



Fundus Image Analysis and Grading for Diabetic Retinopathy

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Agenda

Problem Statement
Proposed Approach
MNet
ANet
CNet
Integration
Learning Outcomes
Impediments

Problem statement

Diabetic retinopathy (DR)

- Leading cause of vision loss in the general population
- Affects up to 80 % of people who have had diabetes for 20 years or more

Challenges

- Detecting the subtle pathological lesion characteristic of early-stage disease
- No large well annotated datasets



Source: <https://nei.nih.gov/health/diabetic/retinopathy>,
accessed on 11.12.2018



Proposed approach

Goal

Convolutional Neural Network based algorithm for:

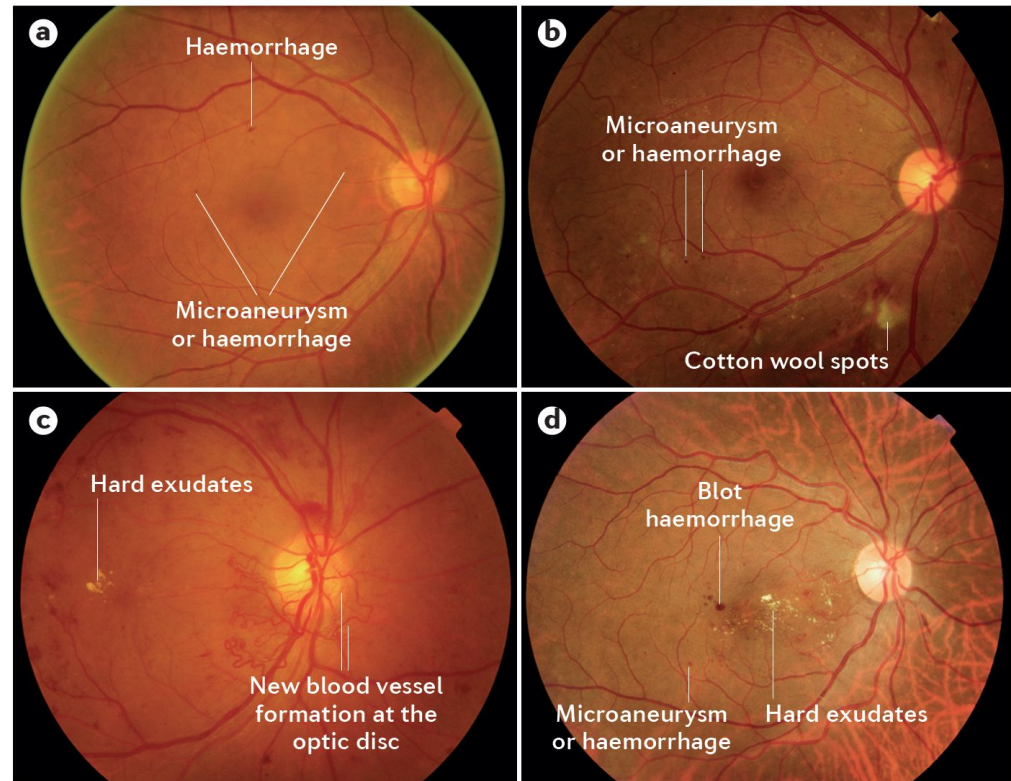
- diagnosing 5 stages of DR
- highlight suspicious regions

DR stages

- 0 – no DR
- 1 – mild
- 2 – Moderate
- 3 – Severe
- 4 – Proliferative

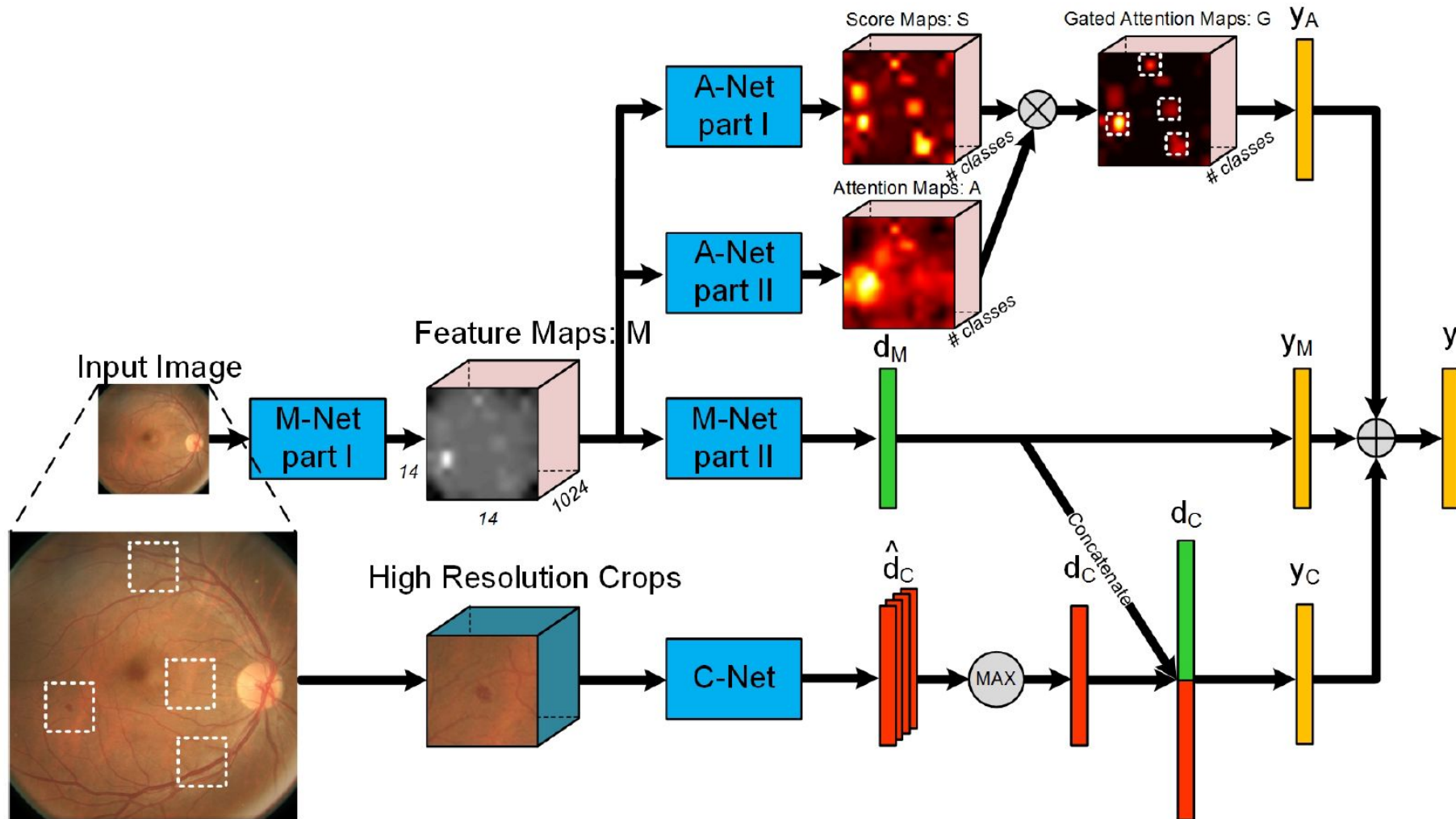
Datasets

- EyePACS
- IDRiD



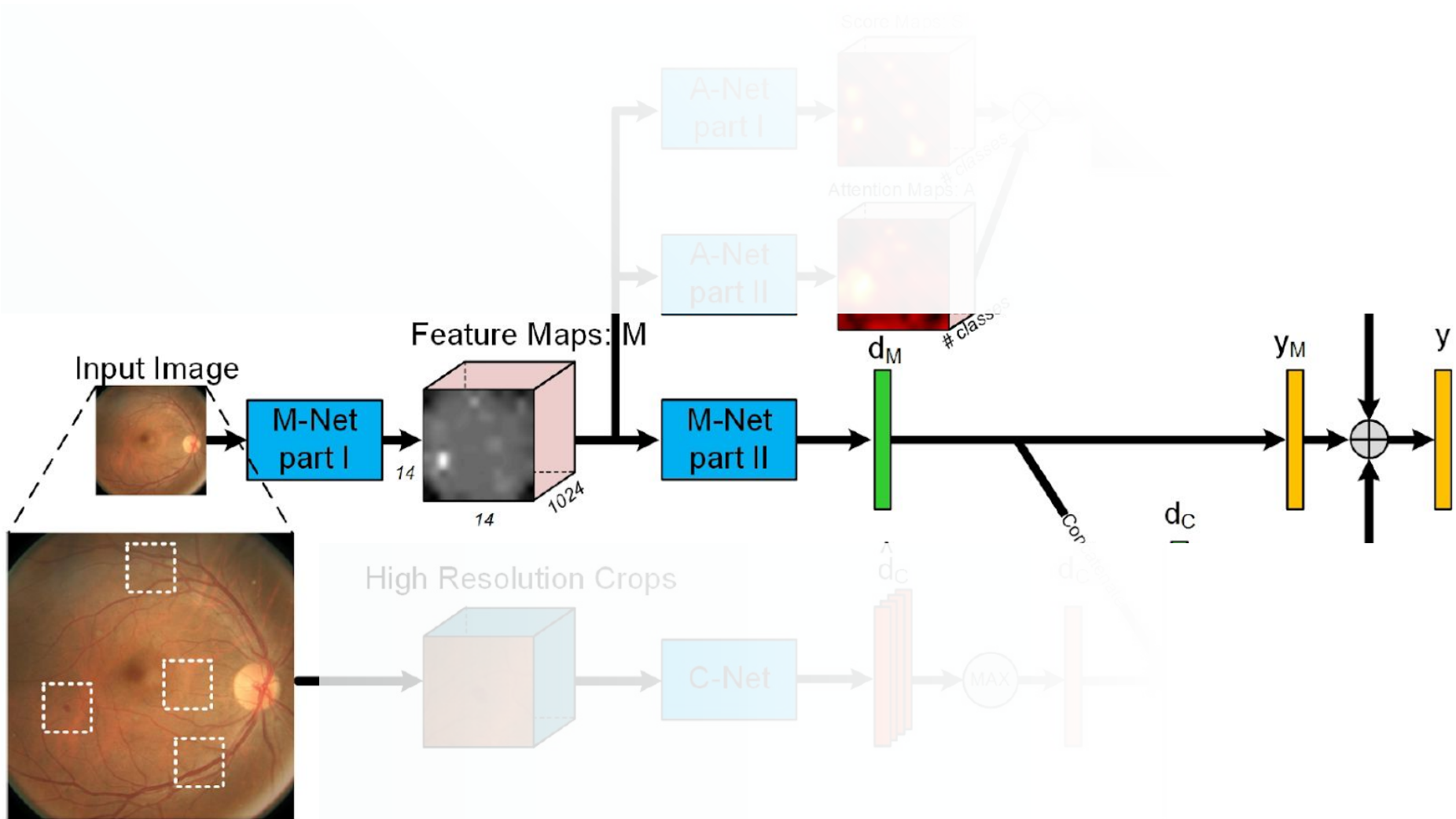
Source: T.Y. Wong, C.M. Cheung, M. Larsen, S. Sharma, and R. Simó. *Diabetic retinopathy*, 16012. Nature Reviews Disease Primers, 2016

Architecture (Zoom-in Net)



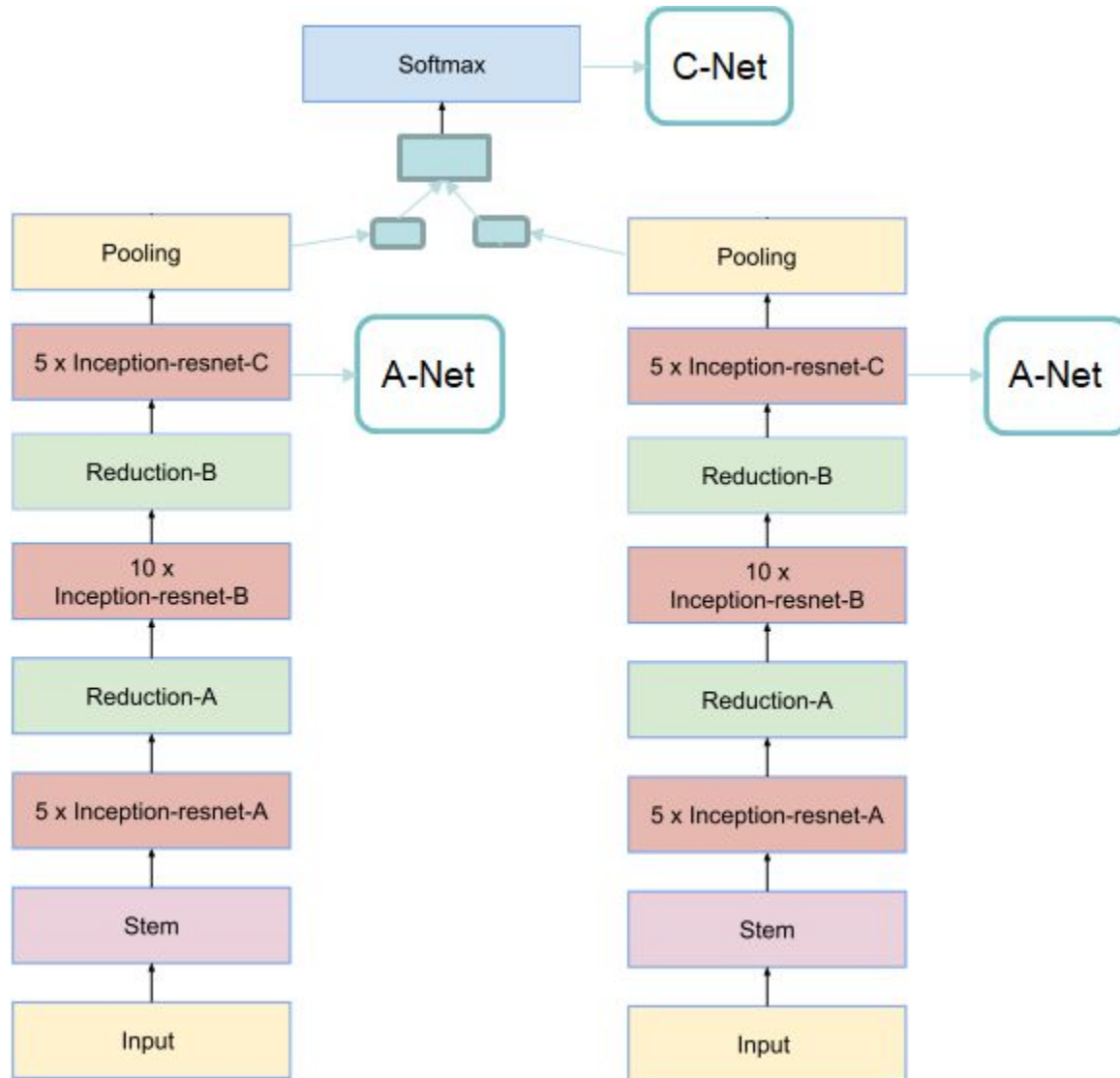
Source: Z.Wang, Y.Yin, J.Shi, W.Fang, H.Li, and X.Wang. *Zoom-in-Net: Deep Mining Lesions for Diabetic Retinopathy Detection*, pages 267–275. Springer International Publishing, 2017

Main Network (M-Net)



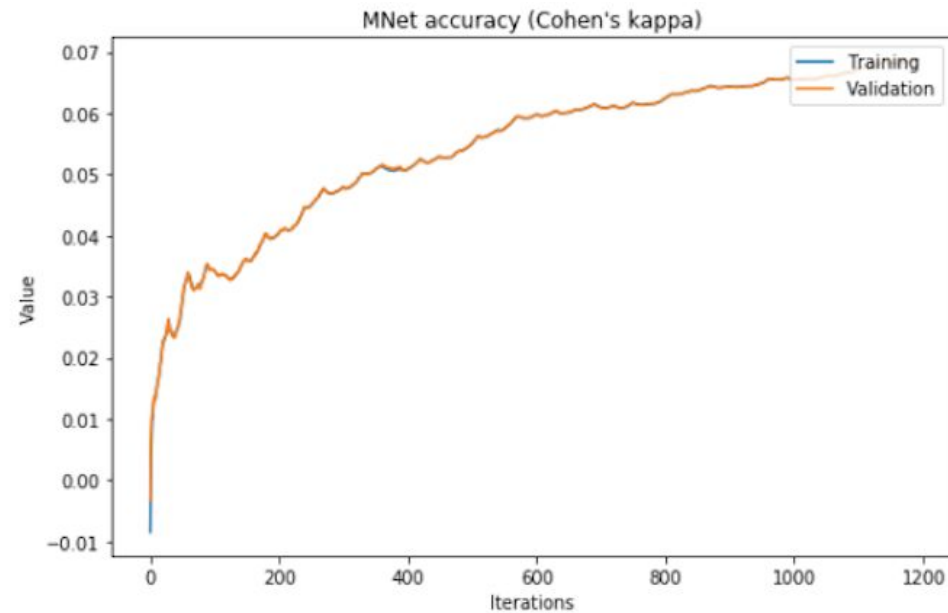
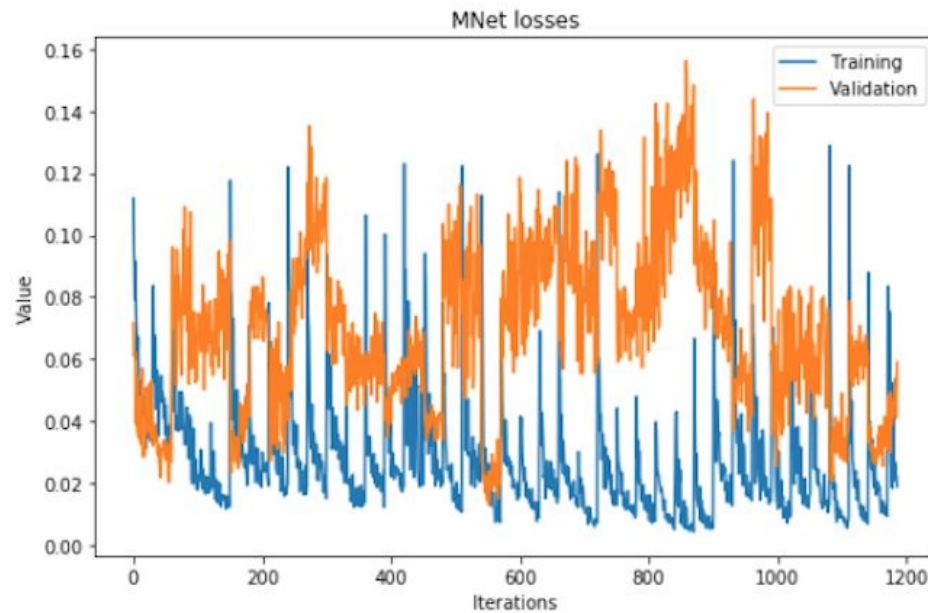
Source: Z.Wang, Y.Yin, J.Shi, W.Fang, H.Li, and X.Wang. *Zoom-in-Net: Deep Mining Lesions for Diabetic Retinopathy Detection*, pages 267–275. Springer International Publishing, 2017

Main Network (M-Net)



- **Input:** Pre-processed images of size 512x512
- **Output:** Probability of the image belonging to each disease level
- Output from layer *5xInception-resnet-C* is taken as input for A-Net.
- Concatenate the left and right eye for classification.
- Weighted loss computation
- **Challenge:** getting the concatenation right

Mnet training. Original approach



Advantages

1. Quick
2. Computational resource friendly
3. Easily portable

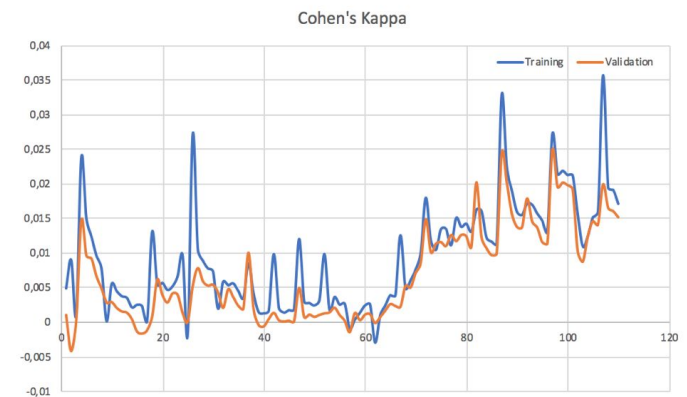
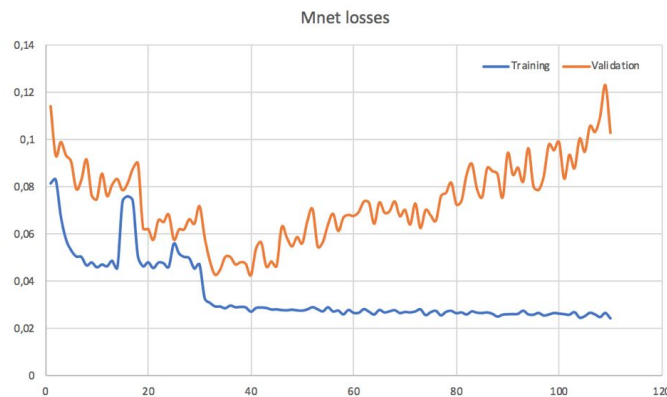
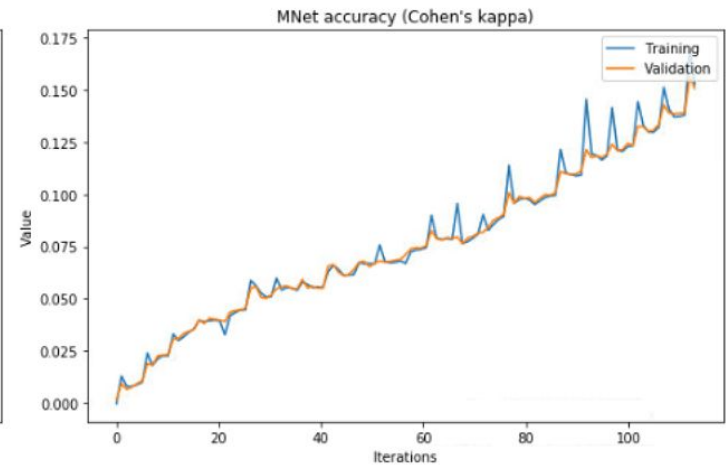
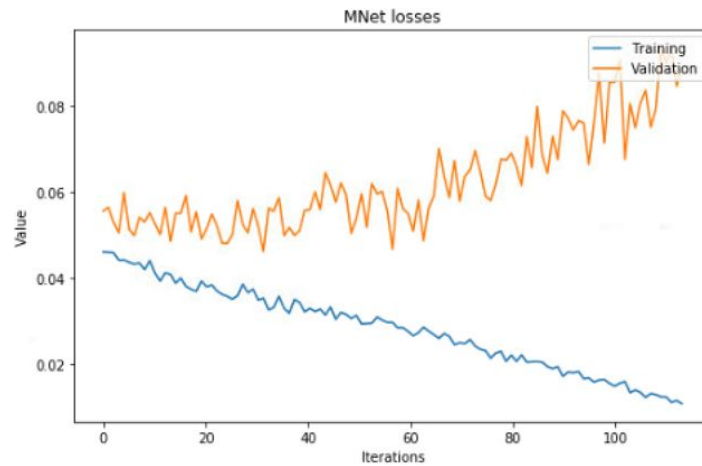
Disadvantages

1. No understanding of what happening

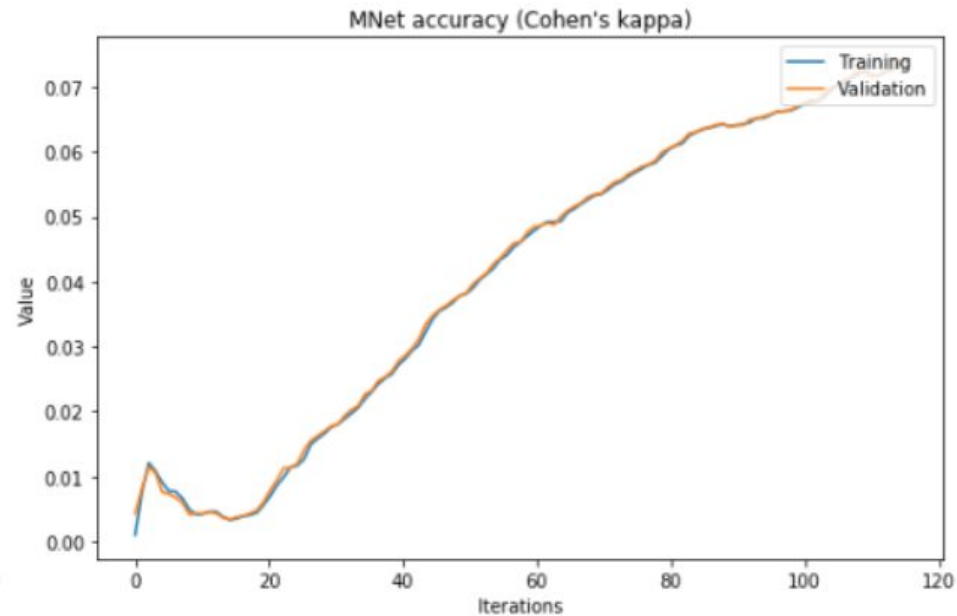
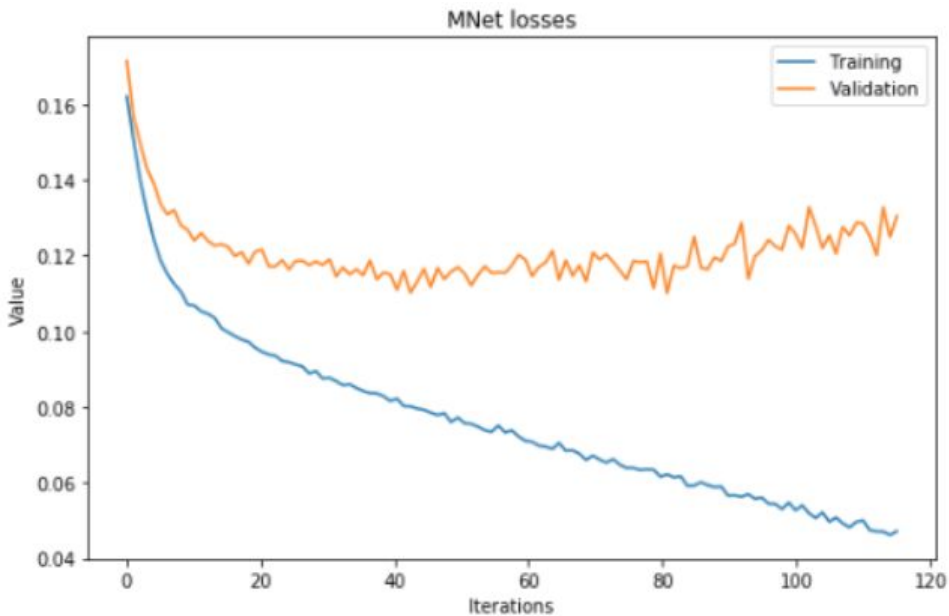


Mnet training. Subsetting

1. L2 regularization
2. Weighted Kappa Score



Mnet. 1 eye

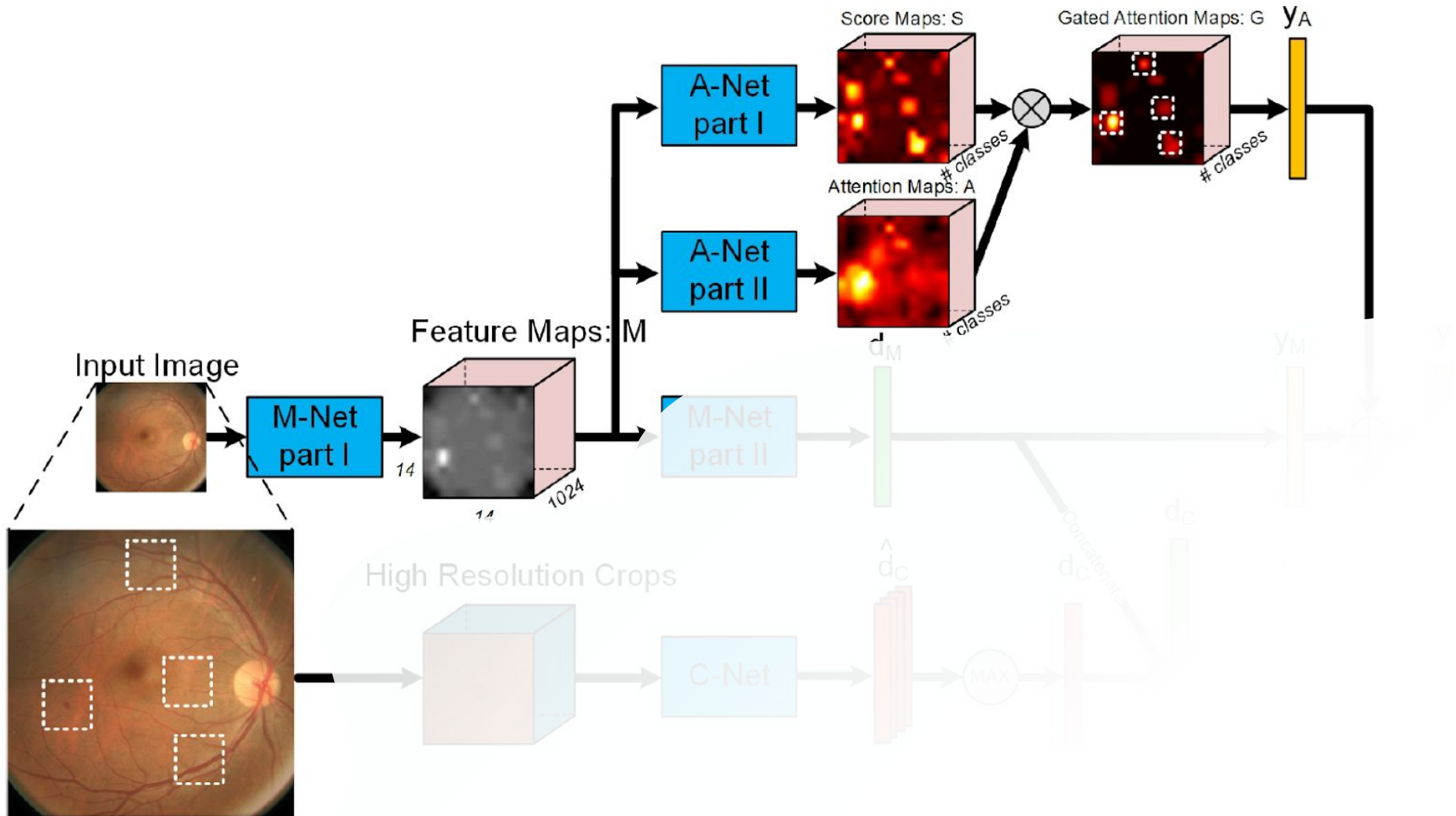


Further plans:

1. Train on more images
2. Double check Cohen's kappa score

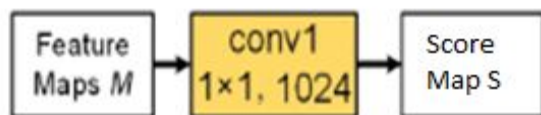


Attention Network (A-Net)

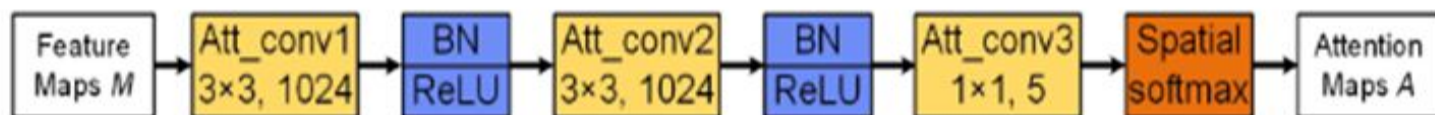
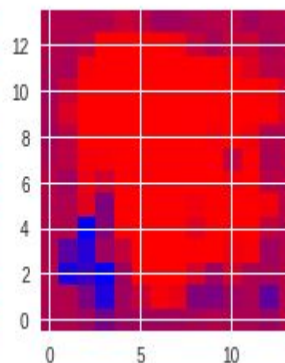
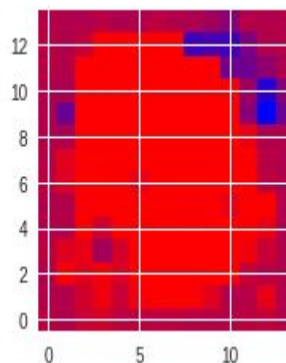
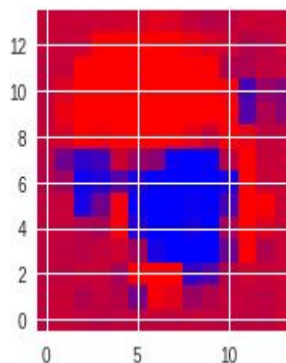
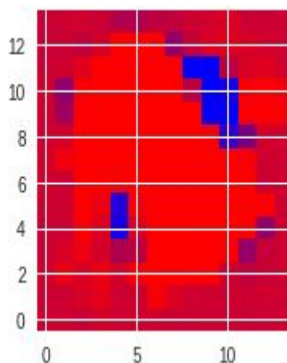
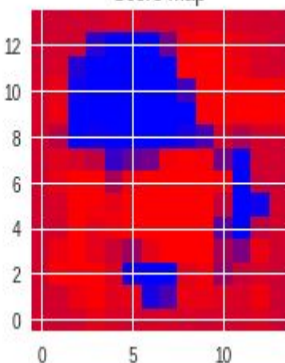


Source: Z.Wang, Y.Yin, J.Shi, W.Fang, H.Li, and X.Wang. *Zoom-in-Net: Deep Mining Lesions for Diabetic Retinopathy Detection*, pages 267–275. Springer International Publishing, 2017

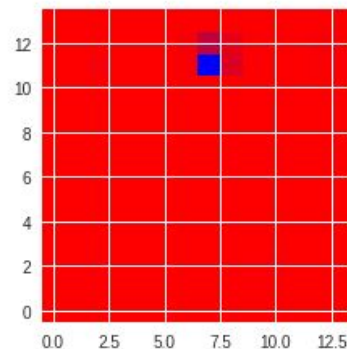
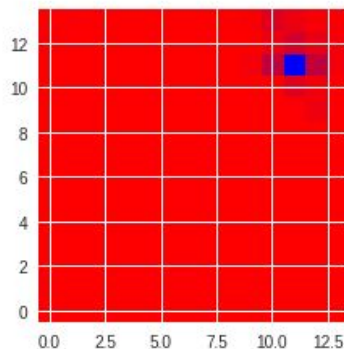
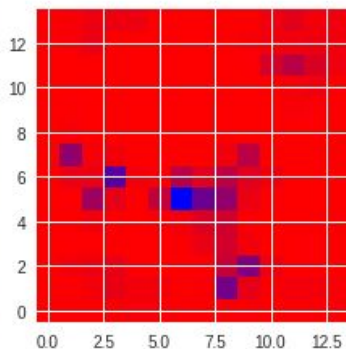
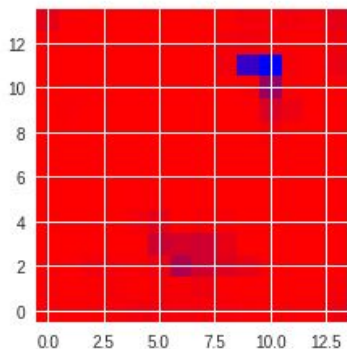
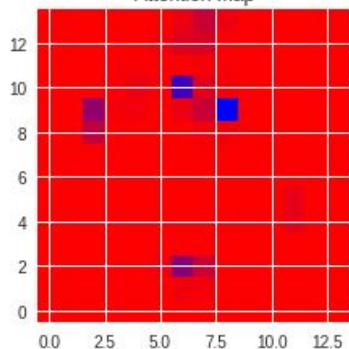
Attention Network (A-Net)



Score map

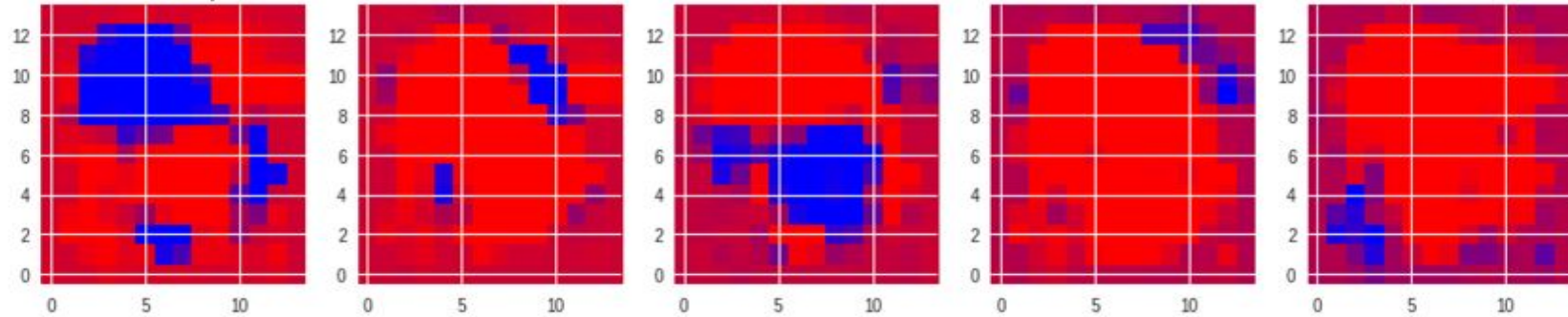


Attention map

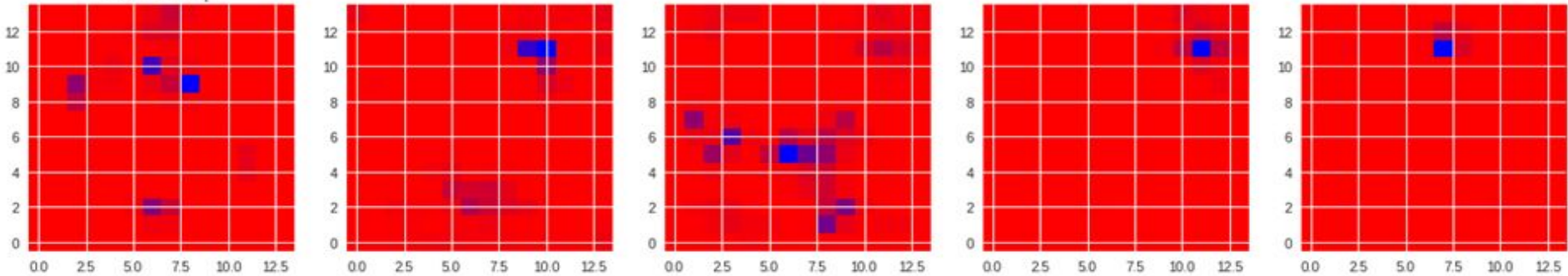


Gated map

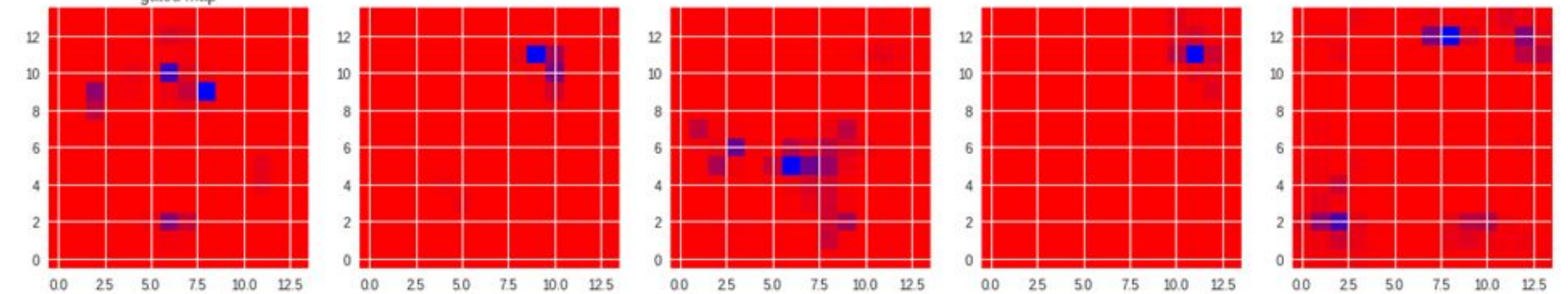
Score map



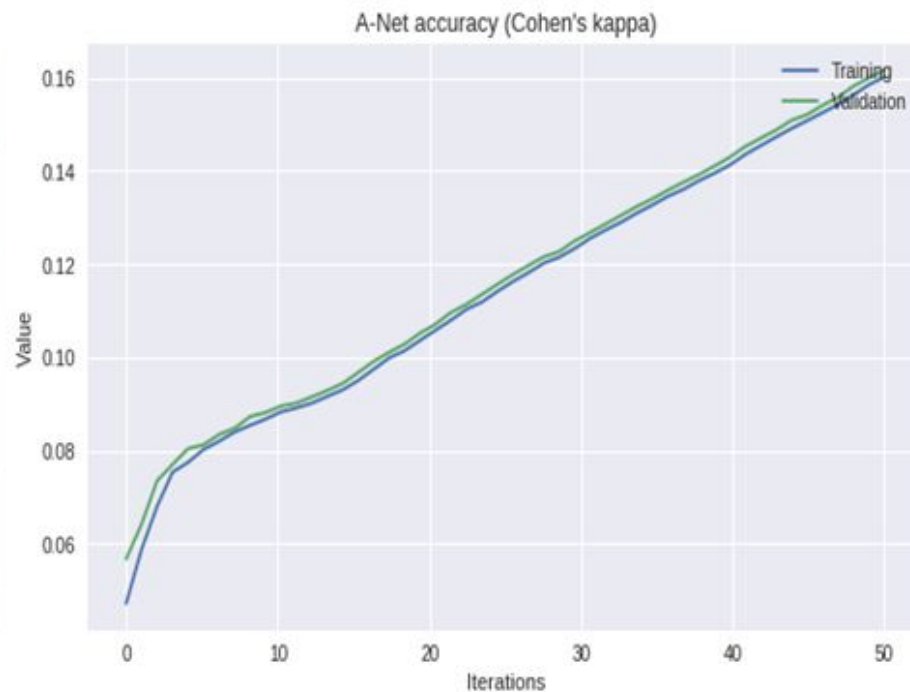
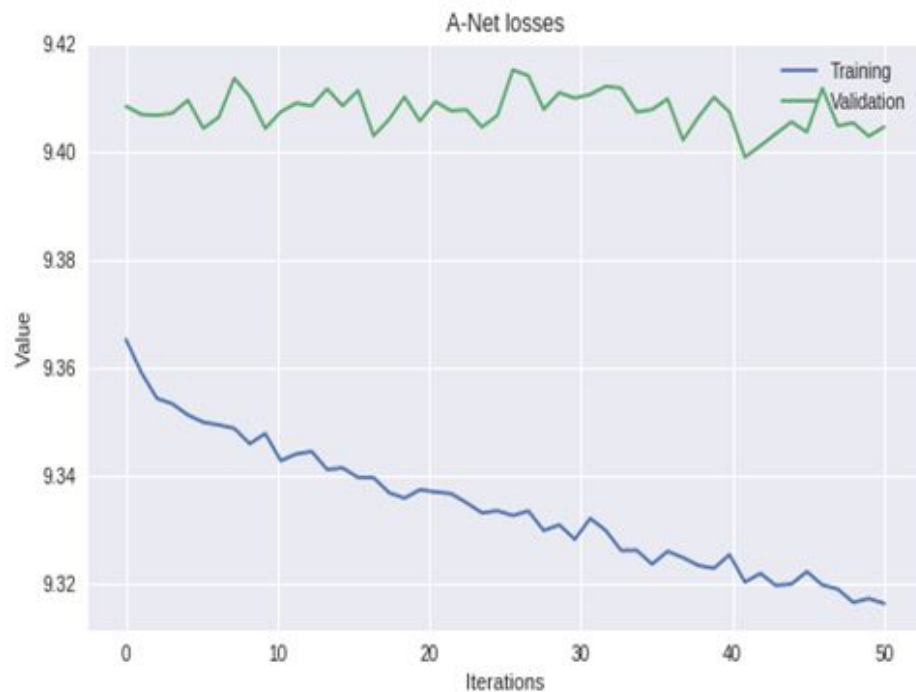
Attention map



gated map



A-Net with 2-eye M-Net

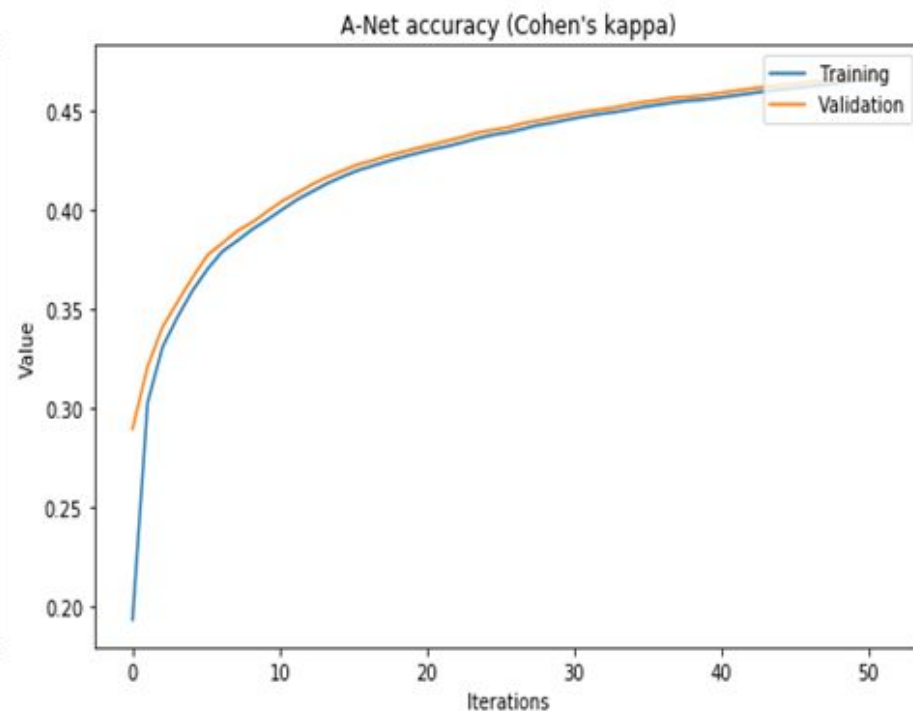
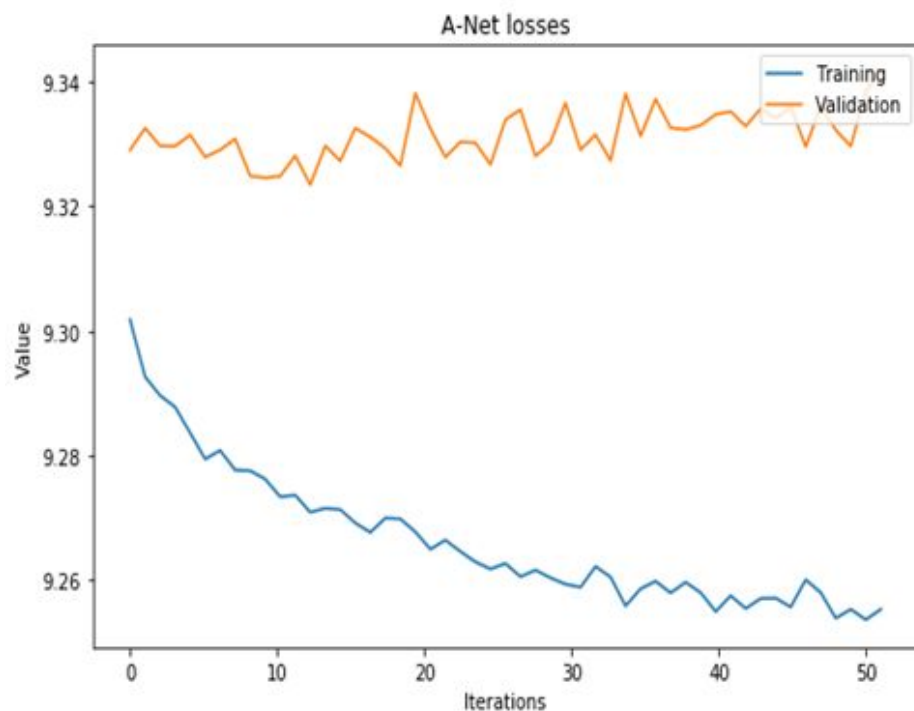


Weighted SoftMax Cross Entropy Loss (with L2 regularization) : 9.30

Kappa Score :0.16



A-Net with 1-eye M-Net Model

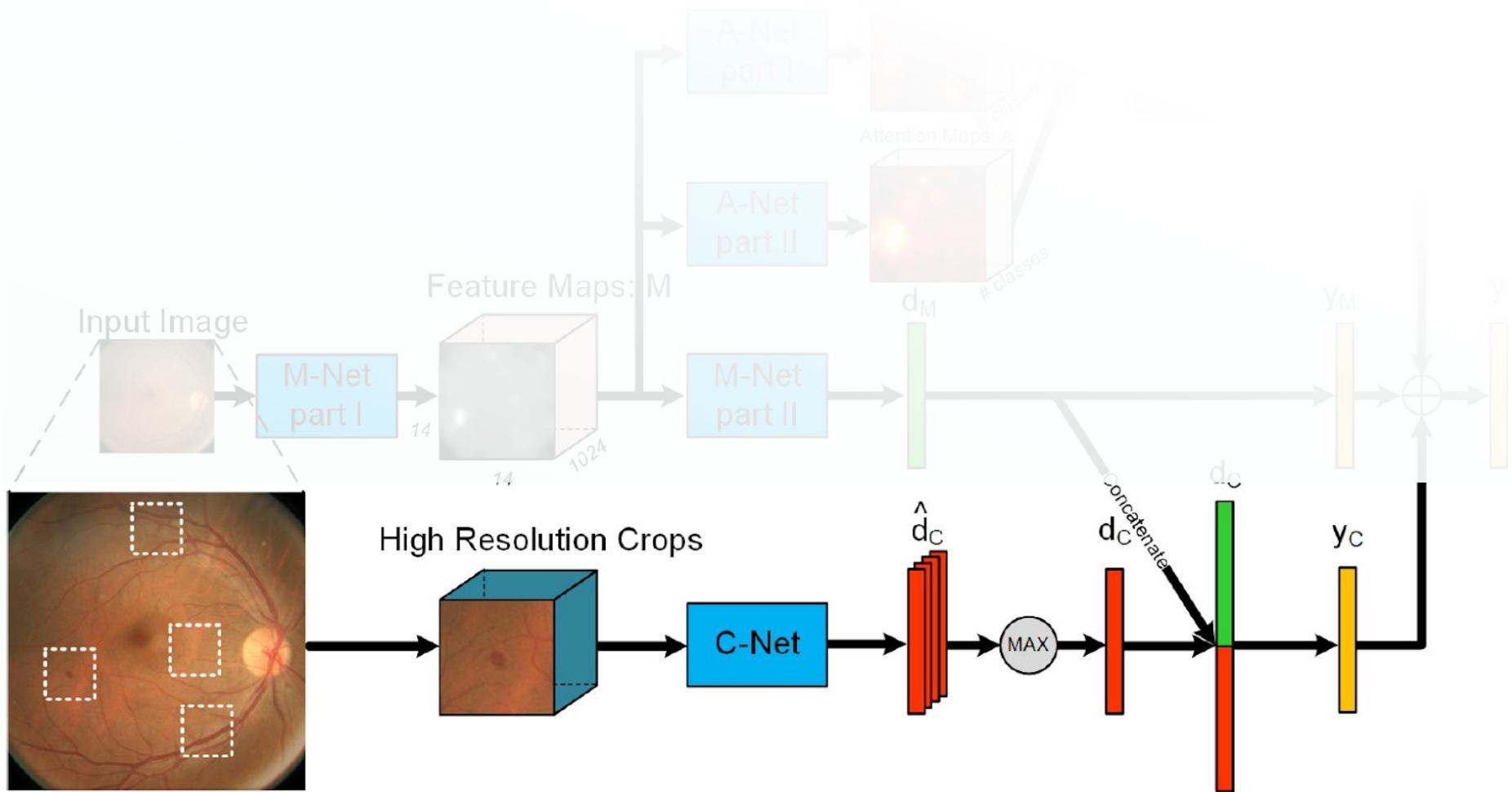


Weighted SoftMax Cross Entropy Loss (with L2 regularization) : 9.25

Kappa Score :0.48



Crop Network (C-Net)



Source: Z.Wang, Y.Yin, J.Shi, W.Fang, H.Li, and X.Wang. *Zoom-in-Net: Deep Mining Lesions for Diabetic Retinopathy Detection*, pages 267–275. Springer International Publishing, 2017

Recap: Initializing Inception

Approach:

- Retrain all layers
- Using TF-Slim implementation
- Create TF-Records of all images then train
- Data set : IDRiD

Result:

- Trained the network up to 20k steps
- We have an initialized model for training with accuracy of 92% and loss of 0,70



Integration

Planned:

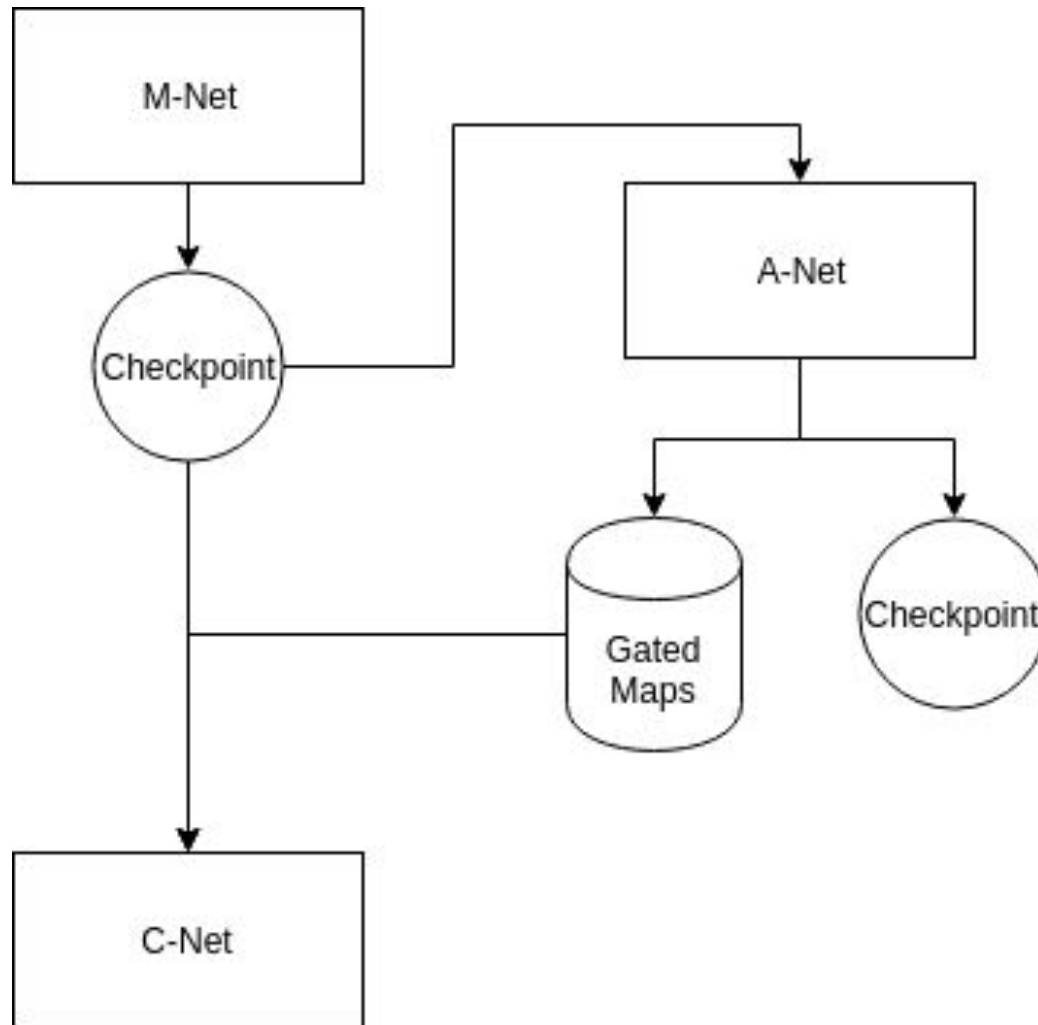
- Initially planned on a single training pipeline for all 5 Neural Nets
- Unfeasible due to highly coupled nature of project

Implementation:

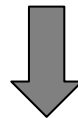
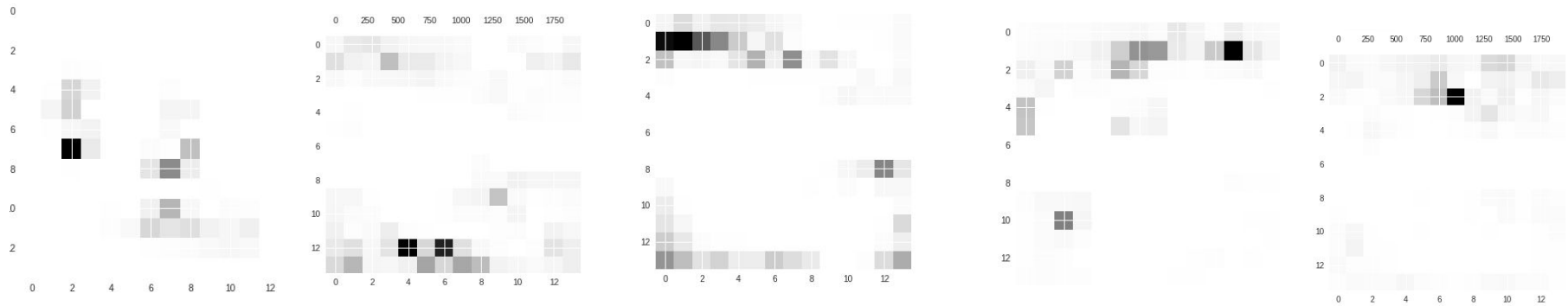
- Write each component independently
- Write output of each component into a binary file
- Saved checkpoints of each component used to get feature maps



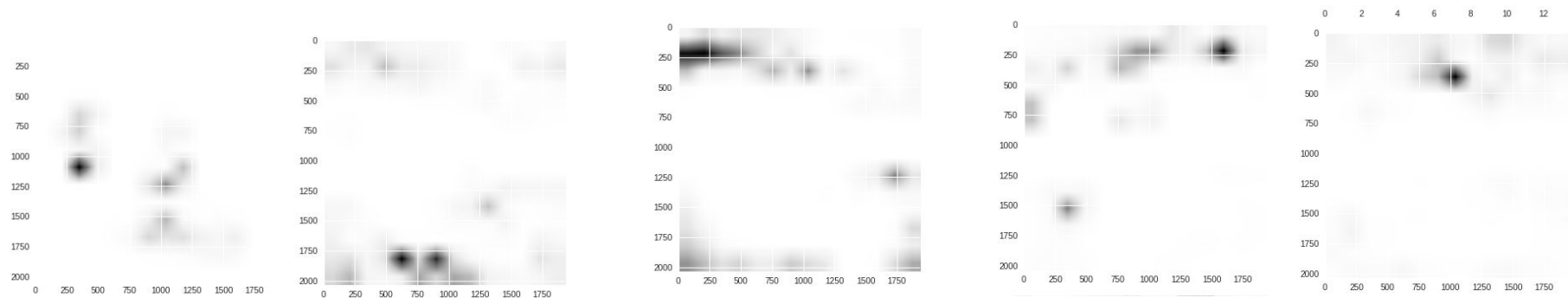
Integration



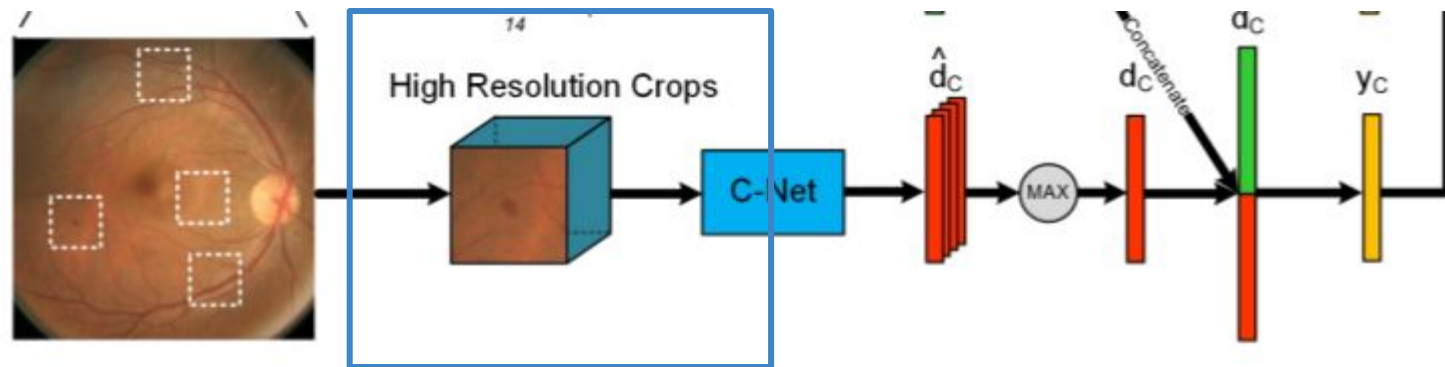
A-net Attention Maps



Resize to size of original Images



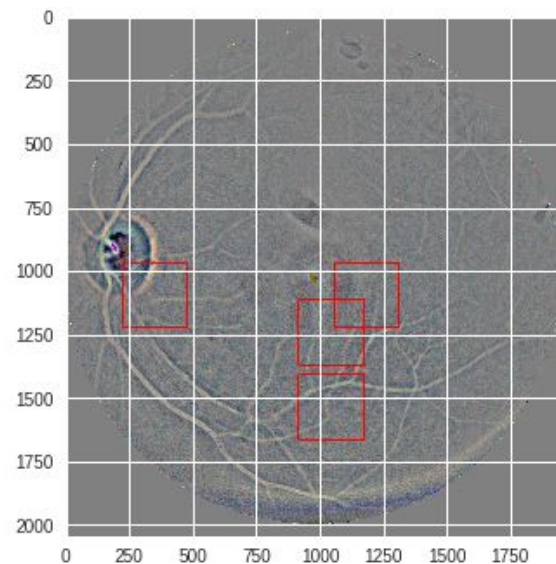
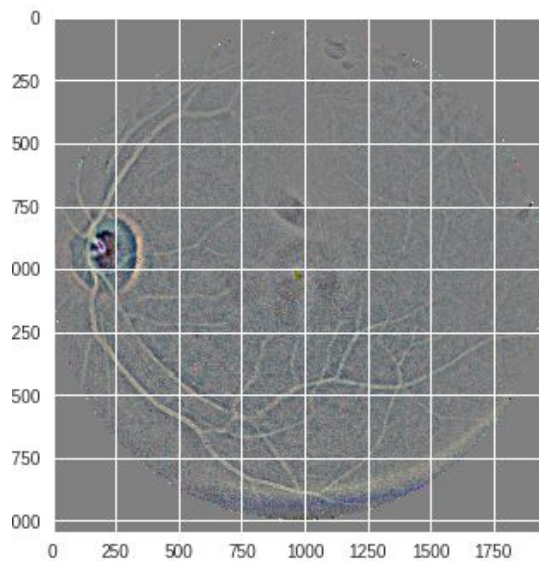
Crop Network (C-Net)



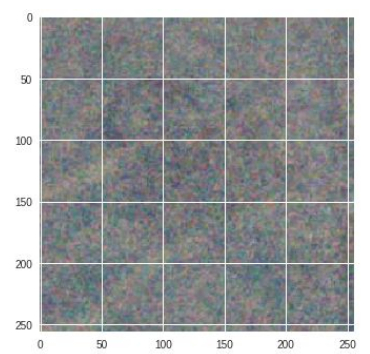
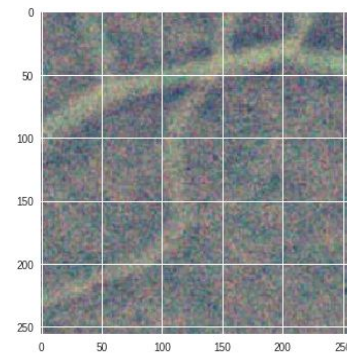
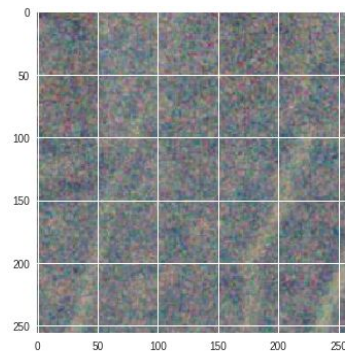
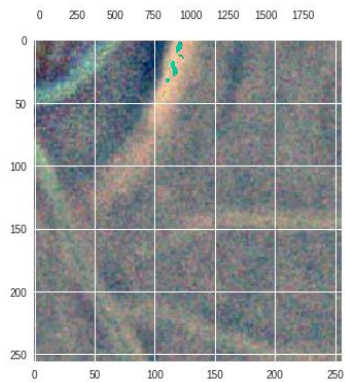
Process

- **Zooming-in** suspicious attention regions
- Record the highest response in the attention map and crop the region
- Mask the region around the crop to avoid re-selection
- Repeat until total of N-coordinates are recorded

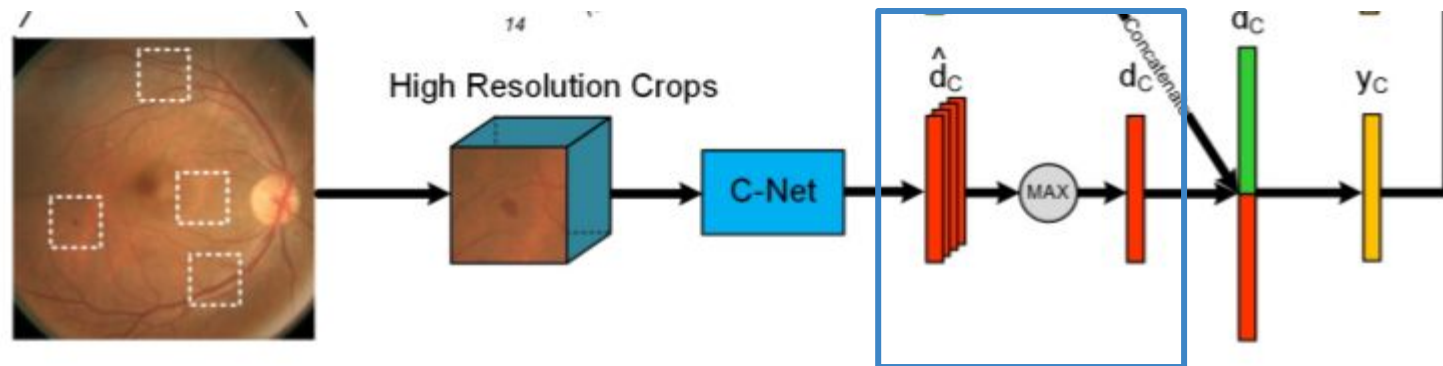
Crop Detection



Crops



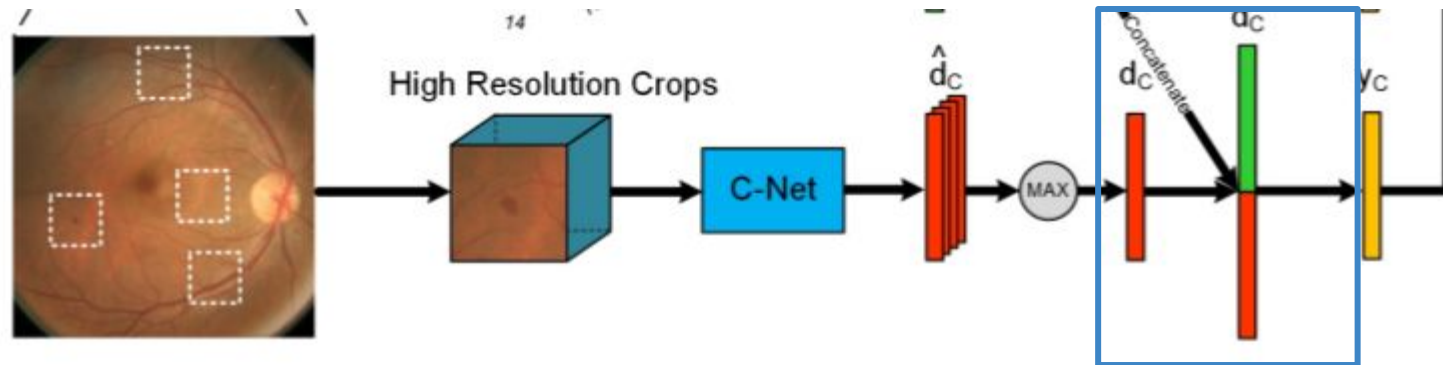
Crop Network (C-Net)



Output

- For all the crops of the same eye, take an element wise max

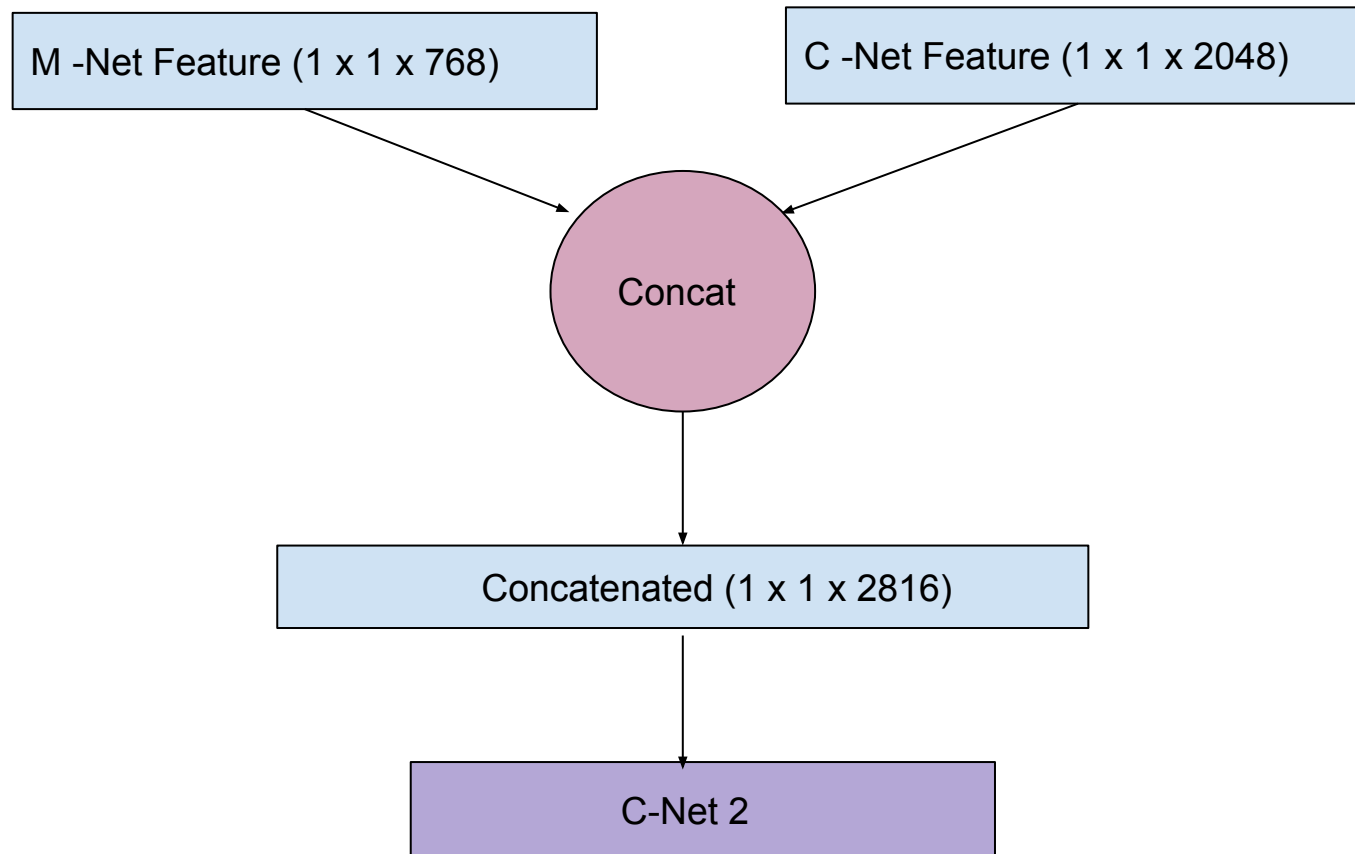
Crop Network (C-Net)



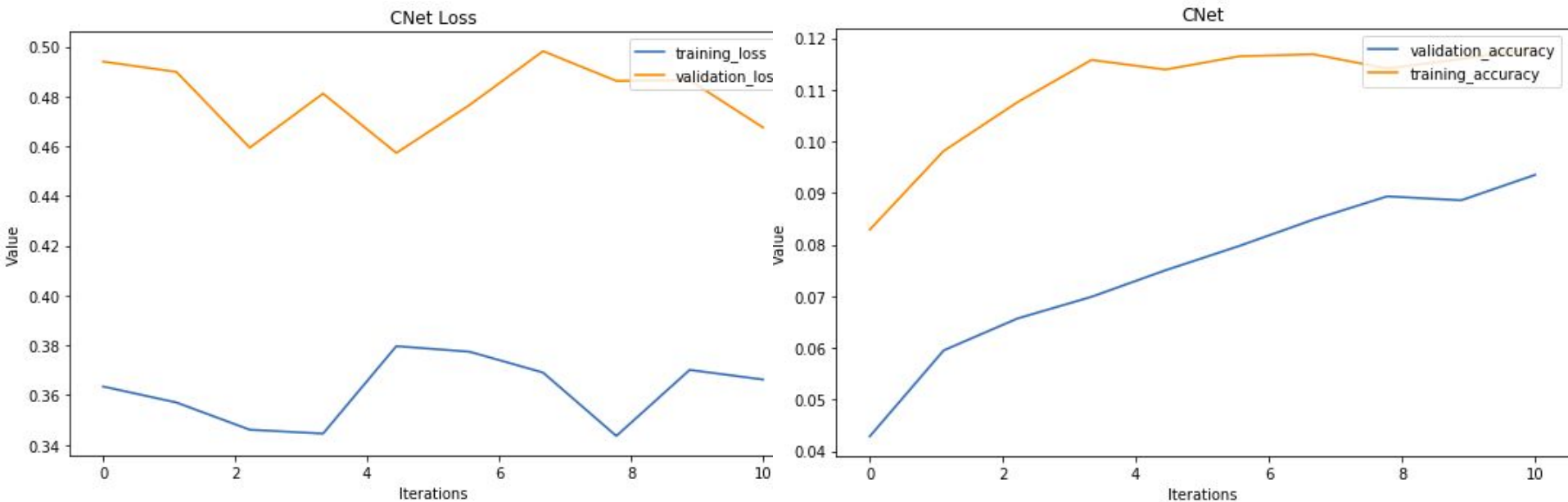
Concatenation:

- Concatenate feature vector from C-Net with feature vector from M-Net
- From C-Net : “Global Pool” layer
- From M-Net: “Conv2d_2a_5x5” layer

Crop Network (C-Net)



C-Net Results



Training Loss: 0.372

Training Cohen's Kappa: 0.118

Checkpoint Used : Pre-trained from IDRiD Dataset



Summary

Network	Training Loss	Training Kappa	Validation Loss	Validation Kappa
M-Net 1 Eye	0.05	0.06	0.13	0.06
M-Net 2 Eye	0.03	0.07	0.05	0.07
A-Net	9.25	0.48	9.26	0.47
C-Net	0.372	0.118	0.47	0.08

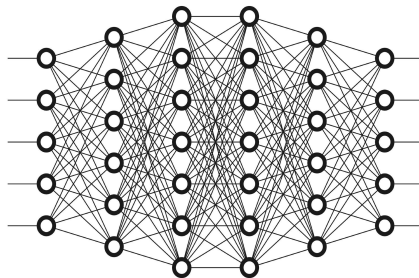
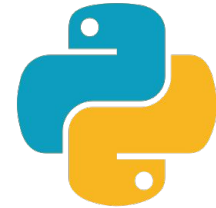


Impediments

- Limitation of resources in proportion to size of the problem
 - 5 Networks
 - 85 GB
- Google Colab with multiple experiments, time out issues
- Strong dependency between groups, and models



Learning Outcomes





Questions?

Topics:

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