100     | 100  | 100     | 100                 |
|               | w/o LRL | 100     | 100            | 100      | 100     | 100  | 100     | 100                 |
Figure 19: Test performance of Xception-71 on several noisy variants of the Cityscapes dataset. Each abscissa corresponds to the averaged Signal-to-Noise ratio over the validation dataset of the respective type of noise. The reference model was trained on the first three intensity levels of speckle noise. It generalizes quite well to a wide variety of noise levels and types. When trained on speckle noise, every model performs worst on our proposed noise model.

### Table 10: Averaged Signal-to-Noise values for noisy variants of the Cityscapes dataset and PASCAL VOC 2012.

| Severity Level | Cityscapes | PASCAL VOC 2012 |
|----------------|------------|-----------------|
|                | Training-Set | Validation-Set | Training-Set | Validation-Set |
| Gaussian Noise |             |                 |              |                |
| 1              | 12.9        | 13.2            | 18.6         | 18.6           |
| 2              | 9.6         | 9.9             | 15.5         | 15.5           |
| 3              | 6.5         | 6.8             | 12.4         | 12.4           |
| 4              | 3.9         | 4.1             | 9.7          | 9.8            |
| 5              | 1.4         | 1.7             | 7.2          | 7.3            |
| Impulse Noise  |             |                 |              |                |
| 1              | 10.8        | 11.2            | 16.6         | 16.7           |
| 2              | 7.8         | 8.1             | 13.7         | 13.8           |
| 3              | 6.1         | 6.4             | 12.0         | 12.1           |
| 4              | 3.3         | 3.6             | 9.2          | 9.3            |
| 5              | 1.3         | 1.6             | 7.2          | 7.2            |
| Shot Noise     |             |                 |              |                |
| 1              | 14.0        | 14.2            | 18.2         | 18.2           |
| 2              | 10.3        | 10.5            | 14.9         | 14.9           |
| 3              | 7.2         | 7.4             | 12.1         | 12.1           |
| 4              | 3.7         | 3.9             | 8.9          | 8.9            |
| 5              | 1.8         | 2.0             | 7.2          | 7.2            |
| Speckle Noise  |             |                 |              |                |
| 1              | 16.9        | 17.0            | 19.3         | 19.3           |
| 2              | 14.5        | 14.5            | 17.1         | 17.1           |
| 3              | 9.7         | 9.8             | 12.9         | 12.8           |
| 4              | 7.8         | 7.9             | 11.0         | 11.0           |
| 5              | 5.7         | 5.8             | 9.2          | 9.2            |
| Realistic Noise (Ours) | | | | |
| 1              | 22.2        | 22.6            | 26.7         | 26.9           |
| 2              | 18.1        | 18.5            | 23.2         | 23.3           |
| 3              | 14.1        | 14.4            | 18.9         | 19.0           |
| 4              | 10.3        | 10.6            | 14.7         | 14.6           |
| 5              | 6.6         | 6.9             | 10.2         | 10.3           |

Table 11: Test performance (mIoU) of MobileNet-V2 and Xception-71 on frosted glass blur, evaluated on Cityscapes. The averaged SNR of the validation set is shown for each severity level. The model are trained on clean or corrupted data (i.e. Gaussian blur).

| Severity Level | Cityscapes | PASCAL VOC 2012 |
|----------------|------------|-----------------|
|                | SNR | Clean | Corrupted |
| Gaussian Noise | 22.4 | 66.6 | 60.7 |
|                | 22.8 | 60.5 | 40.5 |
|                | 18.1 | 49.3 | 33.1 |
|                | 18.8 | 42.6 | 25.6 |
|                | 17.9 | 46.5 | 34.9 |
| MobileNet-V2   | Clean | 67.1 | 63.7 |
|                | Corrupted | 49.6 | 46.2 |
|                | 34.9 | 42.6 | 25.6 |
| Xception-71    | Clean | 72.3 | 69.6 |
|                | Corrupted | 60.9 | 56.9 |
|                | 49.8 | 46.2 | 25.6 |

Table 10: Averaged Signal-to-Noise values for noisy variants of the training and validation set of Cityscapes dataset and PASCAL VOC 2012.
When trained on clean data, the models struggle most for Gaussian blur and frosted glass blur. When trained on corrupted data, the models struggle most for frosted glass blur and motion blur. The performance gap for motion blur, evaluated on Cityscapes (Fig. 20) is hardly given.

**Study on corruptions of category digital.** We again use the SNR also for image corruptions of category digital to make the image corruptions mutually comparable. Table 14 lists the SNR values for various types of digital image corruptions and the corresponding severity level for the Cityscapes dataset and PASCAL VOC 2012. As in the previous section, the SNR values between validation and training set are considerably similar. Please note, that a measure as the Structural Similarity Index (SSIM [69]) could be a more suitable metric for these image corruptions. However, we want to be consistent with the evaluations of previous sections. Fig. 22 shows the performance of several network backbones, evaluated on corrupted variants of Cityscapes and PASCAL VOC 2012 of category digital. Each abscissa represents averaged SNR of an intensity level of both the respective image corruption and the respective validation-set. We trained DeepLabv3+ on the first three intensity levels of saturate. With respect to the evaluation on Cityscapes, the models struggle most for large severity levels of saturate when trained solely on clean data. However, when trained on corrupted data, the models struggle most for contrast. For larger severity levels, training on saturate increases performance on brightness.

With respect to the evaluation on PASCAL VOC 2012, the models struggle most for contrast when trained on both clean data or corrupted data. When trained on corrupted data, the performance on contrast decreases. In general, training on saturate has only a minor effect on the remaining image corruptions of PASCAL VOC 2012.

### Table 13: Averaged Signal-to-Noise values for blurred variants of the training and validation set of Cityscapes dataset and PASCAL VOC 2012.

| Severity Level | Training-Set | Validation-Set | Training-Set | Validation-Set |
|----------------|--------------|----------------|--------------|----------------|
| Motion Blur    |              |                |              |                |
| 1              | 21.8         | 21.5           | 17.4         | 17.2           |
| 2              | 19.1         | 18.8           | 15.6         | 15.4           |
| 3              | 17.1         | 16.7           | 14.2         | 14.0           |
| 4              | 15.6         | 15.3           | 13.1         | 12.9           |
| 5              | 14.9         | 14.6           | 12.5         | 12.4           |
| Defocus Blur   |              |                |              |                |
| 1              | 25.4         | 25.2           | 18.0         | 17.8           |
| 2              | 23.4         | 23.1           | 17.1         | 16.9           |
| 3              | 20.7         | 20.4           | 15.9         | 15.7           |
| 4              | 19.2         | 18.9           | 15.1         | 14.9           |
| 5              | 18.1         | 17.7           | 14.5         | 14.3           |
| Frosted G. Blur|              |                |              |                |
| 1              | 22.6         | 22.4           | 17.0         | 16.9           |
| 2              | 23.0         | 22.8           | 17.2         | 17.0           |
| 3              | 18.4         | 18.1           | 14.7         | 14.5           |
| 4              | 19.1         | 18.8           | 15.1         | 14.9           |
| 5              | 18.3         | 17.9           | 14.7         | 14.5           |
| PSF Blur       |              |                |              |                |
| 1              | 26.9         | 26.6           | –            | –              |
| 2              | 27.0         | 26.7           | –            | –              |
| 3              | 25.8         | 25.5           | –            | –              |
| Gaussian Blur  |              |                |              |                |
| 1              | 29.6         | 29.5           | 20.4         | 20.3           |
| 2              | 24.3         | 24.0           | 17.7         | 17.5           |
| 3              | 21.7         | 21.4           | 16.5         | 16.3           |
| 4              | 20.1         | 19.8           | 15.7         | 15.5           |
| 5              | 18.1         | 17.8           | 14.6         | 14.4           |

### Table 12: Test performance (mIoU) of Xception-based network backbones on frosted glass blur, evaluated on PASCAL VOC 2012. The averaged SNR of the validation set is shown for each severity level. The model are trained on clean or corrupted data (i.e. Gaussian blur).

| Severity Level | 1 | 2 | 3 | 4 | 5 |
|----------------|---|---|---|---|---|
| SNR            | 16.9| 17.0| 14.5| 14.9| 14.5|
| Xception-41    | Clean | 63.4| 53.5| 26.3| 19.6| 14.9|
|                | Corrupted | 70.7| 66.3| 51.6| 46.6| 37.7|
| Xception-65    | Clean | 67.6| 58.5| 27.1| 20.4| 15.0|
|                | Corrupted | 70.7| 66.8| 52.8| 47.9| 40.4|
| Xception-71    | Clean | 67.8| 59.4| 30.2| 24.5| 19.1|
|                | Corrupted | 73.3| 70.2| 57.8| 53.3| 45.0|

### Table 14: Averaged Signal-to-Noise values for corrupted variants of category digital of the training and validation set of Cityscapes dataset and PASCAL VOC 2012.

| Severity Level | Training-Set | Validation-Set | Training-Set | Validation-Set |
|----------------|--------------|----------------|--------------|----------------|
| Brightness     |              |                |              |                |
| 1              | 11.8         | 12.0           | 15.2         | 15.2           |
| 2              | 5.8          | 6.1            | 9.7          | 9.6            |
| 3              | 2.3          | 2.6            | 6.5          | 6.5            |
| 4              | -0.1         | 0.2            | 4.5          | 4.4            |
| 5              | -2.0         | -1.7           | 3.1          | 3.0            |
| Contrast       |              |                |              |                |
| 1              | 10.4         | 10.4           | 11.0         | 10.9           |
| 2              | 9.1          | 9.0            | 9.7          | 9.6            |
| 3              | 7.9          | 7.9            | 8.5          | 8.5            |
| 4              | 6.9          | 6.9            | 7.5          | 7.5            |
| 5              | 6.4          | 6.4            | 7.0          | 7.0            |
| JPEG           |              |                |              |                |
| 1              | 26.2         | 26.3           | 21.5         | 21.4           |
| 2              | 24.6         | 24.8           | 20.7         | 20.5           |
| 3              | 23.7         | 23.9           | 20.2         | 20.0           |
| 4              | 21.4         | 21.7           | 19.0         | 18.8           |
| 5              | 19.7         | 20.0           | 17.9         | 17.8           |
| Saturate       |              |                |              |                |
| 1              | 21.6         | 21.7           | 17.1         | 16.9           |
| 2              | 19.4         | 19.5           | 15.1         | 14.9           |
| 3              | 18.6         | 18.7           | 16.7         | 16.6           |
| 4              | 7.1          | 7.4            | 9.3          | 9.3            |
| 5              | 4.7          | 4.9            | 6.5          | 6.5            |
(a) MobileNet-V2 evaluated on the Cityscapes dataset

Figure 20: Test performance of MobileNet-V2 (a) and Xception-71 (b) on several blurred variants of the Cityscapes dataset. Each abscissa corresponds to the averaged Signal-to-Noise ratio over the validation dataset of the respective type of blur. The reference architecture was trained on the first three intensity levels of Gaussian blur. The models struggle most for Gaussian blur when trained on clean data. Training on Gaussian blur has only a minor effect on the generalization on motion blur.

(b) Xception-71 evaluated on the Cityscapes dataset

Figure 21: Test performance of Xception-41 (a), Xception-65 (b), and Xception-71 (c) on several blurred variants of PASCAL VOC 2012. Each abscissa corresponds to the averaged Signal-to-Noise ratio over the validation dataset of the respective type of blur. The reference architecture was trained on the first three intensity levels of Gaussian Blur. The models struggle most for frosted glass blur (see Tab. 12) when trained on clean data. Training on Gaussian blur has less effect on the generalization on motion blur.
Figure 22: Test performance of several network backbones on corrupted variants of category digital of Cityscapes and PASCAL VOC 2012. Each abscissa corresponds to the averaged Signal-to-Noise ratio over the validation dataset of the respective type of image corruption. The reference architecture was trained on the first three intensity levels of saturate. The models struggle on Cityscapes most on large severity levels of the image corruption saturate when solely trained on clean data (see (a) and (b)). Training on saturate has for PASCAL VOC 2012 only a minor effect on the remaining image corruptions. When trained on corrupted data, the performance on contrast decreases (c – e).