Adversarial-Robust Transfer Learning for Medical Imaging via Domain Assimilation

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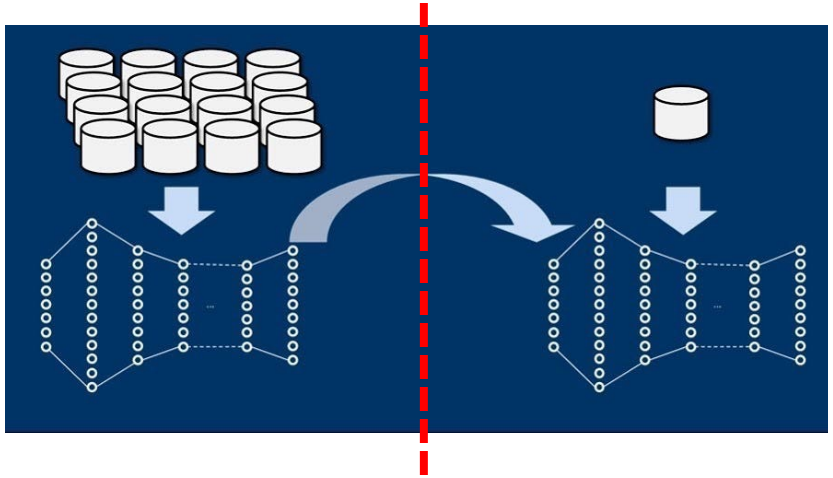
The Ubiquitous Transfer Learning



- Transfer learning has been extremely successful and almost ubiquitous in DL
  - ❑ It takes a base model <u>pretrained</u> on large datasets and then <u>fine-tunes</u> it on a small dataset pertaining to a specific (downstream) task
- Medical AI (esp. medical imaging) is <u>no exception</u>
  - ❑ Due to the lack of reliably annotated public large medical datasets
    - ✓ *"So yeah, it makes sense to use TL."*
  - ❑ Plus, "Everybody is using it!" and "It works well!" Hence, …

The Fall of Panacea

(In the following, we focus on CV, but the same principle should apply similarly to other domains such as NLP and audio.)

A crucial factor is overlooked

- *"Not all images are created equal"*
- Pretrained models are all trained on natural images (e.g. ImageNet), but medical images have some distinct properties
  - which lead to higher vulnerability of medical AI models to adversaries

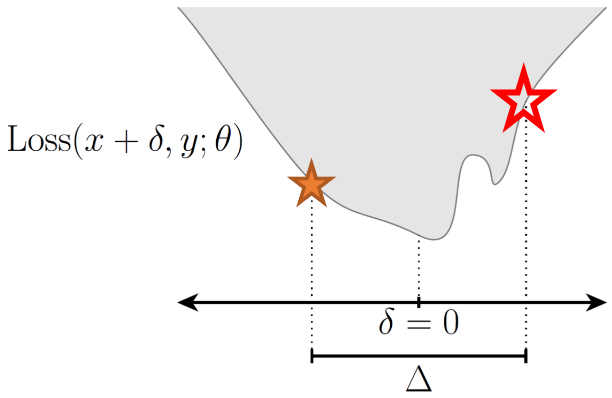
A little background: Adversarial Attacks in medical domain

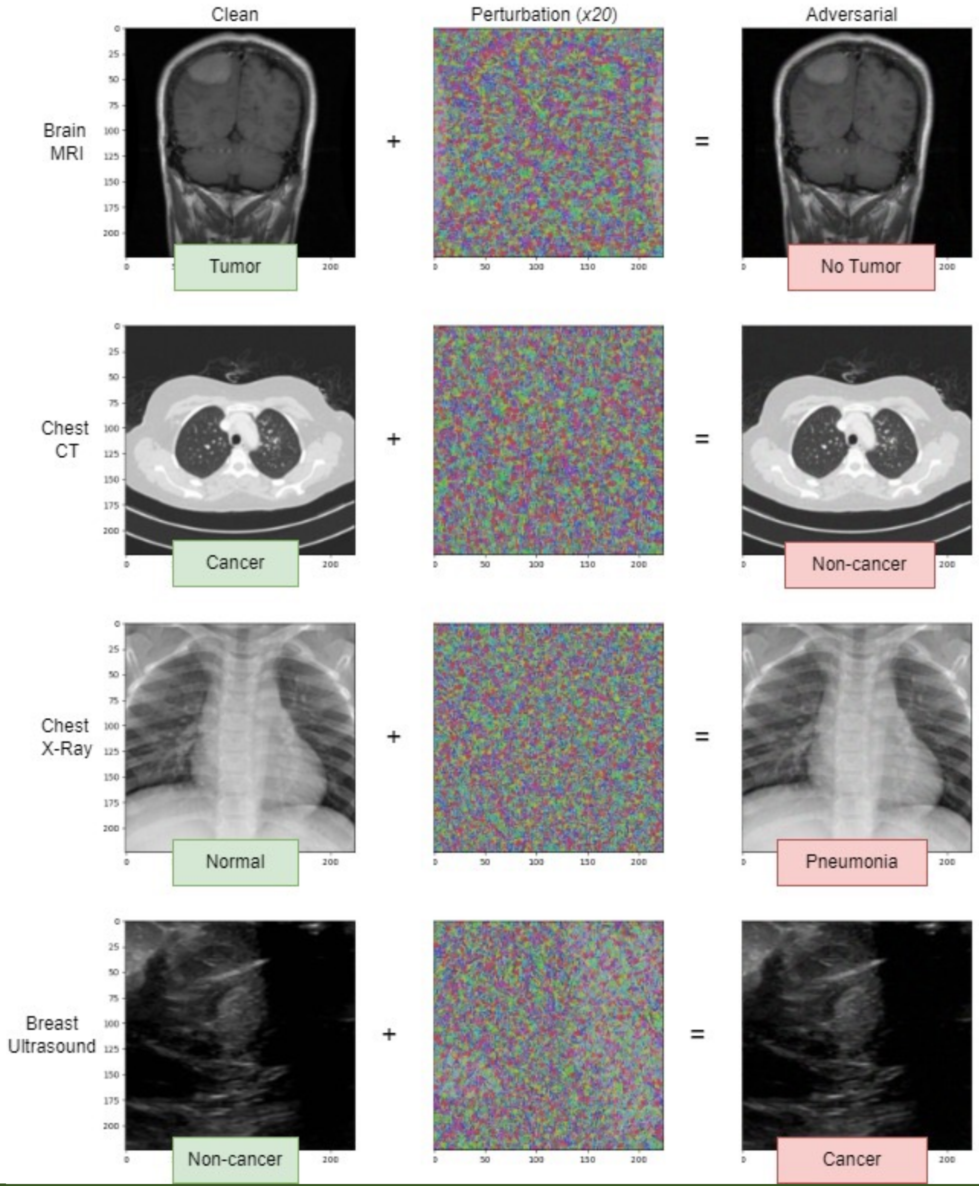
In this paper, we focus on Adversarial Examples, which is a popular type of attacks and can be formulated as

$$\underset{\|\delta\|_p \leq \epsilon}{\operatorname{argmax}}\, l(\theta, x + \delta, y)$$

Original Input + carefully crafted noise
↓ Model
Wrong prediction

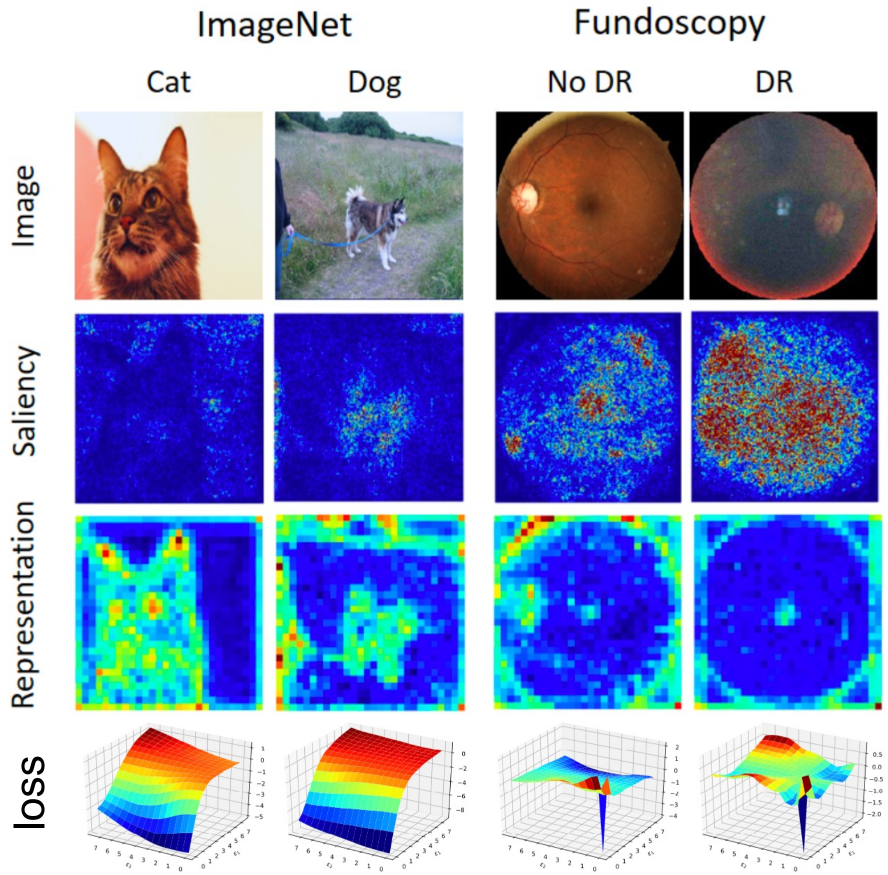
where an adversary aims to find a *small perturbation δ* (constrained by ϵ-ball around original input x) to maximize the loss, such that the model would makea wrong prediction for the new input $x' = x + \delta$





Why are medical AI models more vulnerable?

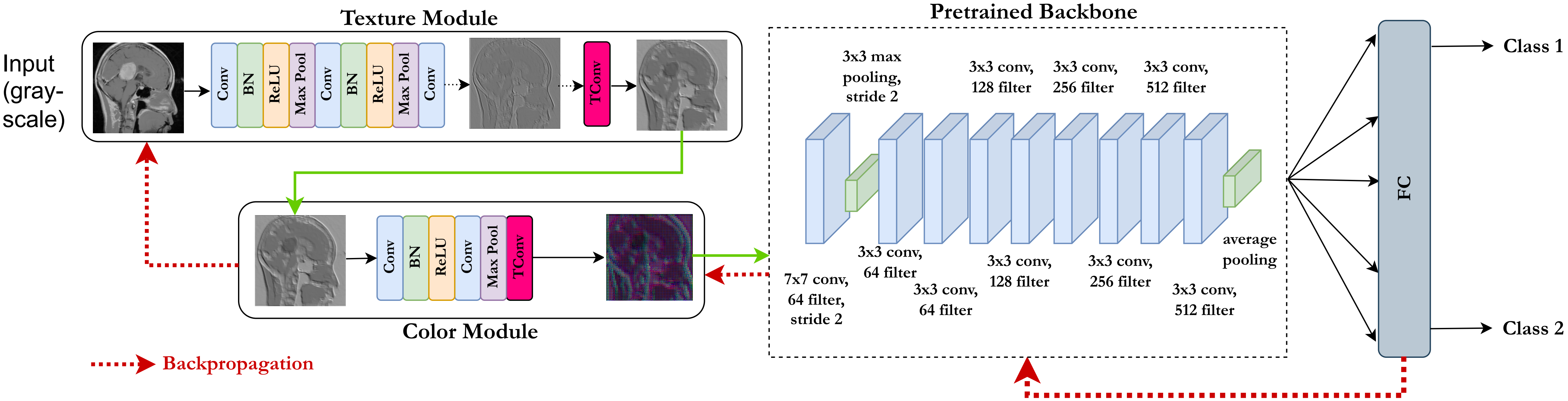
- **Large attention region:**
  - Unlike natural images, medical images typically have monotonic biological texture, which tends to mislead DNNs to pay attention to areas irrelevant to diagnosis
  - In these attention regions, it is easier for small perturbations to cause significant changes in output
- **Sharp loss landscape:**
  - Medical images have rather simple representations (only features related to lesion) as compared to natural images
  - DNNs are typically overparameterized (e.g., ResNet50); using them to learn simple patterns from a large attention region tend to create sharp loss landscape
  - On a sharp loss landscape, a small perturbation can cause drastic changes



Ma, X., Niu, Y., Gu, L., Wang, Y., Zhao, Y., Bailey, J., Lu, F.: Understanding adversarial attacks on deep learning based medical image analysis systems. *Pattern Recognition* (2021).

Bridging The Gap

- "Domain Discrepancy": substantial gap between natural & medical images
- We propose a Domain Assimilation strategy to bridge this gap:-
  - ❑ **Colorize and adapt texture** of medical images to resemble nature images
  - ❑ Retain essential texture (over-adaptation can lead to misdiagnoses!)



- **Texture and color adaptation:**

$$< \theta_T, \theta_C, \theta_B, \theta_F > = \underset{\theta_T, \theta_C, \theta_B, \theta_F}{\operatorname{argmin}} L\Bigg(F\bigg(B\Big(C\big(T(X, \theta_T), \theta_C\big), \theta_B\Big), \theta_F\bigg), y\Bigg)$$

  - ❑ T: texture module, C: color module, B: pretrained backbone, F: final classifier.

- **Retain essential texture:** restrict distortion using GLCM loss
  - ❑ Gray Level Co-occurrence Matrix (GLCM) is a texture descriptor quantifying texture features and describing local spatial relationships at intensity levels.

$$< \theta_T, \theta_C, \theta_B, \theta_F > = \underset{\theta_T, \theta_C, \theta_B, \theta_F}{\operatorname{argmin}} \Bigg(\alpha \times \text{CrossEntropyLoss}\Big(F(B(C(T(X, \theta_T), \theta_C), \theta_B), \theta_F), y\Big) + (1 - \alpha) \times \text{GLCMLoss}\Big(C(X, \theta_C), X\Big)\Bigg) \quad (18)$$

Measure distortion using second-order texture features:

$$\text{GLCMLoss} = \max_{1 \leqslant i \leqslant m} \sum_{j=1}^{n} \left| SOT\Big(grayscale\big(C(X)\big)\Big)_{i,j} - SOT(X)_{i,j} \right|$$

SOT: second-order texture feature matrix

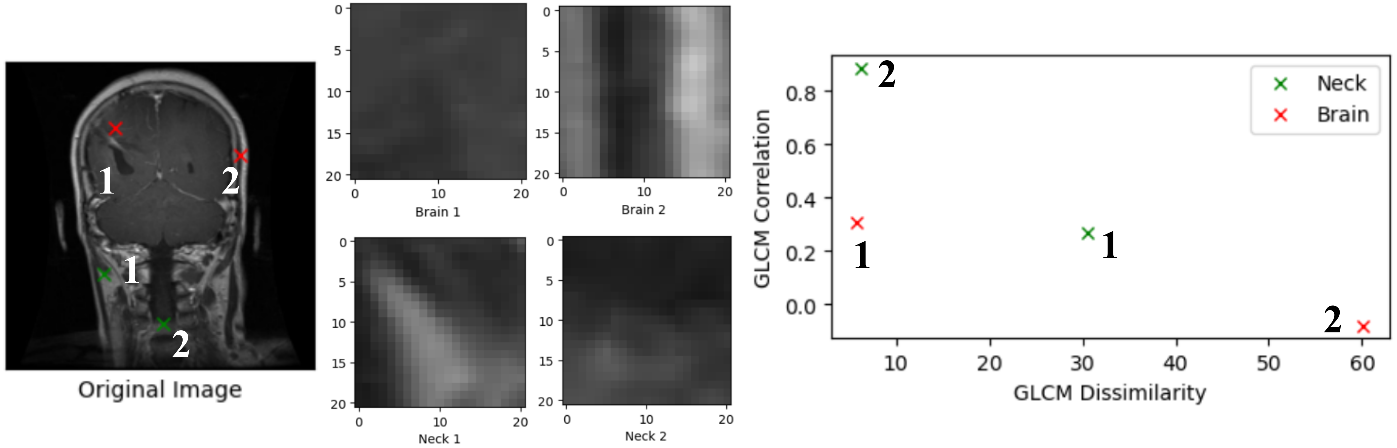
GLCM

- Given an image I, let i and j represent the grayscale values, (x, y) the spatial locations of pixels, and $(\nabla x, \nabla y)$ the offset determined by a predefined distance and orientation (angle)

$$P_{\nabla x, \nabla y}(i, j) = \sum_{x=1}^{w} \sum_{y=1}^{h} \begin{cases} 1, & if\ I(x, y) = i\ and\ I(x + \nabla x, y + \nabla y) = j \\ 0, & otherwise \end{cases}$$

Think of GLCM as a frequency matrix

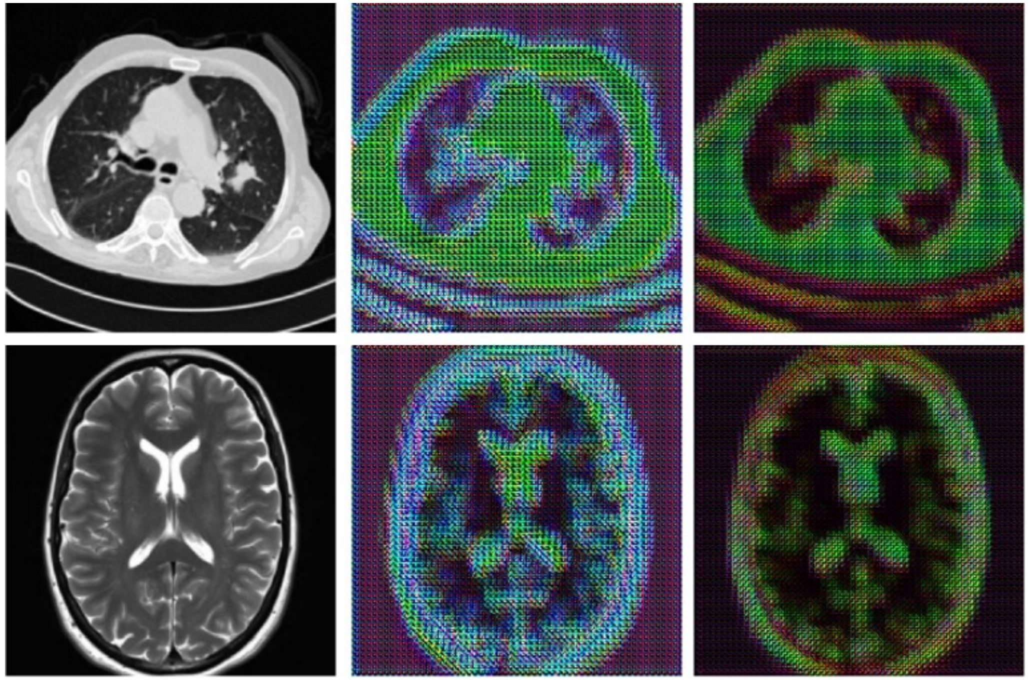
- Each combination of distance and orientation will generate a GLCM (8 in our case)
- For each GLCM, we further extract second-order texture features for each small area (20x20):
  - ❑ $Angular\ Second\ Moment(ASM) = \sum_{i,j} P(i,j)^2$
  - ❑ $Contrast = \sum_{i,j} |i - j|^2 P(i,j)$
  - ❑ $Homogeneity = \sum_{i,j} \frac{P(i,j)}{1+|i-j|^2}$
  - ❑ $Correlation = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sqrt{\sigma_i^2 \sigma_j^2}}$
  - ❑ $Disimilarity = \sum_{i,j} P(i,j)|i - j|$



Intermediate Result:
Post Texture and Color adaptation

Chest CT

Brain MRI



Original | w/o GLCM loss | w/ GLCM loss

Experiments

- Datasets:

	Classes	Class Size
Brain MRI	no-tumor, tumor(glioma/meningioma/pituitary)	1595, 1595
Chest Xray	normal, pneumonia	1583, 1583
Chest CT	no-cancer(normal/benign), cancer	536, 536
Breast UltraSnd	no-cancer(normal/benign), cancer	210, 210

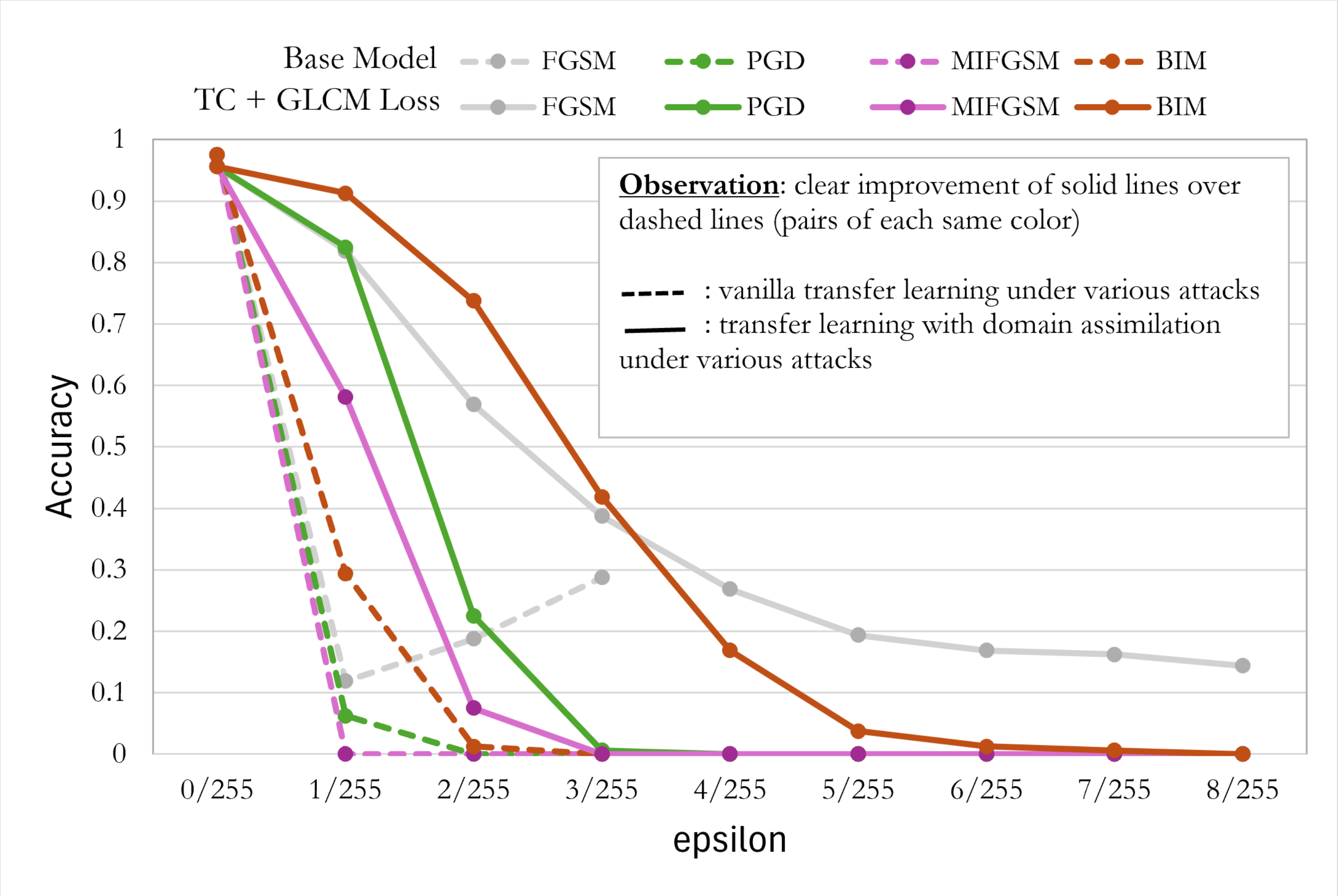
- Models and training:

Pretrained Model Selection		Parameters
ResNet18, ResNet50, DenseNet121	Epochs	300
	Learning Rate	1e-4
	Batch Size	32
	EarlyStopping	30
	Input Size	(224,224,1)

- GLCM parameters: Distance = 3, Orientation = 0/45/90/135/180/225/270/315 (degrees)
- **Attacks: FGSM, BIM, MIFGSM, PGD**
  - Perturbation size $\epsilon \in \{\frac{1}{255}, \frac{2}{255}, \frac{3}{255}, \frac{4}{255}, \frac{5}{255}, \frac{6}{255}, \frac{7}{255}, \frac{8}{255}\}$

Results

- Model accuracy vs. attack strength (Chest CT)



Clear winning margin of solid over dashed lines (same-color pairs)

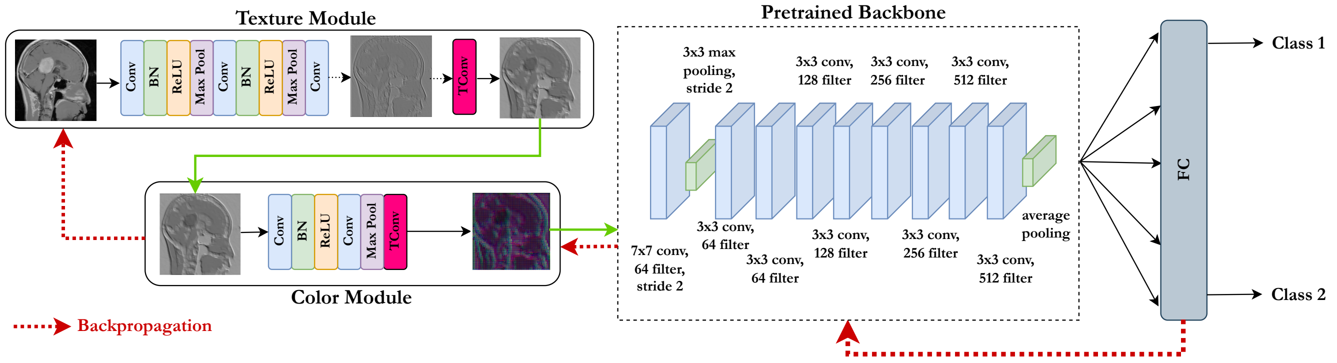
Dashed lines: vanilla transfer learning under various attacks

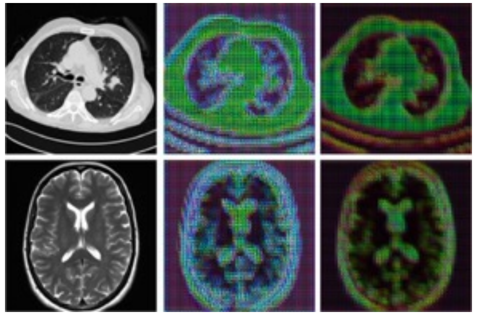
Solid lines: transfer learning with domain assimilation under various attacks

Vanilla FGSM (dashed gray line) is an outlier, because it moves gradient only one step, so increasing epsilon does not help but may result in it moving a big step toward a worse place (while all the other attacks do iterative gradient ascent). So for FGSM, one should focus on small espilon values.

Take-Home Message

- **Transfer Learning should be used with caution** on “Domain Discrepancy”
  - ❑ More vulnerable to adversarial attacks
- Domain Assimilation as a solution:
  - ❑ **Colorization and texture adaptation** (lightweight)
  - ❑ **Retain essential texture** (GLCM to avoid over-adaptation)





- **Future work:** more in-depth texture analysis and enhancement

Thank you!