M.Sc. in AI - Thesis Presentation

Grad-CAM vs HiResCAM: A comparative study via quantitative evaluation metrics

June 7, 2023

Contents

1. XAI algorithms & Motivation

For a CNN we denote by $\{A^f\}_{f=1,..,F}$ a convolutional layer, $A^f \in \mathbb{R}^{D_1 * D_2}$

Definition

For class $m = 1, 2, .., M$,

- the Grad-CAM (2019) attribution map w.r.t. $\{A^f\}_{f=1,..,F}$ is given by

$$\mathcal{A}_m^{\text{Grad-CAM}} = \text{ReLU}\left(\sum_{f=1}^{F} a_m^f A^f\right)$$

$$\text{where } a_m^f = \frac{1}{D_1 D_2} \sum_{i=1}^{D1} \sum_{j=1}^{D_2} \frac{\partial s^m}{\partial A_{ij}^f} \quad \text{(Gradient Averaging step)}$$

- the HiResCAM (2021) attribution map w.r.t. $\{A^f\}_{f=1,..,F}$ is given by

$$\mathcal{A}_m^{\text{HiResCAM}} = \text{ReLU}\left(\sum_{f=1}^{F} \frac{\partial s^m}{\partial A^f} \odot A^f\right)$$

where $\odot$ stands for the Hadamard product

- Setting? (CNN structure? Gradients wrt which Conv layer?)

Definition (Faithfulness)

For the purposes of this study, *an attribution map method is faithful to a CNN model* if the sum of the attribution map values reflects the class score calculation.

Table: Grad-CAM vs HiResCAM - Theory summary

CNN structure	Gradients wrt last Conv layer	Grad-CAM vs HiResCAM
Conv - GAP - Class Scores	yes	Equivalent & Faithful
	no	Not equivalent & Not faithful
Conv - Flatten - Class Scores	yes	Not equivalent. Only HiResCAM is faithful
	no	Not equivalent & Not faithful
Conv - GAP/Flatten - Dense - Class Scores	yes	Not equivalent & Not faithful
	no	

The *setting* of this study:

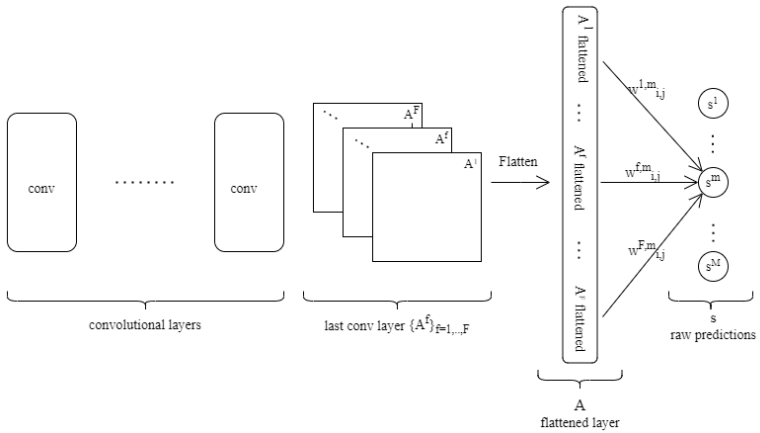


Figure: CNN ending in one fully connected layer

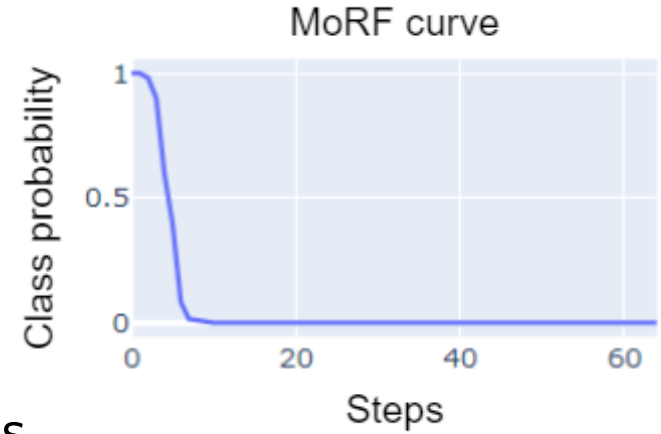
$\Rightarrow$ If gradients wrt last conv layer, one can show that HiResCAM is faithful to the model:

$$s^m = \sum_{i,j} \left(\mathcal{A}_m^{\text{HiResCAM}} \right)_{i,j} + b^m$$

$\Rightarrow$ On the other hand, this is not true for Grad-CAM!

- *Goal*: In this *unique* setting, we want to quantify the quality of the Grad-CAM and HiResCAM attribution maps and examine *if faithfulness aligns with quantitative evaluation metrics results*.

2. Quantitative evaluation metrics



AOPC score

- For image x and its heatmap
- $\mathcal{O}$: heatmap regions in descending order
- Iteratively:
  - apply perturbations to most relevant regions
  - calculate difference in predicted class probabilities
- Results in *MoRF Perturbation Curve* (for image x)
- Idea: large Area Over MoRF curve
  - $\Rightarrow$ class probability decreases after *a few* steps
  - $\Rightarrow$ the heatmap can accumulate class info in *a few* regions

Definition (AOPC, 2015)

$$AOPC = \frac{1}{L+1}\text{Avg}\Big(\underbrace{\sum_{k=1}^{L}[f(x_{MoRF}^{(0)}) - f(x_{MoRF}^{(k)})]}_{\text{controls area over MoRF curve}}\Big)_{\text{test set}}$$

Max Sensitivity score

- Idea: Measures the degree to which the class explanation is affected by small perturbations in the test image.
- Naturally, we desire explanations with *low* sensitivity.

Definition (Max Sensitivity, 2019)

For explanation method Φ and radius r, we define the Max Sensitivity of explanation $\Phi(f, x)$ as:

$$SENS_{MAX}(\Phi, f, x, r) = \max_{y:\|x-y\|_\infty \leq r} \|\Phi(f, x) - \Phi(f, y)\|_{Euclidean}$$

HAAS score

- Idea: If an attribution map gives an accurate explanation then *tuning* the image pixels according to the attribution map could reduce the number of misclassifications.
- How to tune? Positive attribution values to emphasize pixel values.
  Negative attribution values to de-emphasize pixel values.

Definition (HA image, HAAS, 2022)

- For image x and attributions a we compute the *Heatmap Assisted* (HA) image:

$$HA(x, a) = \max\{-1, \min\{1, x_{norm}(1 + a_{norm}\}\}$$

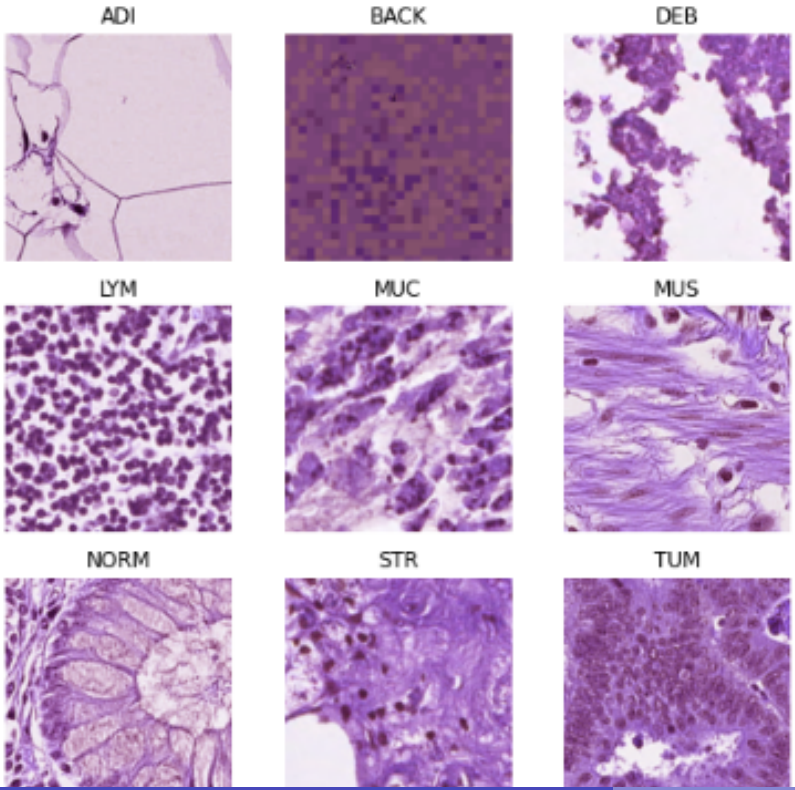
- $HAAS = \frac{\text{Accuracy over HA images}}{\text{Accuracy over original images}}$

- Interpretation: if HAAS value above 1
  $\Rightarrow$ the HA images improve the model's accuracy
  $\Rightarrow$ the attribution maps explain well the pixels' importance

3. Datasets

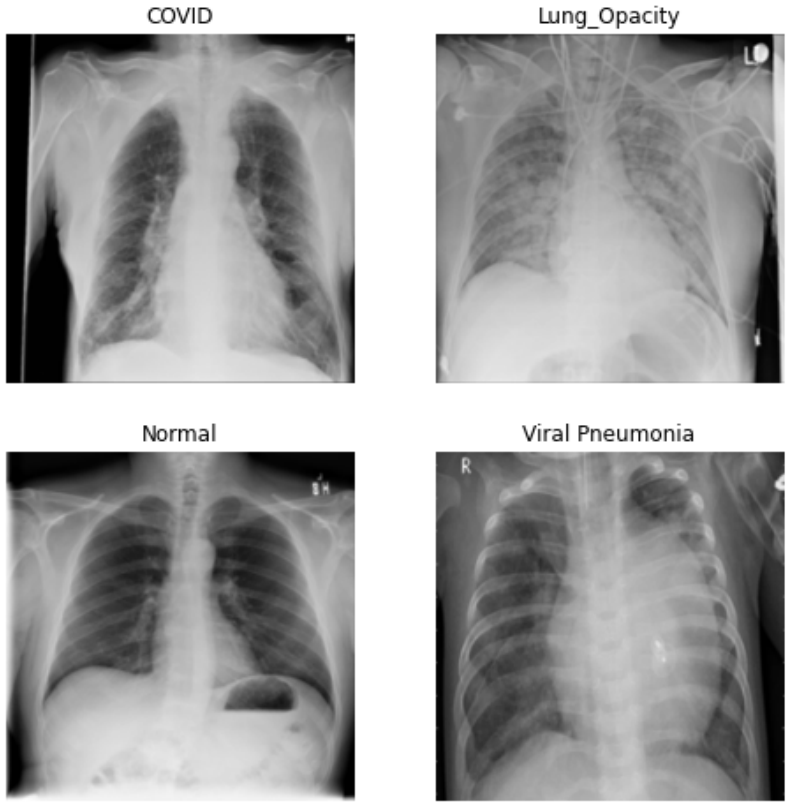
CRC Dataset

- Colon tissues (100K train)(7.1K test)
- ADI(10.4%), BACK(10.6%), DEB(11.5%), LYM(11.5%), MUC(8.9%), MUS(13.5%), NORM(8.8%), STR(10.5%), TUM(14.3%)



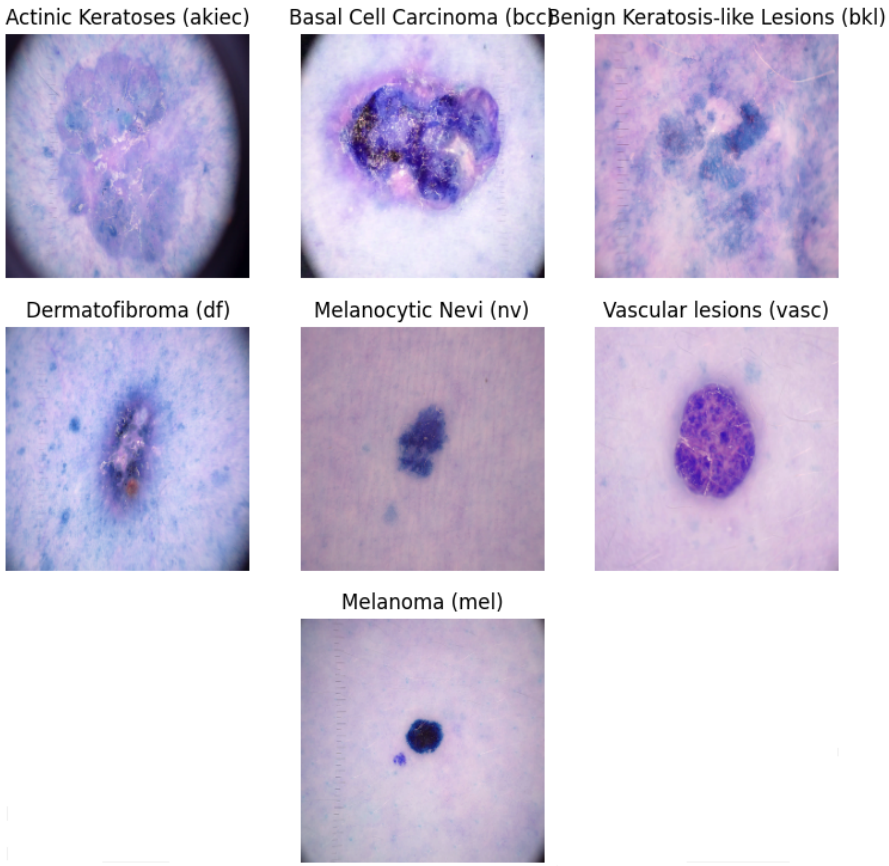
Covid-19 Radiography Database

- X-Rays (21.1K)
- Covid(17%), Lung Opacity (28.4%), Normal (48.15%), Viral Pneumonia (6.35%)



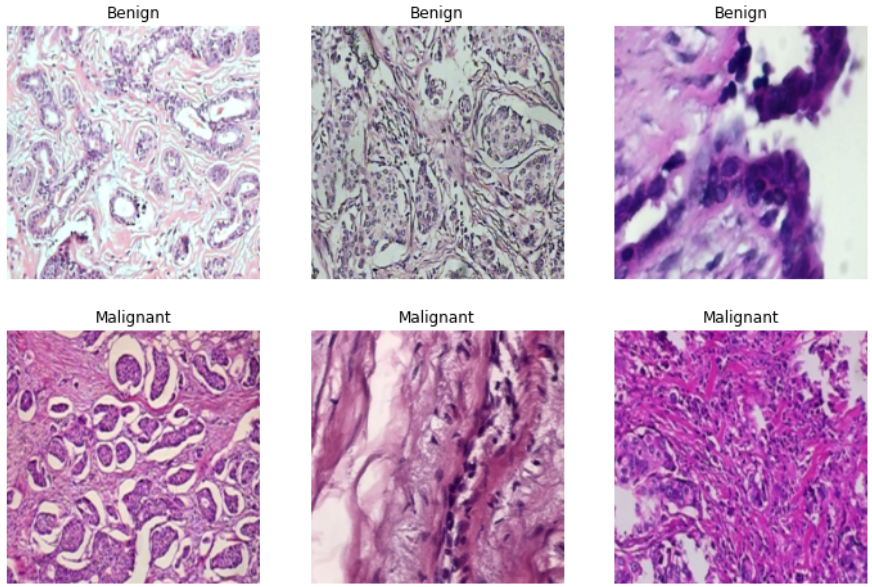
HAM10000 Dataset

- Skin lesion images (10K)
- akiec(3.27%), bcc(5.13%), bkl(10.97%), df(1.15%), nv(66.95%), vasc(1.42%), mel(11.11%)



BreakHis Dataset

- Breast tumor tissues (7.9K)
- Benign(31.4%), Malignant(68.6%)



Remark: These two datasets contain many examples of the same image at different scale. Train-Val-Test sets were constructed via an *image independent* approach.

4. Experimental results & Discussion

Models

Per dataset:

- we trained one ResNet and one VGG19 model
- each customized to the *Conv - Flatten - Class scores* architecture

  (s.t. HiResCAM is faithful to the model when gradients are computed wrt last convolutional layer)

Table: Testing Results

	CRC		Covid-19		HAM10000		BreakHis	
	ResNet34	VGG19	ResNet34	VGG19	ResNet50	VGG19	ResNet50	VGG19
Bal. Accuracy	0.89	0.94	0.97	0.95	0.69	0.73	0.87	0.84
Mean AUC	0.993	0.997	0.995	0.992	0.934	0.938	0.942	0.932

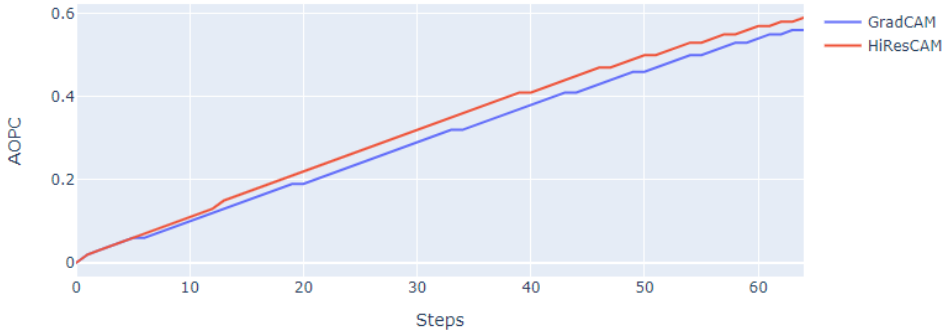
AOPC results

- Per dataset, model and attribution method, we calculated AOPC score at heatmap sizes: $4*4, 8*8, 11*11$ and $14*14$, utilizing uniform random noise.

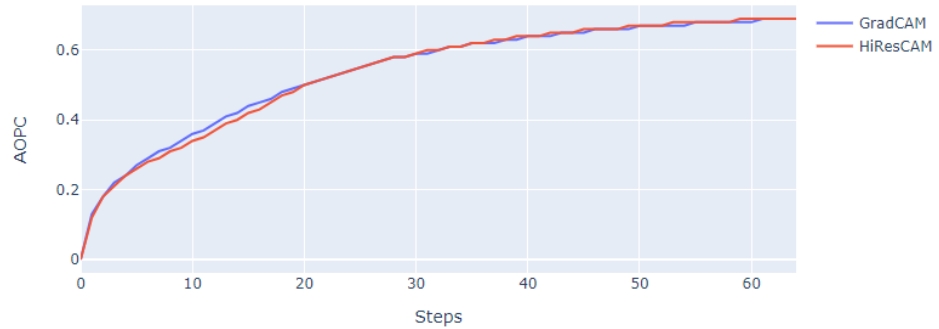
Table: AOPC Scores

			CRC		Covid-19		HAM10000		BreakHis	
			ResNet34	VGG19	ResNet34	VGG19	ResNet50	VGG19	ResNet50	VGG19
Heatmap size	4×4	Grad-CAM	0.57	0.5	0.71	0.64	0.57	0.35	0.32	0.35
		HiResCAM	0.57	**0.52**	**0.73**	**0.65**	**0.58**	**0.37**	**0.34**	**0.42**
	8×8	Grad-CAM	0.59	0.56	0.72	0.69	0.63	0.36	0.27	0.35
		HiResCAM	0.59	**0.59**	**0.73**	0.69	**0.64**	**0.37**	**0.28**	**0.45**
	11×11	Grad-CAM	0.6	0.59	0.73	0.71	0.65	0.37	**0.28**	0.35
		HiResCAM	0.6	**0.62**	**0.74**	0.71	**0.67**	**0.39**	0.27	**0.45**
	14×14	Grad-CAM	0.58	0.6	0.73	**0.7**	0.66	0.36	0.27	0.35
		HiResCAM	**0.6**	**0.62**	**0.74**	0.69	**0.68**	0.36	0.27	**0.48**

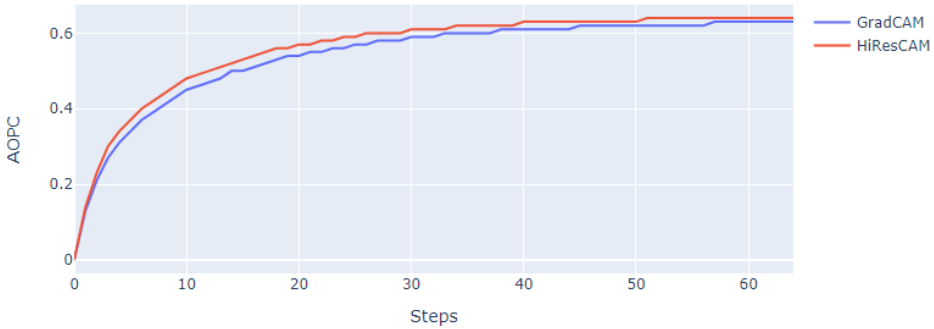
- At heatmap size $4*4$ HiResCAM prevails 7/8 cases. As size increases, the effect fades out.
- For each model and over all heatmap sizes, HiResCAM prevails 7/8 cases.



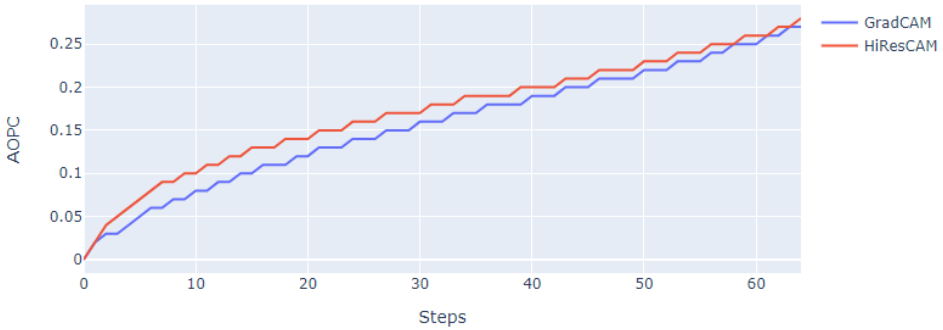
(a) CRC - VGG19



(b) Covid-19 - VGG19



(c) HAM10000 - ResNet50



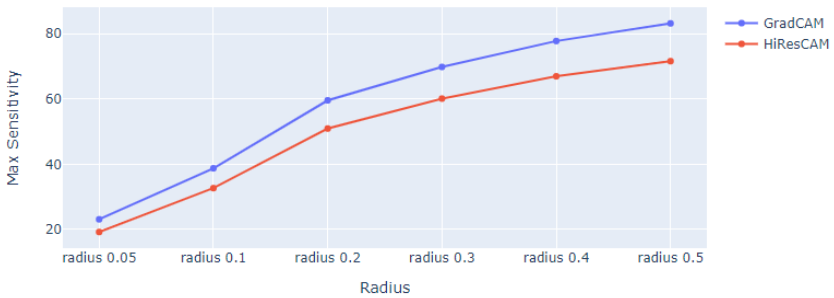
(d) BreakHis - ResNet50

Figure: AOPC Graphs for Heatmaps 8*8 size

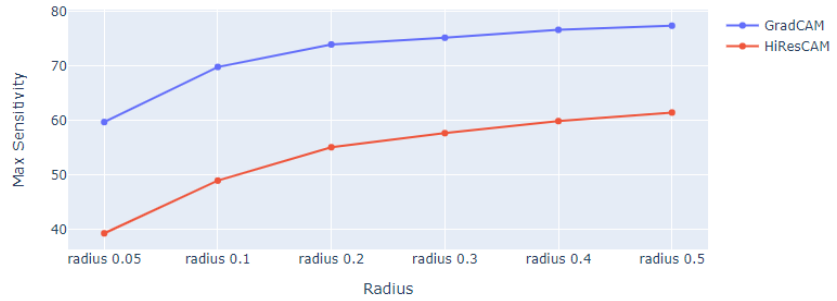
Max Sensitivity results

Table: Experiment configurations

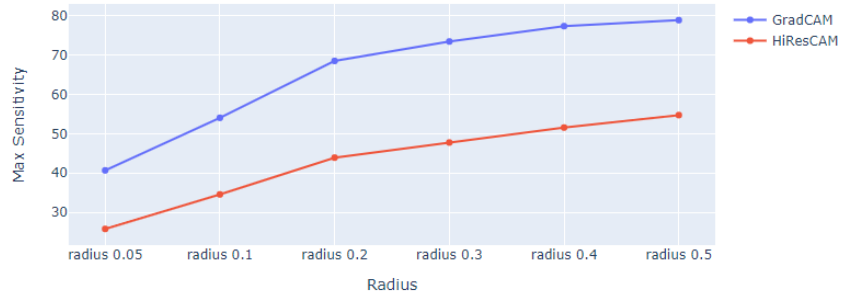
Radius (r)	No. of samples (y)
0.05	20
0.1	20
0.2	30
0.3	30
0.4	40
0.5	40



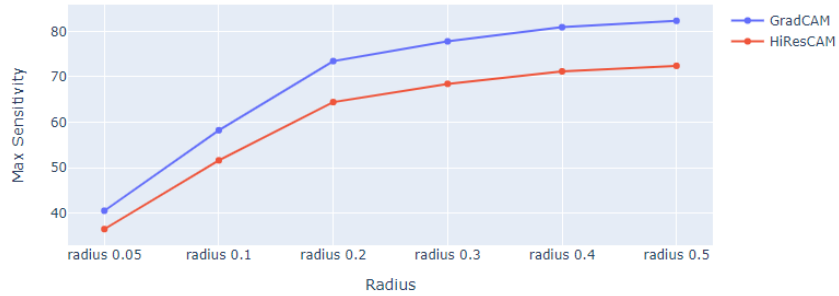
(a) CRC - VGG19



(b) Covid-19 - VGG19



(c) HAM10000 - ResNet50



(d) BreakHis - ResNet50

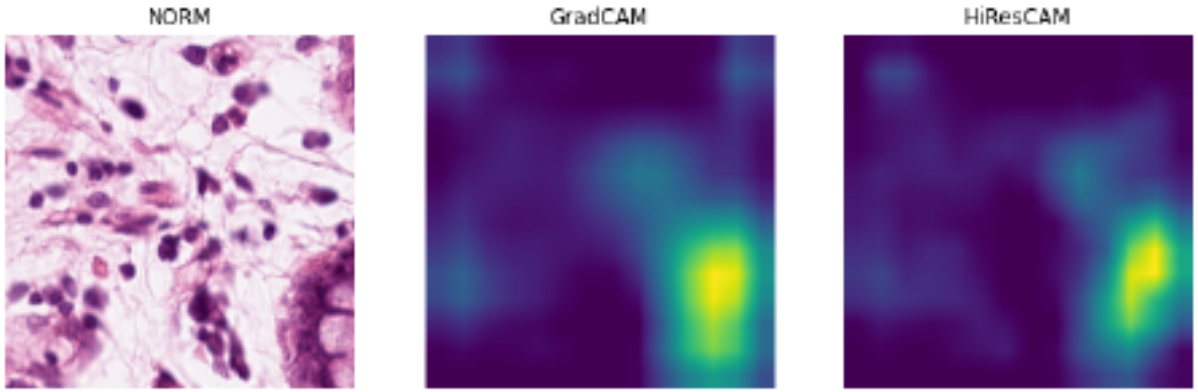
- Overall, HiResCAM prevails 8/8 cases.

Why AOPC and Max Sensitivity favor HiResCAM?

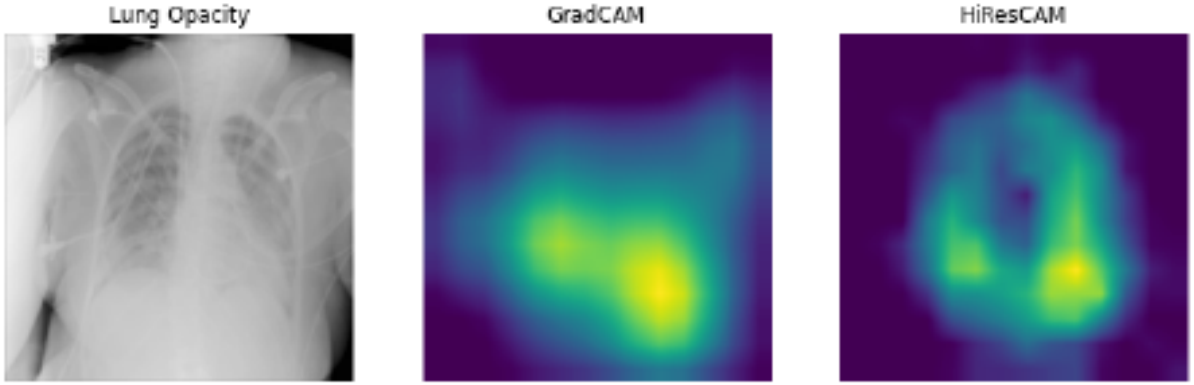
- Grad-CAM and HiResCAM treat gradients in a different way:

$$\left(\frac{1}{D_1 D_2} \sum_{i=1}^{D1} \sum_{j=1}^{D_2} \frac{\partial s^m}{\partial A_{ij}^f} \right) A^f \qquad \text{vs} \qquad \frac{\partial s^m}{\partial A^f} \odot A^f$$

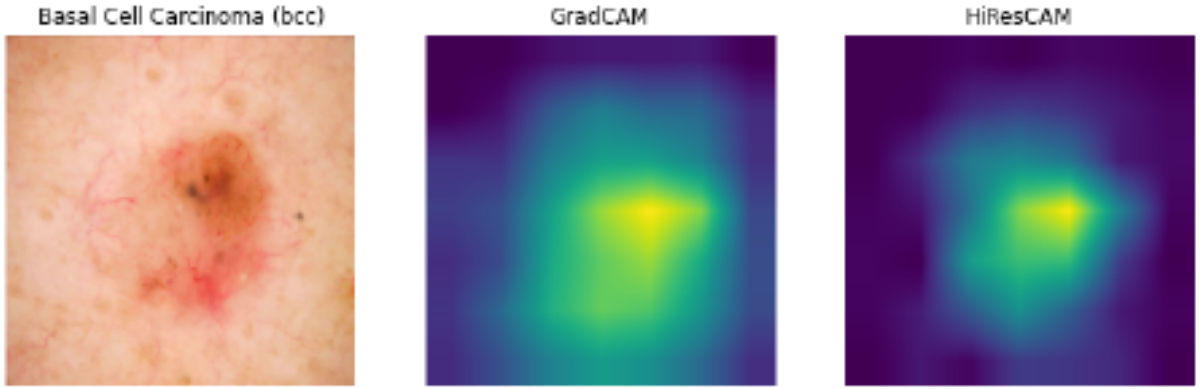
Grad-CAM	HiResCAM
Gradient values and signs are camouflaged into the average	Preserves gradient effect on pixel level and utilizes both value and sign
Larger, smoother, less-detailed attention areas	High-resolution maps with precise class localization



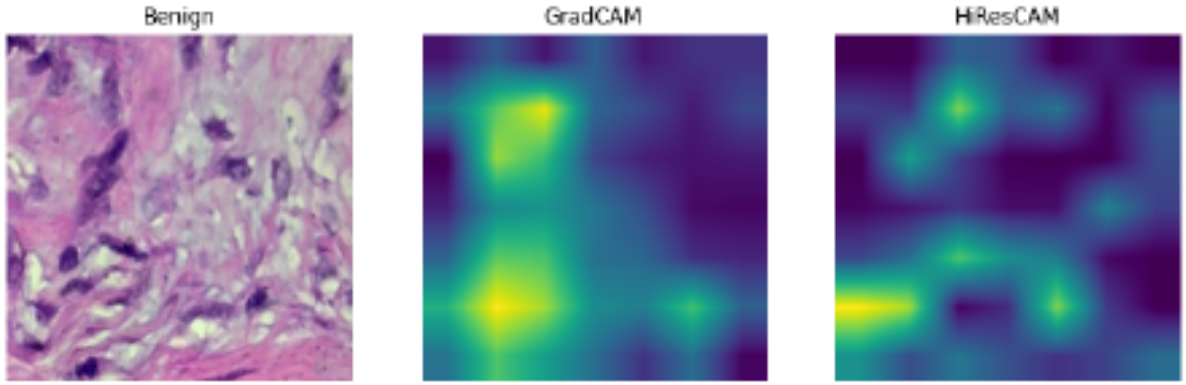
(a) CRC dataset - VGG19



(b) Covid-19 dataset - VGG19



(c) HAM10000 dataset - ResNet50



(d) BreakHis dataset - ResNet50

Table: HAAS Scores (Medical datasets)

	CRC		Covid-19		HAM10000		BreakHis	
	ResNet34	VGG19	ResNet34	VGG19	ResNet50	VGG19	ResNet50	VGG19
Grad-CAM	0.47	0.76	**0.86**	**0.89**	**0.831**	0.714	0.927	0.985
HiResCAM	**0.53**	**0.8**	0.67	0.84	0.83	**0.834**	**0.936**	**1.081**

- HAAS doesn't acknowledge any quality in the medical attribution maps
- Why ?

  - 1st approach: *HA image pixels can have considerable value difference when compared to the original image pixels.*

  ex. For $a = \frac{1}{2}$ attribution, if pixel $x = \frac{1}{2}$ then $HA_x = \frac{3}{4}$
  and if pixel $x = -\frac{1}{2}$ then $HA_x = -\frac{3}{4}$
  Thus, HA image might be *far* from the distribution that the model was trained on.

- 2nd approach: *HAAS incompatible with medical images?*

Non-Medical data tested so far	Medical data
Classes have strong shape dependency	Classes are more densely populated
Weak or No colour dependency	Could have colour dependency

As a result, for medical datasets, could changing the pixels' intensity affect the model's ability to recognize the learned pattern?

Visible color differences in the following:

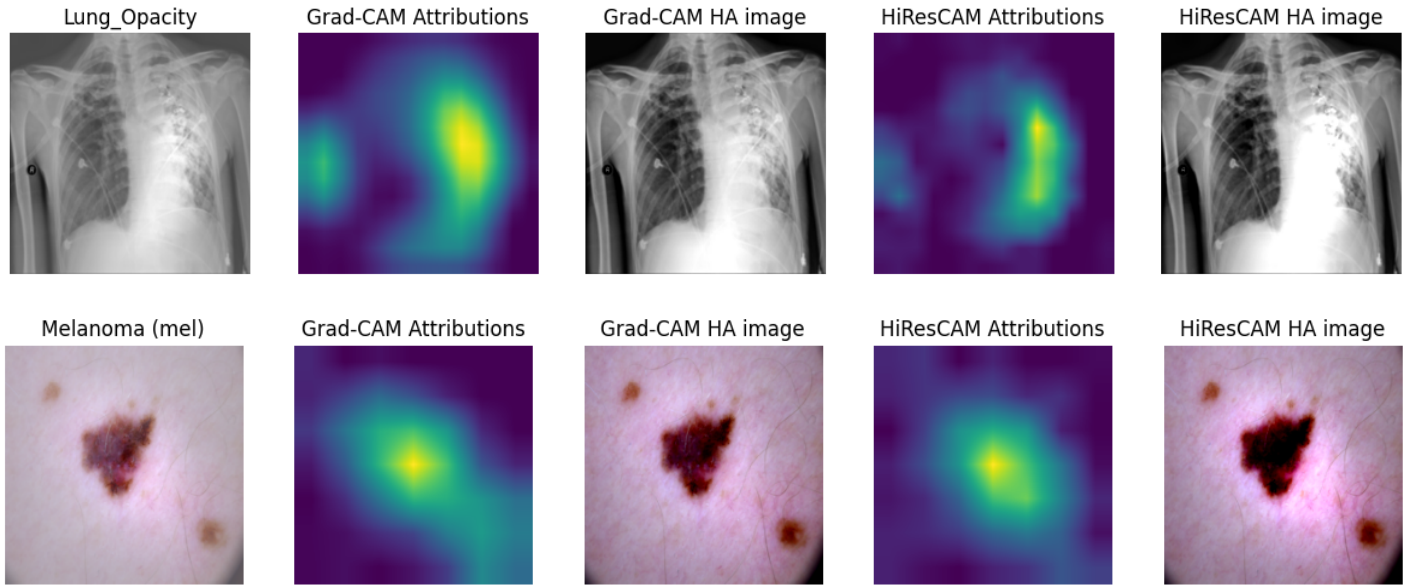


Figure: Examples of HA images

How to test our hypothesis?

- Over Non-Medical data
- Build *random* models (of decent performance)
- Track min-max HAAS values

Table: HAAS Scores (Non Medical datasets)

		Cifar-10	STL-10	Imagenette
		VGG19*	VGG19*	VGG19*
HiResCAM	Max HAAS Score	**1.009**	**1.034**	**1.002**
	Mean AUC	0.981	0.966	0.995
	Min HAAS Score	**0.970**	**0.978**	**0.986**
	Mean AUC	0.969	0.899	0.889

Note: * loop of 16 models for different batch size, learning rate, scheduler and weight decay

Thus, over non-medical datasets, we extracted *meaningful scores* with 16 random models.

Connecting accuracy with HiResCAM metrics values

Is *good* Bal. Accuracy value coupled with *good* metrics results?

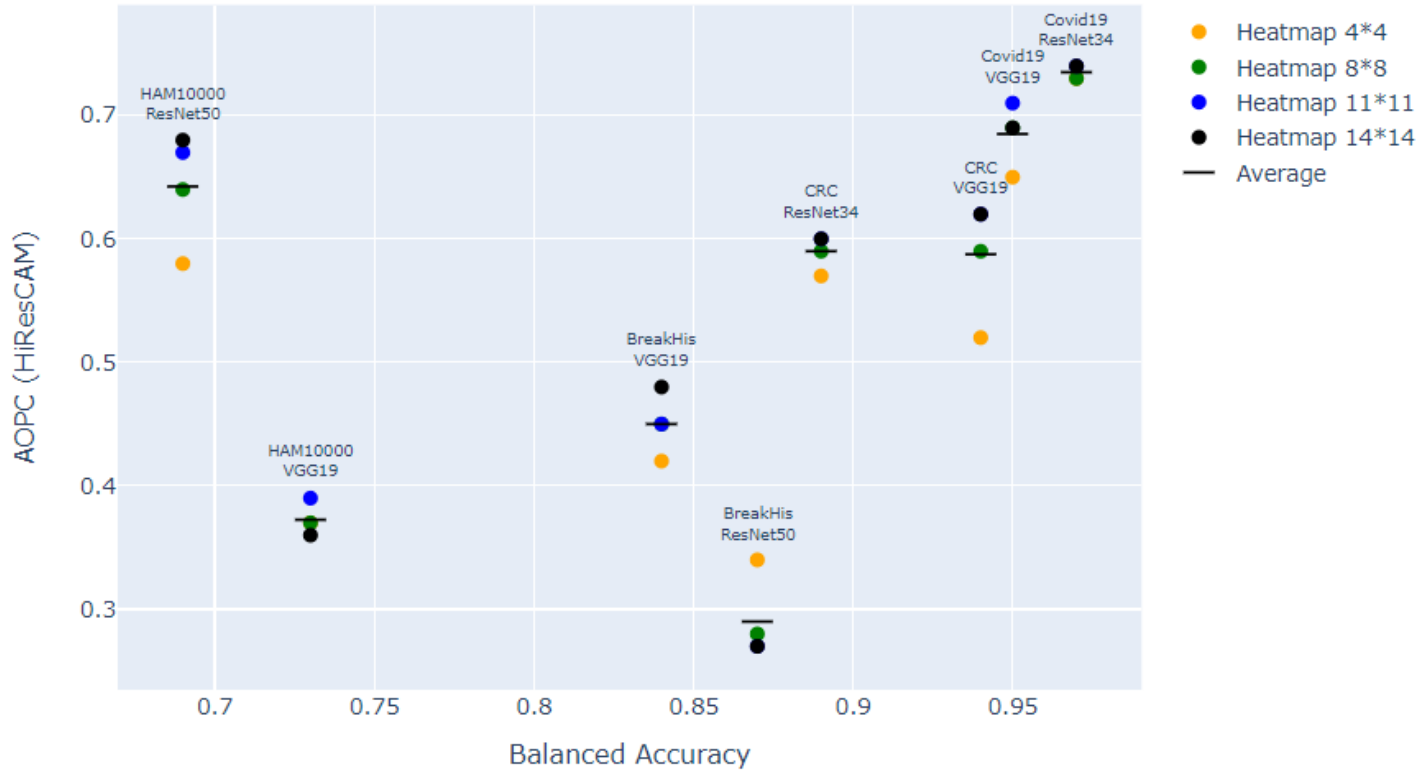


Figure: Bal. Accuracy vs AOPC

- Top 4 models wrt Bal. Accuracy: *almost* increasing pattern wrt average value
- VGG19 models: increasing pattern wrt average value

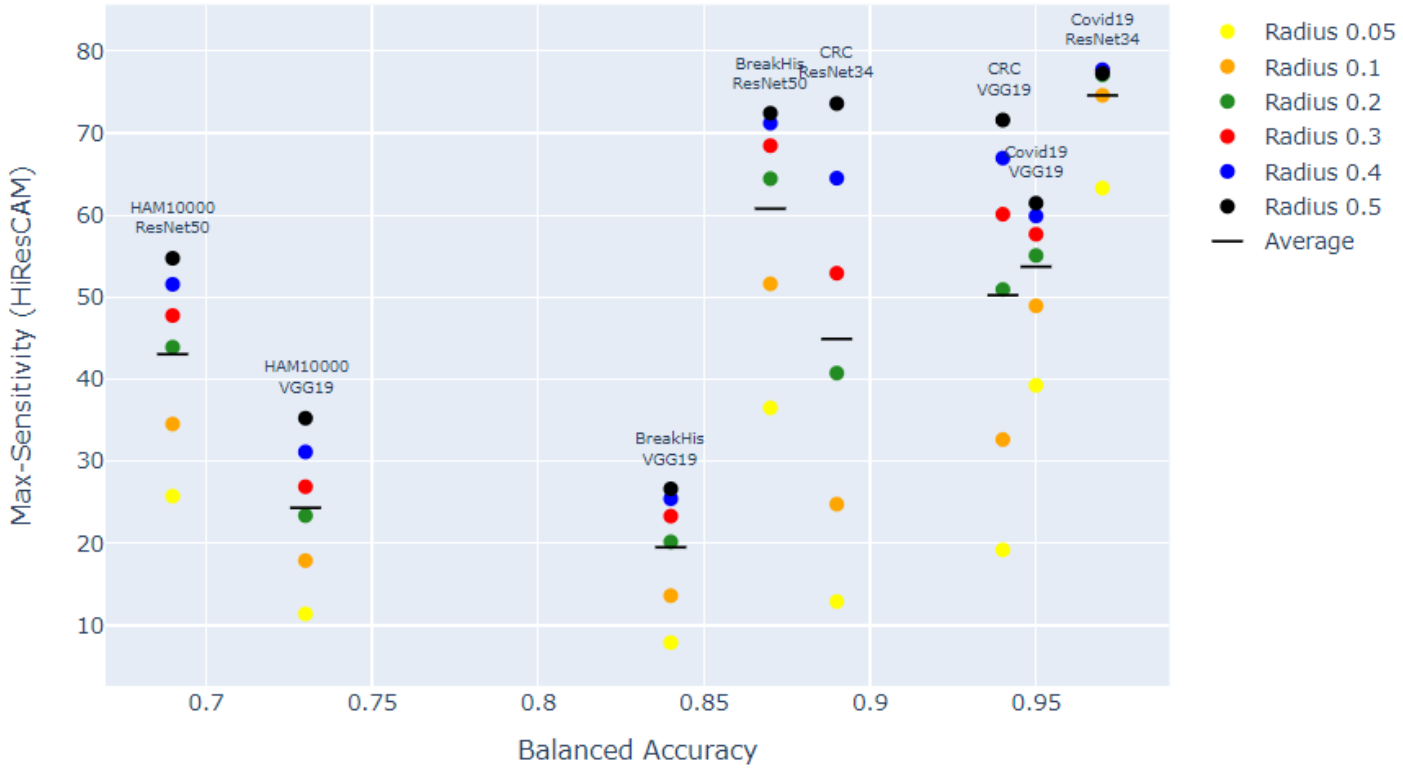


Figure: Bal. Accuracy vs Max Sensitivity

- No pattern (overall models, at dataset level, at model level)

Thank you !