

cases	doc_1		doc_2		decision	id
	authors	<ul style="list-style-type: none">Chengyin HuWeiwen Shi	authors	<ul style="list-style-type: none">Chengyin HuWeiwen Shi	NOT DUPLICATES	190
	title	Impact of Scaled Image on Robustness of Deep Neural Networks	title	Impact of Colour Variation on Robustness of Deep Neural Networks		
	publication_date	2022-09-02 00:00:00	publication_date	2022-09-02 00:00:00		
	source	SupportedSources.INTERNET_ARCHIVE	source	SupportedSources.INTERNET_ARCHIVE		
	journal		journal			
	volume		volume			
	doi		doi			
	urls	<ul style="list-style-type: none">https://web.archive.org/web/20220909155507/https://arxiv.org/ftp/arxiv/papers/2209/2209.02132.pdf	urls	<ul style="list-style-type: none">https://web.archive.org/web/20220910231135/https://arxiv.org/ftp/arxiv/papers/2209/2209.02832.pdf		
	id	id-1610094424964756418	id	id-4744802676055221493		
	abstract	Deep neural networks (DNNs) have been widely used in computer vision tasks like image classification, object detection and segmentation. Whereas recent studies have shown their vulnerability to manual digital perturbations or distortion in the input images. The accuracy of the networks is remarkably influenced by the data distribution of their training dataset. Scaling the raw images creates out-of-distribution data, which makes it a possible adversarial attack to fool the networks. In this work, we propose a Scaling-distortion dataset ImageNet-CS by Scaling a subset of the ImageNet Challenge dataset by different multiples. The aim of our work is to study the impact of scaled images on the performance of advanced DNNs. We perform experiments on several state-of-the-art deep neural network architectures on the proposed ImageNet-CS, and the results show a significant positive correlation between scaling size and accuracy decline. Moreover, based on ResNet50 architecture, we demonstrate some tests on the performance of recent proposed robust training techniques and strategies like Augmix, Revisiting and Normalizer Free on our proposed ImageNet-CS. Experiment results have shown that these robust training techniques can improve networks' robustness to scaling transformation.	abstract	Deep neural networks (DNNs) have have shown state-of-the-art performance for computer vision applications like image classification, segmentation and object detection. Whereas recent advances have shown their vulnerability to manual digital perturbations in the input data, namely adversarial attacks. The accuracy of the networks is significantly affected by the data distribution of their training dataset. Distortions or perturbations on color space of input images generates out-of-distribution data, which make networks more likely to misclassify them. In this work, we propose a color-variation dataset by distorting their RGB color on a subset of the ImageNet with 27 different combinations. The aim of our work is to study the impact of color variation on the performance of DNNs. We perform experiments on several state-of-the-art DNN architectures on the proposed dataset, and the result shows a significant correlation between color variation and loss of accuracy. Furthermore, based on the ResNet50 architecture, we demonstrate some experiments of the performance of recently proposed robust training techniques and strategies, such as Augmix, revisit, and free normalizer, on our proposed dataset. Experimental results indicate that these robust training techniques can improve the robustness of deep networks to color variation.		
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