Evaluating Grad-CAM heatmaps of X-ray images

Vaggelis Lamprou

Presentation

Contents

- Data
- Classifier Models
- Grad-CAM Algorithm
- Area Over Perturbation Curve (AOPC)
- Results (Train & Test, Heatmaps Visualization, AOPC graphs)

1. Data

- COVID-19 Radiograhy Database (link)
- Classes: Covid, Lung Opacity, Normal, Viral Pneumonia
- Down-sampling: 1345 images per class
- Training set (80% per class): 1076 * 4 = 4304 images
 Validation set (10% per class): 134 * 4 = 536 images
 Test set (10% per class): 135 * 4 = 540 images

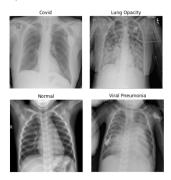


Figure: X-ray examples

2. Classifier Models

• Transfer Learning approach

Layer (type)	Output Shape	Param #	Layer (type)	Output Shape
vgg16 (Functional)	(None, 9, 9, 512)	14714688	densenet201 (Functional)	(None, 9, 9, 1920)
max_pooling2d (MaxPooling2D)	(None, 2, 2, 512)	0	max_pooling2d_1 (MaxPooling 2D)	(None, 2, 2, 1920)
flatten (Flatten)	(None, 2048)	0	flatten_1 (Flatten)	(None, 7680)
dense (Dense)	(None, 64)	131136	dense_2 (Dense)	(None, 64)
dense_1 (Dense)	(None, 4)	260	dense_3 (Dense)	(None, 4)
otal params: 14,846,084 rainable params <mark>: 131,396</mark> on-trainable params: 14,714,688		Total params: 18.813,828 Trainable params <mark>: 491,844</mark> Non-trainable params: 18,321,984		

Compiled with Categorical Crossentropy loss and Adam optimizer

Param #

18321984

491584 260

3. The Grad-CAM algorithm

- Post-hoc
- Visual explanations
- Local explanations
- Denote by A₁, A₂, ..., A_K the activation maps of the last convolutional layer of the CNN-based model.

Class dependent heatmaps are constructed as follows:

$$L_{Grad-CAM}^{c} = ReLU(\sum_{k} \underbrace{\left[\frac{1}{Z}\sum_{i}\sum_{j}\frac{\overbrace{\partial y^{c}}}{\partial A_{ij}^{k}}\right]}_{\text{step 2: }a_{c}^{k}} A^{k})$$

https://arxiv.org/pdf/1610.02391.pdf



4. Area Over Perturbation Curve

- How do we choose among two heatmaps ?
- Use MoRF technique to evaluate heatmaps.
 Looks at the heatmaps as a decreasing sequence of importance regions {r₁, r₂, ..., r_L}. For image x, compute images sequence by:

$$x_{MORF}^{(0)} = x$$

 $x_{MORF}^{(k)} = g(x_{MORF}^{(k-1)}, r_k), \quad k = 1, 2, ..., L$

and consider the MoRF perturbations graph as defined by the points

$$\{(k, f(x_{MoRF}^{(k)})), k = 0, 1, ..., L\}.$$

• Denote by $<\cdot>$ the average over the entire test set

$$AOPC = \frac{1}{L+1} < \sum_{k=1}^{L} [f(x_{MoRF}^{(0)}) - f(x_{MoRF}^{(k)})] >$$

per image controls area over MoRF curve

4 D > 4 B > 4 B > 4 B > B

5. Results: Train & Test

- The models were trained for 20 epochs and monitored with Model Checkpoint callback
- After training, get model instance that maximizes the diseases validation recall scores.
- Eventually, kept VGG16 based model of epoch 16 and DenseNet201 based model of epoch 15.

	precision	recall	f1-score	support
Covid	0.88	0.84	0.86	135
Lung Opacity	0.82	0.82	0.82	135
Normal	0.79	0.82	0.80	135
Viral Pneum	0.96	0.96	0.96	135
accuracy	-	-	0.86	540
macro avg	0.86	0.86	0.86	540
weighted avg	0.86	0.86	0.86	540

	precision	recall	f1-score	support
Covid	0.91	0.87	0.89	135
Lung Opacity	0.79	0.81	0.80	135
Normal	0.83	0.86	0.85	135
Viral Pneum	0.99	0.98	0.98	135
accuracy	-	-	0.88	540
macro avg	0.88	0.88	0.88	540
weighted avg	0.88	0.88	0.88	540

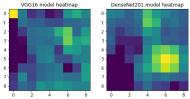
Figure 4: VGG16 based model - Classification report

Figure 5: DenseNet201 based model - Classification report

Note DenseNet201 has better recall and f1 scores! What about AOPC score?

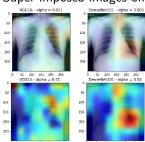
5. Results: Grad-CAM Heatmaps Visualization

- Consider Covid test image correctly classified by both models
- The heatmaps of the top predicted class are:



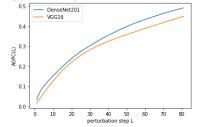
Note that they are divided in 81 regions (approx (34,34) pixel blocks)

 \bullet Super-imposed images on different α levels:



5. Results: AOPC graphs

- Per classifier compute AOPC values as function of perturbation step L, considering only correctly classified test images.
- Perturbations via random normal noise of mean 0 and standard deviation 0.1 (function g).



Scores summary:

Base model	Test Recall	Test F1	AOPC
VGG16	86%	86%	0.45
DenseNet201	88%	88%	0.49

Thank You!