Adversarial Attacks Against Medical Deep Learning Systems

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Deep Learning in Medicine

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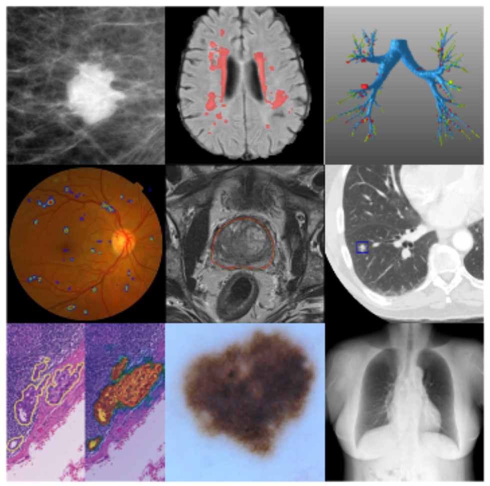

[9]

FDA U.S. FOOD & DRUG ADMINISTRATION

[3]

Adversarial Attacks

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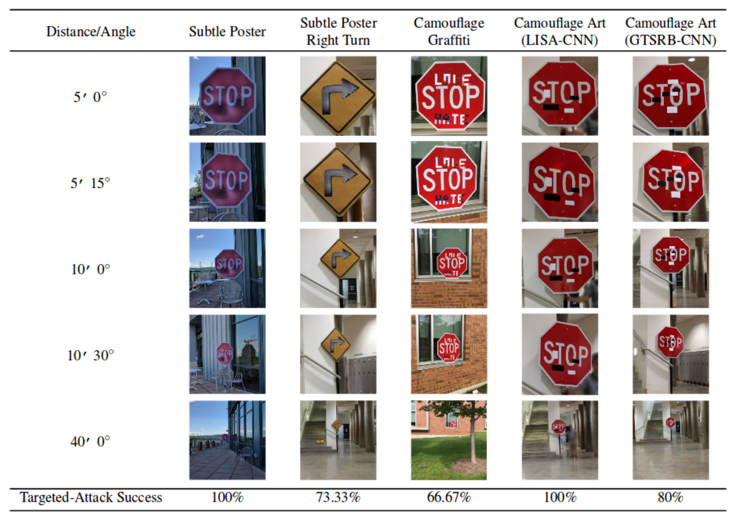

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Adversarial Attacks

Fool Google’s InceptionV3 image classifier video. [1, 7]

Why Medicine?

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- Healthcare economy is huge and fraud is already a major problem [8]
- Increasing use in clinical trials [12]

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- Ambiguous ground truth [11]
- Images are standardised
- Popular Architectures are often used
- Many potential adversaries

Create Adversarial Examples

Fast Gradient Sign Method

Let θ be the parameters of a model, x an input to the model and y the target associated with x. We also have a well defined loss function $L(\theta, x, y)$.

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Then FGSM computes an adversarial example as:

$$x + \epsilon \cdot \text{sign}(\nabla_x L(\theta, x, y))$$

[6]

Projected Gradient Descent

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$$x^{t+1} = \Pi_{x+\mathcal{S}}(x^t + \epsilon \cdot \text{sign}(\nabla_x L(\theta, x, y)))$$

[10]

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- If we only have access to predicted class, use a Monte Carlo approximation [7]

Patch Attack

Some major differences:

- Targeted

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- Universal

Patch Attack

Some major differences:

- Targeted
- Universal
- Robust

[2]

Example Patch Attack

video [2]

Building Adversarial Patches

Given an image x, a patch p, a location l and transformations t (rotation and scaling) we define a *patch application operator* $A(p, x, l, t)$.

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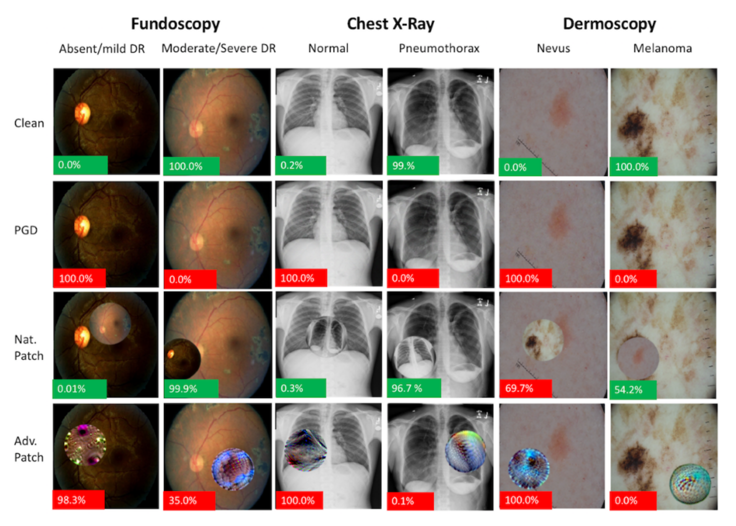
To obtain the final adversarial patch $\hat{p}$ we compute:

$$\hat{p} = \arg\max_{p} \mathbb{E}_{x\sim X, l\sim L, t\sim T}(\log P(\hat{y}|A(p, x, l, t)))$$

where $\hat{y}$ is the target class. [1, 2]

Current Research

Current Research



[5]

Our Plan

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- Break the best deep learning systems

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Our Plan

- Break the best deep learning systems
- Understand how they were broken
- Make them more robust

References

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