Supplementary - Deflecting Adversarial Attacks with Pixel Deflection

Results on various classifiers

Original classification accuracy of each classifier on selected 1000 images is reported in the table. However, we omit the images that were originally incorrectly classified, thus the accuracy of clean images without defense is always 100%. Weights for each classifier were obtained from Tensorflow GitHub repository ¹.

Model	$ oldsymbol{L}_2 $	No Defense	With Defense		
			Single	Ens-10	
Res	Net-50,	original classi	fication 7	6%	
Clean	0.00	100	98.3	98.9	
FGSM	0.05	20.0	79.9	81.5	
IGSM	0.03	14.1	83.7	83.7	
DFool	0.02	26.3	86.3	90.3	
JSMA	0.02	25.5	91.5	97.0	
LBFGS	0.02	12.1	88.0	91.6	
C&W	0.04	04.8	92.7	98.0	
		original classifi			
Clean	0.00	100	99.8	99.8	
FGSM	0.05	12.2	79.3	81.3	
IGSM	0.04	9.79	79.2	81.6	
DFool	0.01	23.7	83.9	91.6 09.5	
JSMA LBFGS	0.01 0.03	29.1 13.8	95.8 83.0	98.5 93.9	
Lbrgs C&W	0.03	0.00	83.0 93.1	93.9 97.6	
		3, original class			
Clean	0.00	100	98.1	98.5	
FGSM	0.05	22.1	85.8	87.1	
IGSM	0.04	15.5	89.7	89.1	
DFool	0.02	27.2	82.6	85.3	
JSMA	0.02	24.2	93.7	98.6	
LBFGS	0.02	12.5	87.1	91.0	
C&W	0.04	07.1	93.9	98.5	

Table 1: Params: $\sigma = 0.04$, Window=10, Deflections=100

Top-1 accuracy on applying pixel deflection and wavelet denoising across various attack models.

¹https://github.com/tensorflow/models/tree/master/research/slim#Pretrained

Comparison of small and large perturbations

Model	$ L_2 $	No Defense	With Defense		
			Single	Ens-10	
Clean	0.00	100	98.3	98.9	
FGSM	0.05	20.0	79.9	81.5	
IGSM	0.03	14.1	83.7	83.7	
DFool	0.02	26.3	86.3	90.3	
JSMA	0.02	25.5	91.5	97.0	
LBFGS	0.02	12.1	88.0	91.6	
C&W	0.04	04.8	92.7	98.0	
	L	arge perturbatio	ons		
FGSM	0.12	11.1	61.5	70.4	
IGSM	0.09	11.1	62.5	72.5	
DFool	0.08	08.0	82.4	88.9	
JSMA	0.05	22.1	88.9	92.1	
LBFGS	0.04	12.1	77.0	89.0	

Table 2: Params: $\sigma = 0.04$, Window=10, Deflections=100

Top-1 accuracy on applying pixel deflection and wavelet denoising across various attack models. We evaluate nonefficient attacks at larger $|L_P|$ which leave visible perturbations to show the robustness of our model.

Comparison of various shrinkage

Model	Hard	VISU	SURE	Bayes
Clean	39.5	96.1	92.1	98.9
FGSM	35.9	63.8	79.7	81.5
IGSM	42.5	67.8	81.1	83.7
DFool	37.2	78.4	87.7	90.3
JSMA	39.9	93.0	93.0	97.0
LBFGS	37.2	81.1	90.4	91.6
C&W	36.8	93.4	92.8	98.0

Table 3: Params: $\sigma = 0.04$, Window=10, Deflections=100

Comparison of various thresholding techniques, after application of pixel deflection.

In Table 3 we present a comparison of various shrinkage methods on wavelet coefficients after pixel deflection. All the results reported are for applying the given thresholding after pixel deflection. BayesShrink, which learns separate Gaussian parameters for each coefficient, does better than other soft-thresholding techniques. VisuShrink is a faster technique as it uses a universal threshold but that limits its applicability on some images. SUREShrink has been shown to perform well with compression but as evident, in our results, it is less well suited to denoising.

Ablation studies of various parameters

Attack	$ L_2 $	No Defense	With Defense			
Window=10, Deflections \longrightarrow		10	100	1K	10K	
Clean	0.00	100	98.4	98.1	94.7	80.3
FGSM	0.04	19.2	75.7	79. 7	71.7	69.1
IGSM	0.03	13.8	78.4	81.7	75.2	71.2
DFool	0.02	25.0	83.7	87.7	81.0	77.0
JSMA	0.02	25.9	91.7	93.0	87.7	67.7
LBFGS	0.02	11.6	85.0	90.3	82.4	73.0
C&W	0.04	05.2	89.4	93.1	86.8	69.7

Table 4: Top-1 accuracy with different deflections.

Attack	L2	No Defense	With Defense			
Deflection	ns=100,	$Window \longrightarrow$	5	10	50	100
Clean	0.00	100	98.6	98.1	96.4	94.4
FGSM	0.04	19.2	79. 7	79.7	78.4	76.7
IGSM	0.03	13.8	81.0	81.7	79.7	78.4
DFool	0.02	25.0	86.4	87.7	87.7	85.0
JSMA	0.02	25.9	92.3	93.0	91.7	90.3
LBFGS	0.02	11.6	89.4	90.3	89.0	88.1
C&W	0.04	05.2	91.8	93.1	90.5	89.2

Table 5: Top-1 accuracy with different window sizes.

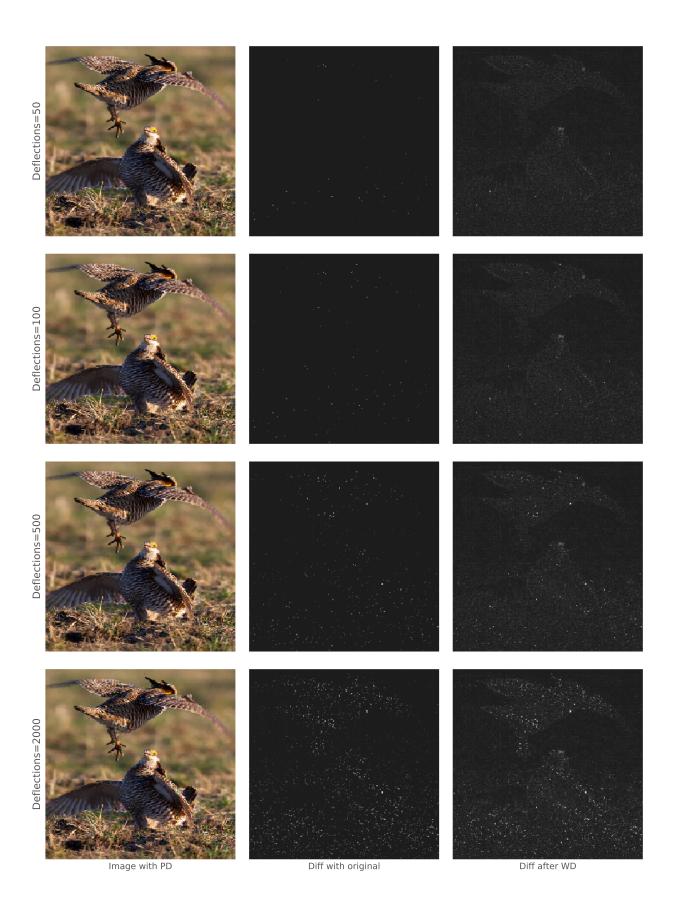
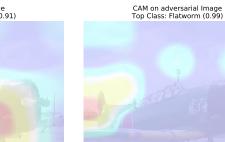


Figure 1: This is same image as Figure 1 on the paper but with a better color scheme. Impact of Pixel Deflection (PD) on a natural image and subsequent denoising using wavelet transform (WD). Left: Image with given number of pixels deflected. Middle: Difference between clean image and deflected image. Right: Difference between clean image and deflected image after denoising. Enlarge to see details.

CAM on clean Image Top Class: Warplane (0.91)



CAM on clean Image Top Class: Warplane (0.91)

CAM on adversarial Image Top Class: Meat Loaf (0.99)



Robust CAM on adversarial Image Top Class: Meat Loaf (0.99)



CAM on clean Image Top Class: Cabbage Butterfly (0.84)



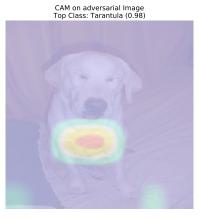


Robust CAM on adversarial Image Top Class: Spatula (0.99)



CAM on clean Image Top Class: Labrador Retriever (0.97)





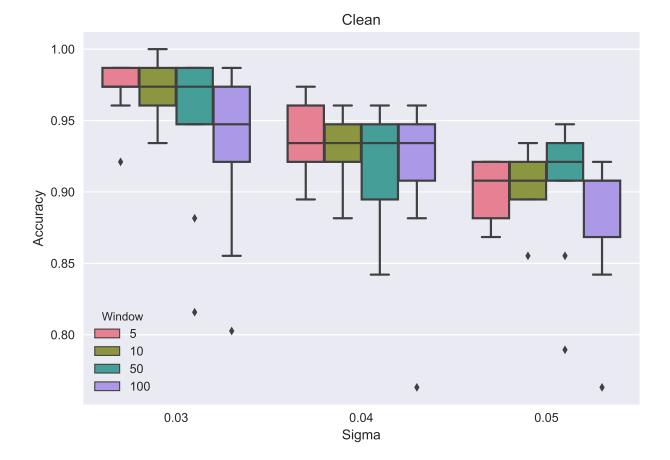


Robust CAM on adversarial Image Top Class: Tarantula (0.98)

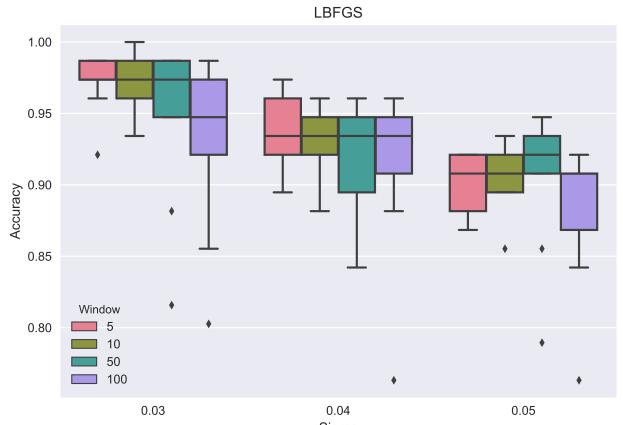


Figure 2: Comparison of Class activation maps and Robust Activation maps

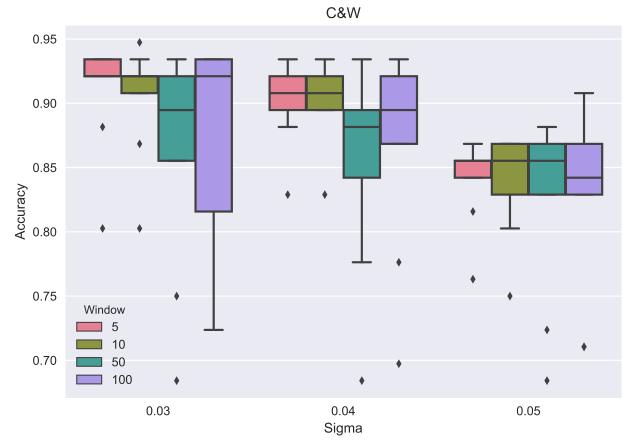
CAM on adversarial Image Top Class: Spatula (0.99)

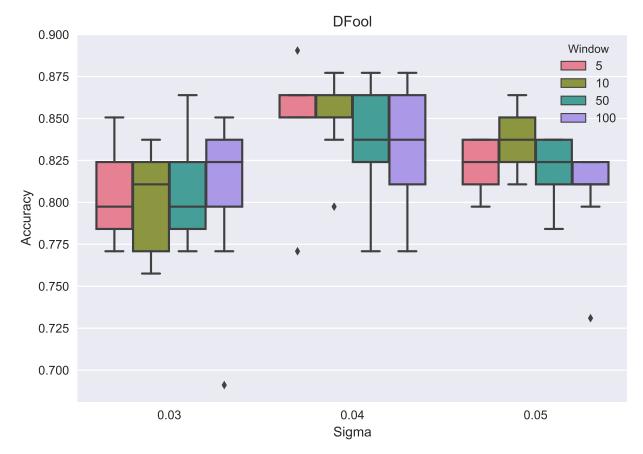


Full size figures of Figure 5 (Linear search for model parameters on training data)

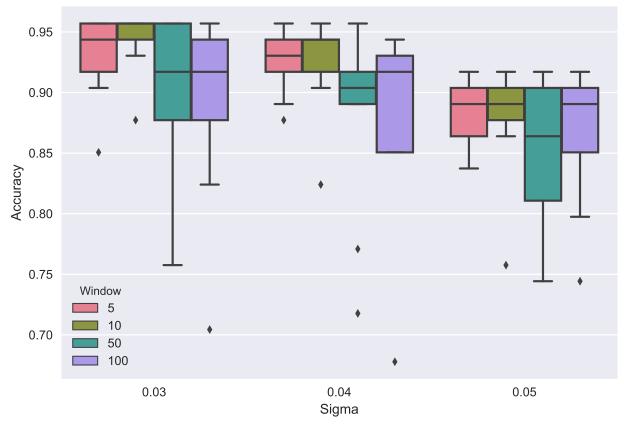


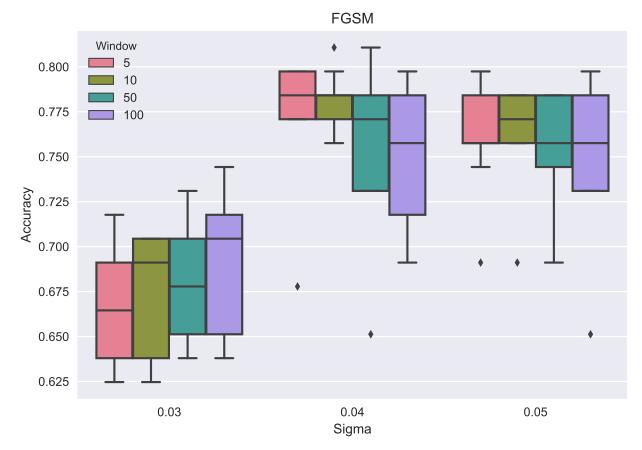
Sigma











IGSM

