



Analysis of Adversarial Attacks on Skin Cancer Recognition

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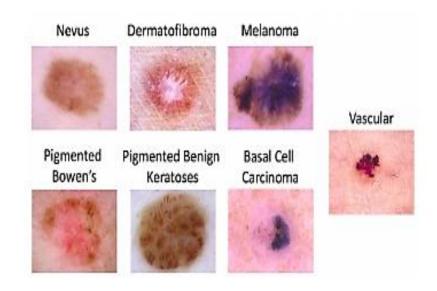






Introduction

- "Humans Against Machines with 10000 Training Images" ${\sf HAM10000}^{[1]}$ comprising of 10015 dermatoscopic images
- Seven classes:
 - 1. Melanoma
 - 2. Melanocytic nevus
 - 3. Basal cell carcinoma
 - 4. Intraepithelial carcinoma
 - 5. Benign keratosis
 - 6. Dermatofibroma
 - 7. Vascular lesion









Classification Models

Models	Top-1 ImageNet Accuracy	Million Parameters
VGG16 ^[2]	0.715%	138M
MobileNet ^[3]	0.706%	4.2M







Adversarial Machine Learning

FAST GRADIENT SIGN METHOD^[4]

$$x^{adv} = x + \varepsilon \cdot \text{sign}(\nabla_x J(x, y_{true}))$$

where

X is the input (clean) image,

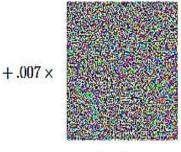
 X^{adv} is the perturbed adversarial image,

J is the classification loss function,

 y_{true} is true label for the input x.



"panda" 57.7% confidence



 $sign(\nabla_x J(\theta, x, y))$ "nematode"
8.2% confidence



x +csign $(\nabla_x J(\theta, x, y))$ "gibbon"

99.3 % confidence







Adversarial Machine Learning

ITERATIVE ADVERSARIAL ATTACKS (PGD) [5]

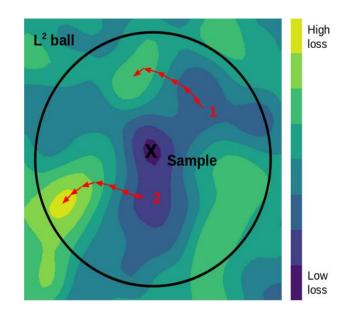
$$min_{\theta} p(\theta)$$
, $where p(\theta) = \mathbb{E}_{(x,y)\sim\mathcal{D}} [max_{\delta\in\mathcal{S}} L(\theta, x + \delta, y)]$

Step 1 Start from a random perturbation in the L^p ball around a sample

Step 2 Take a gradient step in the direction of greatest loss

Step 3 Project perturbation back into L^p ball if necessary

Step 4 Repeat 2–3 until convergence

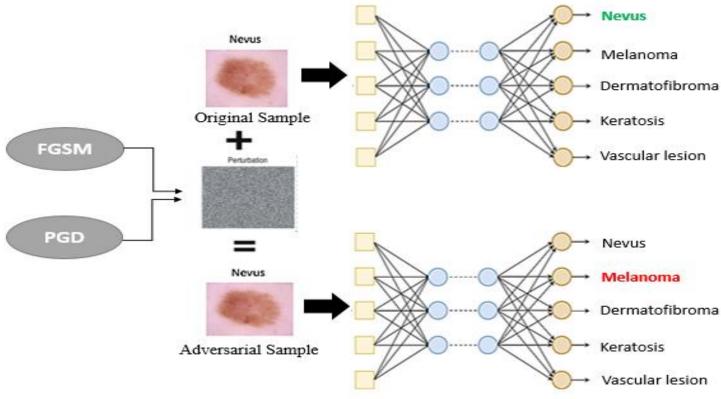








Effect of Attacks(Standard Training)









Performance Analysis

Table 1. FGSM & PGD Attack results (% accuracy) on Standard Training

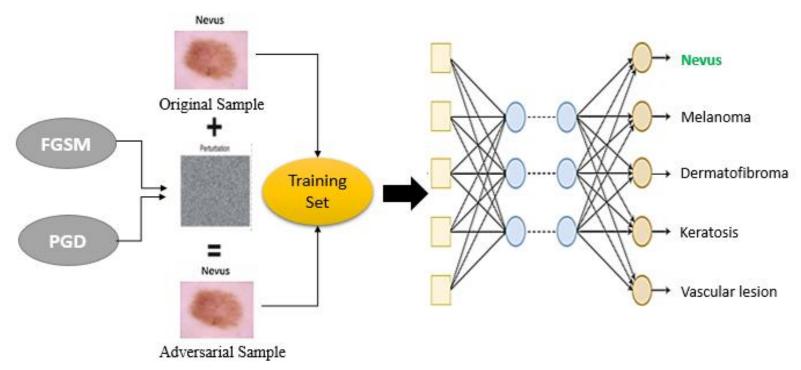
Training Approach	Models	Testing Approach		
		Standard	PGD	FGSM
Standard	MobileNet	77.24	2.89	3.48
	VGG16	71.72	8.68	9.88







Effect of Attacks(Adversarial Training)









Performance Analysis

Table 2. FGSM & PGD Attack results (% accuracy) on Standard Training and Adversarial Training

Training Approach	Models	Testing Approach		
		Standard	PGD	FGSM
Standard	MobileNet	77.24	2.89	3.48
	VGG16	71.72	8.68	9.88
Adversarial	MobileNet	76.14	75.94	63.17
	VGG16	70.47	71.05	50.79







Performance Analysis

Table 3. Transferability of standardly trained models(% accuracy) by testing with PGD Adversarial Images

Models	MobileNet	VGG16
MobileNet	2.89	6.08
VGG16	12.77	8.68







References

- [1] Tschandl, P., Rosendahl, C. & Kittler, H. The HAM10000 dataset, a large collection of multisource dermatoscopic images of common pigmented skin lesions. Sci. Data 5, 180161 doi:10.1038/sdata.2018.161 (2018).
- [2] Howard, Andrew G., et al. "Mobilenets: Efficient convolutional neural networks for mobile vision applications." *arXiv preprint arXiv:1704.04861* (2017).
- [3] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv:1409.1556 (2014).
- [4] Goodfellow, Ian J., Jonathon Shlens, and Christian Szegedy. "Explaining and harnessing adversarial examples." *arXiv preprint arXiv:1412.6572* (2014).
- [5] Madry, Aleksander, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. "Towards deep learning models resistant to adversarial attacks." *arXiv preprint arXiv:1706.06083* (2017).







Thank You

