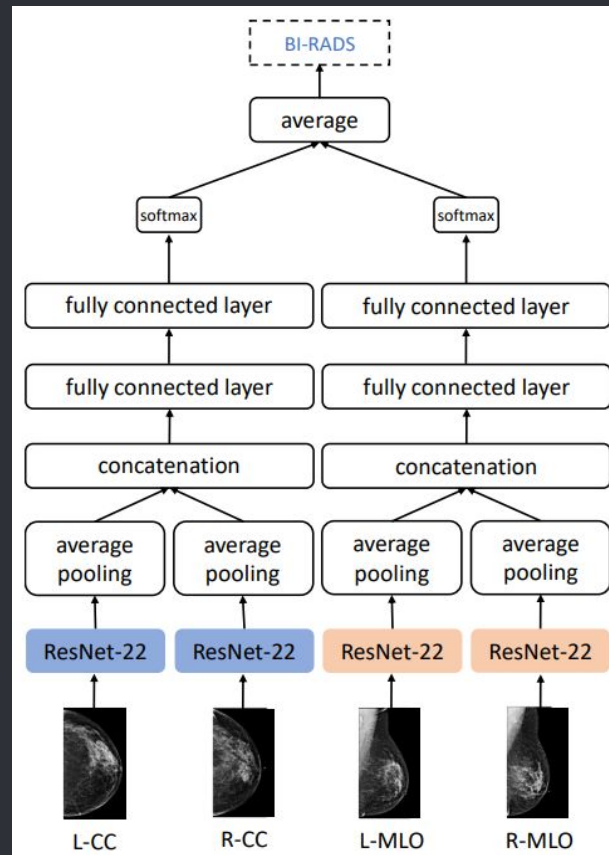# Medical Imaging
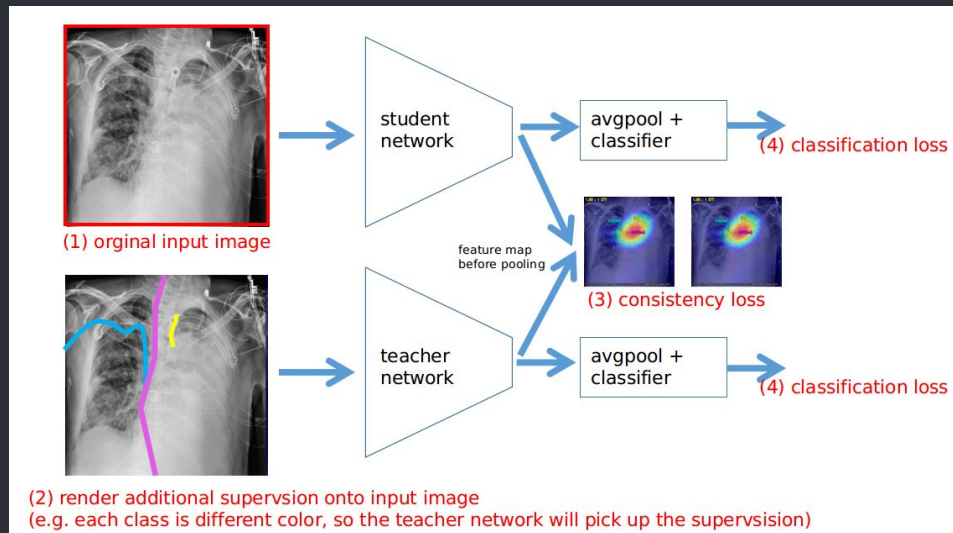# RANZCR CLIP

Paolo Sofia, Matteo Carollo

# Similar approaches - classification

We started our work taking into consideration this initial approach. Unfortunately, due to the limited time available, we simplified this approach, using a single model and attached a different head for each label group.

# Similar approaches: distillation

We took inspiration also from other proposed method on kaggle, such as this one. We simplified our model by training a simple siamese net and then we fine tuned the model.



(1) orginal input image

feature map before pooling

(3) consistency loss

(4) classification loss

(2) render additional supervsion onto input image
(e.g. each class is different color, so the teacher network will pick up the supervsision)

# Our work - Dataset

## Dataset issue:

- Unbalanced labels
- Data leakage

## Solution:

- Compute weights for each label
- Split train and validation set by patient maintaining the same label distribution
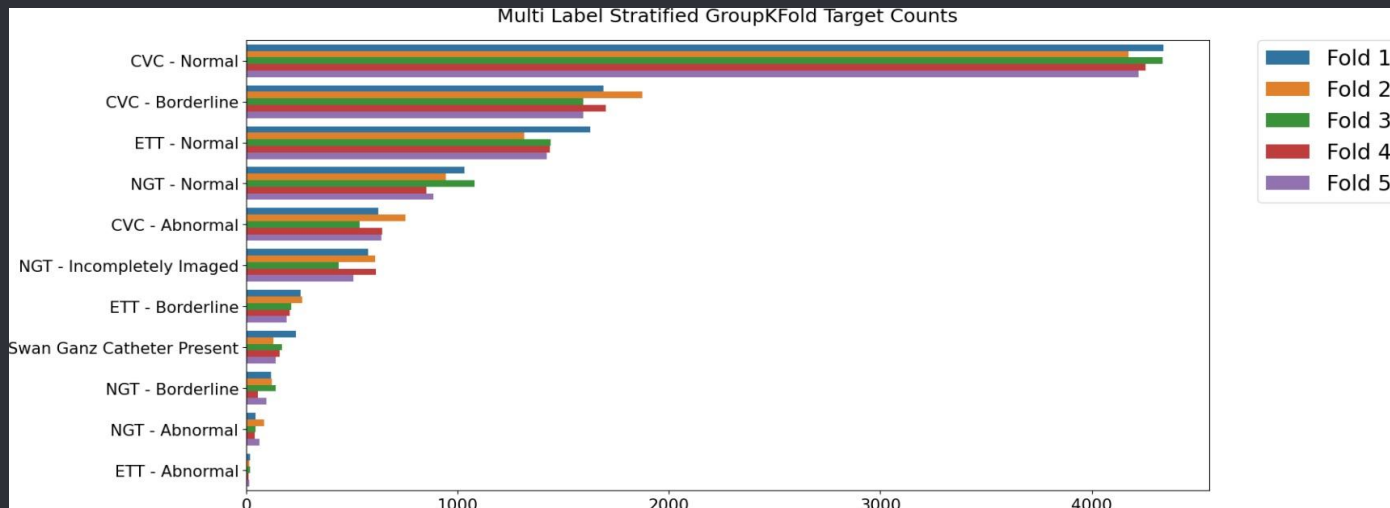
# Our work - Models, Losses, Optimizers comparison

Our initial approach was to compare different CNN, loss functions and optimizers to find the best combination of them

### CNN

- Resnet18
- Resnet101
- Resnest50
- Inception V3
- Densenet169
- EfficientNetB2
- Xception

### LOSS FUNCTIONS

- BCE
- Weighted BCE
- Weighted BCE + L1
- Weighted BCE + L2
- Weighted BCE + L1 L2
- ELR
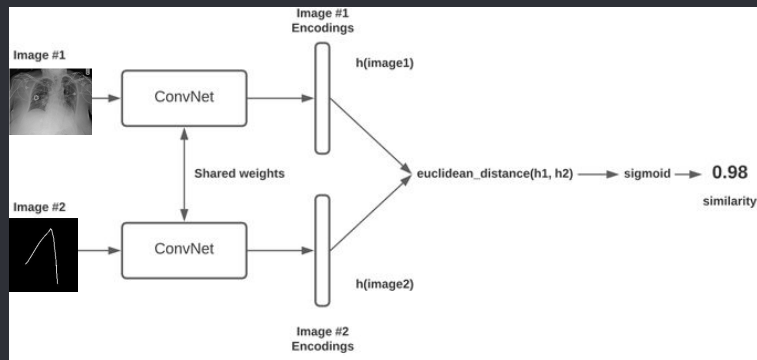- Focal Loss

### OPTIMIZERS

- Adam
- Adam w. Decaying Momentum
- SGD w. Decaying Momentum
- Yogi
- Adabound
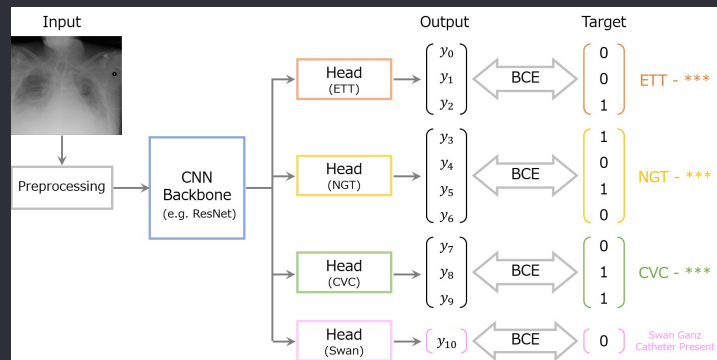- Adabelief

# Our work - Other approaches

## Siamese Net

2 stages training

1. Train siamese net
2. Transfer learning siamese net weights to original net



## Multi headead net

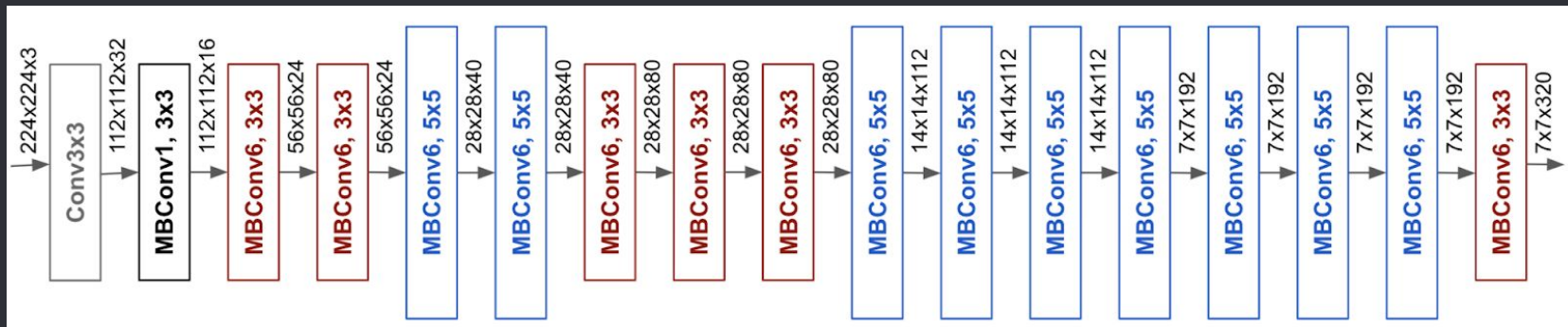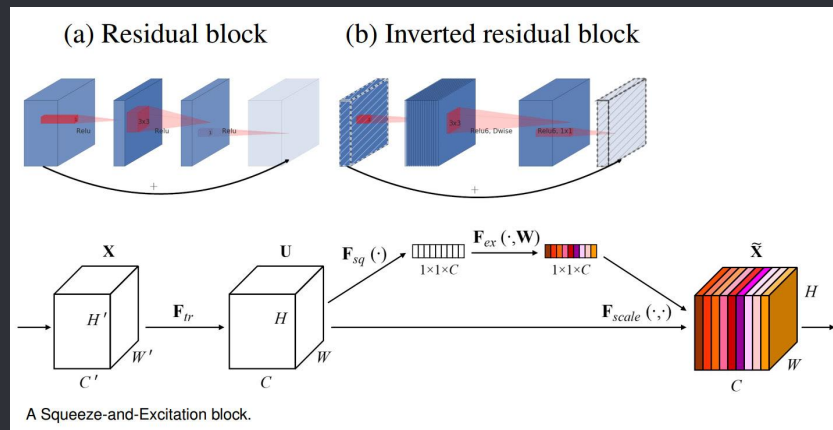◦ Different Head for each group of labels

# Architecture - EfficientNet B2

It has the best tradeoff between speed and performance

How it works:

- Inverted residual block
- Squeeze and excitation block



(a) Residual block   (b) Inverted residual block

A Squeeze-and-Excitation block.

# Results - Optimizer

Adam is less stable, but it is faster to converge and achieves best results, so we chose it as optimizer. Then we used Adabelief for a second stage training as it behaves better in proximity of the minima
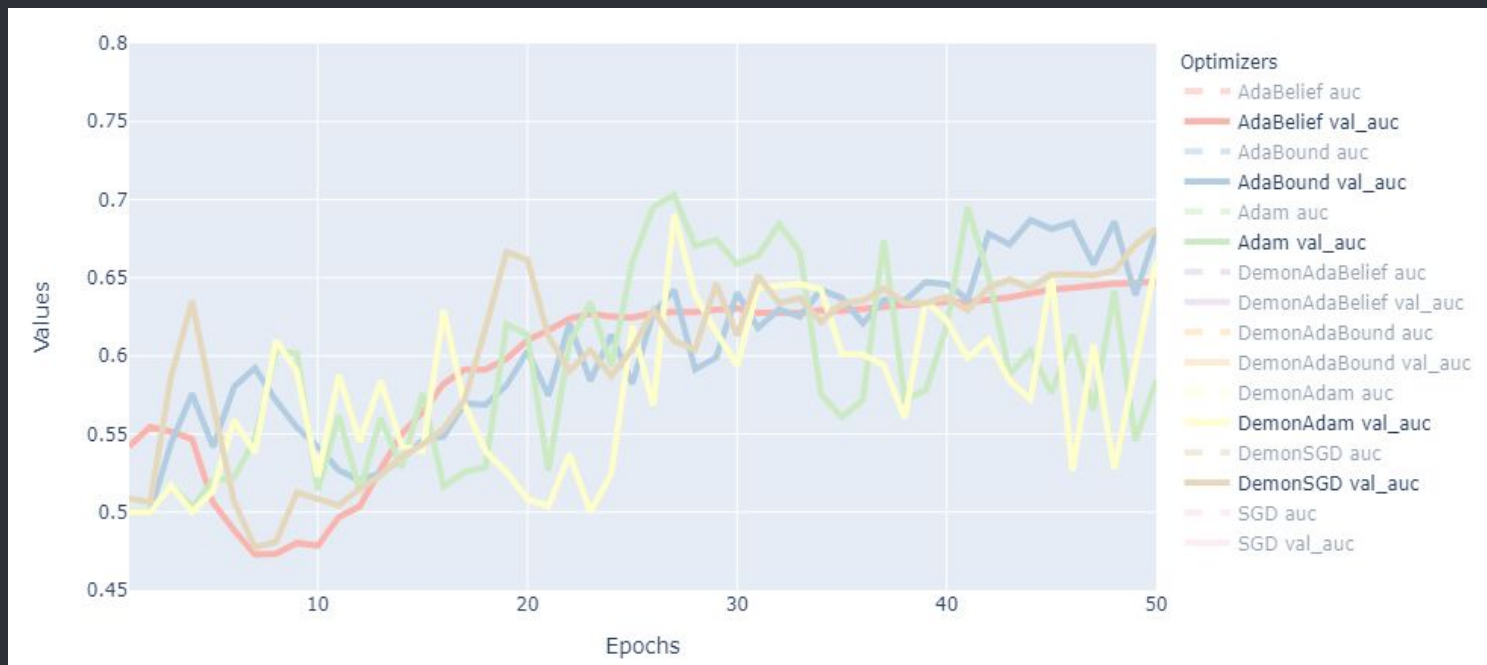
# Results - Models

EfficientNetB5 has slightly better performance than EfficientNetB2, but it is larger and and slower, so we chose EfficientNetB2 also to avoid overfitting.
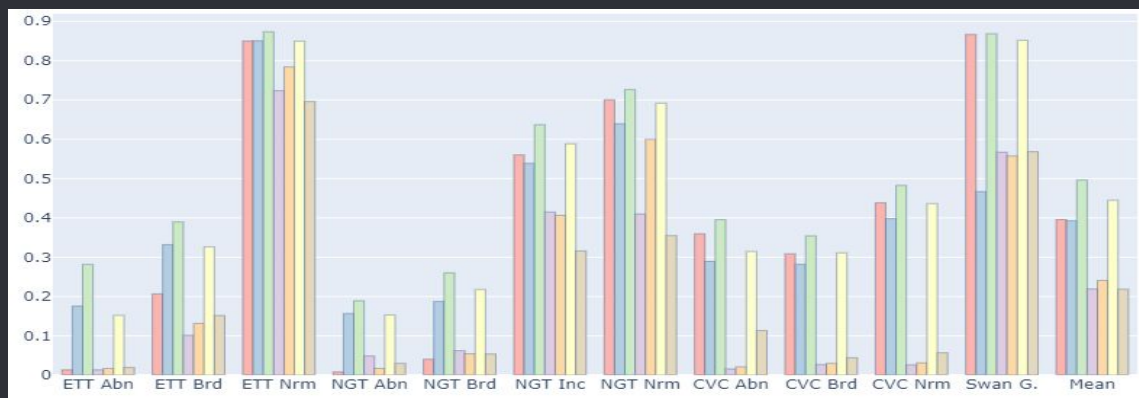
# Results - EfficientNet B2

AUC

Training 0.9575

Validation 0.93



Area MCC

Training 0.5585

Validation 0.4962

- ## Conclusion

  - The model used is very simple, but performance are good, even though, with better design of either siamese net or multi headed net, higher scores could be achieved.

  - Compared to other models on kaggle, our performance may appear inferior, but on kaggle they focus on winning competition, ignoring three important aspects:
    - Data leakage
    - Loss functions
    - Noise as data augmentation technique

# Future work

### Instance segmentation

Use the dataset annotations to use instance segmentation and then classify the segmented images

### Distillation methods

Use teacher-student model using also annotation data

### Multi headed net

Improve the design of the head, or use a different model for each group of data and then concatenate the results. In this case the models does not share the weights

# Thanks for your attention