Towards Balancing the Complexity of Convolutional Neural Network with the Role of Optical CoherenceTomography in Retinal Conditions

Anca Marginean [1]
Adrian Groza [1]
Simona Nicoara [2]
George Muntean [2]
Radu Razvan Slavescu [1]
Ioan Alfred Letia [1]

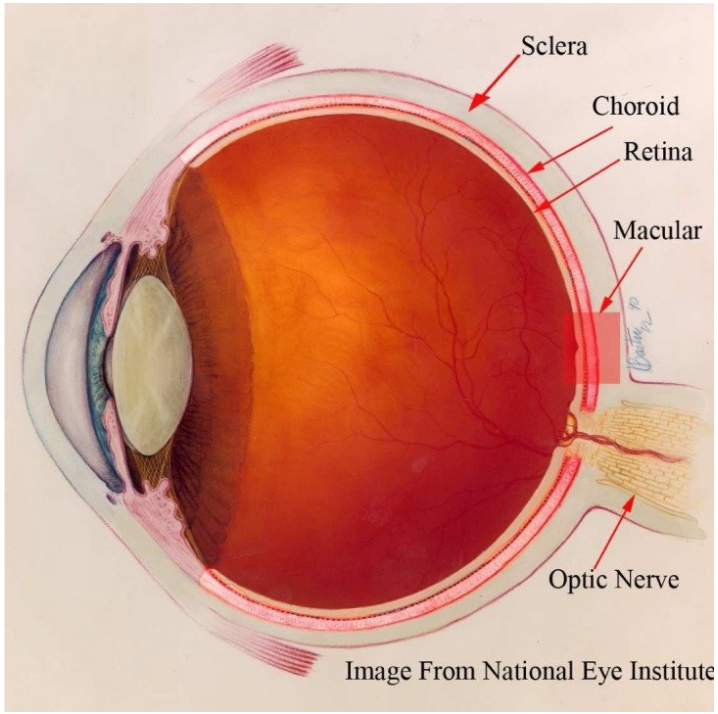
[1]Technical University of Cluj Napoca

[2]Iuliu Hatieganu" University of Medicine and Pharmacy, Cluj-Napoca

ICCP 2019

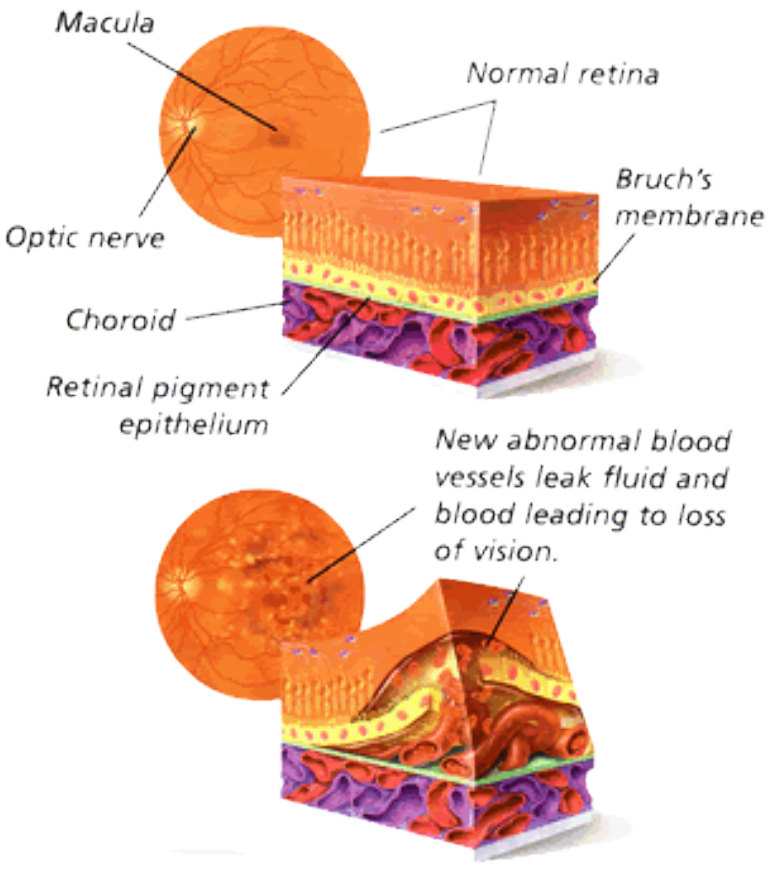
Context

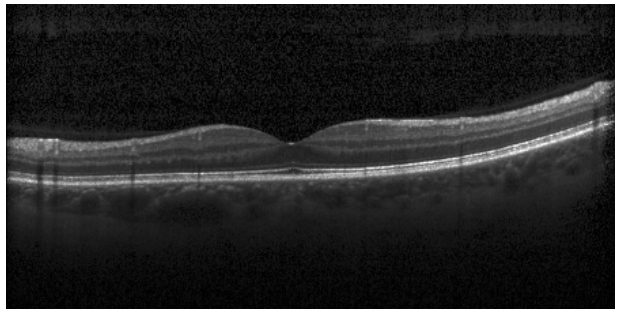
- Age-related macular degeneration (AMD) - leading cause of legal blindness and severe visual impairment in industrialized countries



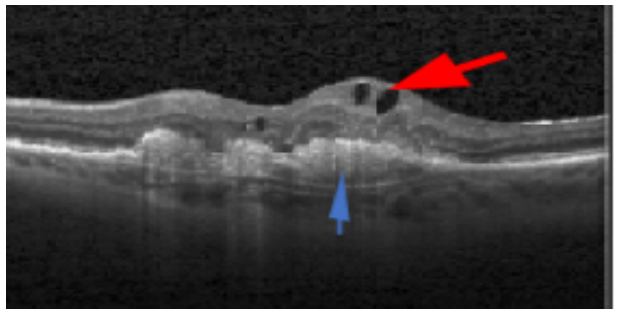
- Optical Coherence Tomography (OCT) - leading diagnostic tool in modern ophthalmology
  - a non-invasive imaging test
  - uses light waves to take cross-section pictures of the retina

Context - Normal vs abnormal retina





Normal OCT



Abnormal OCT

- OCT biomarkers: retinal thickness, intraretinal cystoid fluid, subretinal fluid, alterations of outer retinal layers, hyperreflective foci

Objectives

How the pathological features of the retinal conditions can be connected to what might be found from the CNNs produced by training on various data sets

- Train two different architectures
  - with transfer knowledge
  - without transfer knowledge
- Analyse the results
  - quantitative analysis
  - from the ophthalmologist perspective
  - with heatmaps built with occlusion test

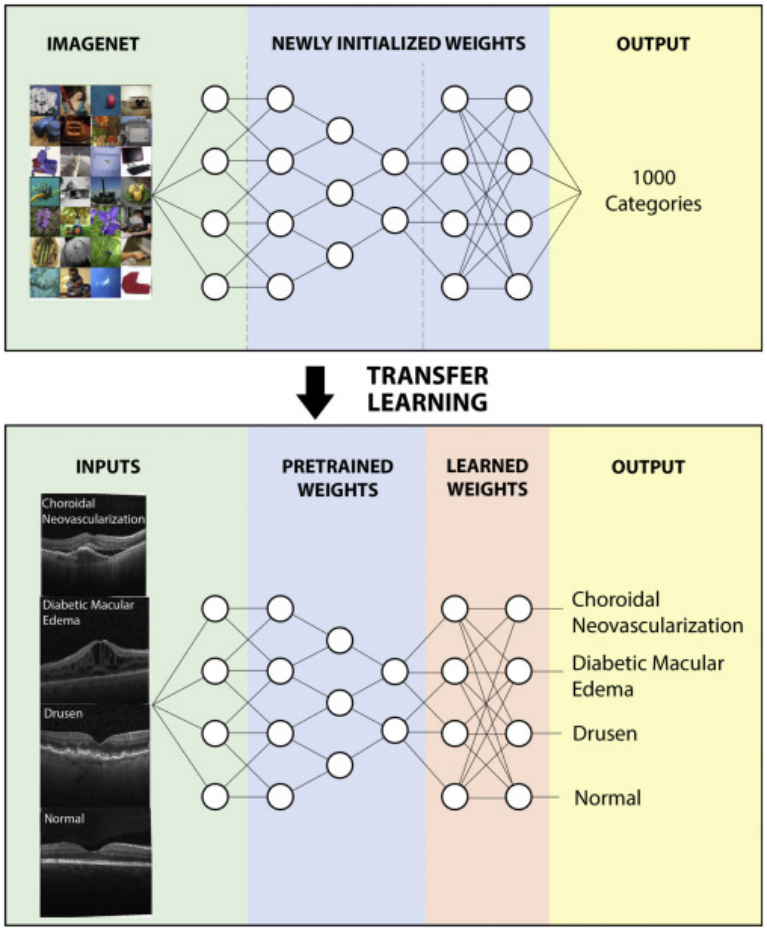
Dataset - OCT 2017

- Train

Retinal Conditions	Number of images
CNV	37,206
DME	11,349
AMD(DRUSEN)	8617
Normal	51,140

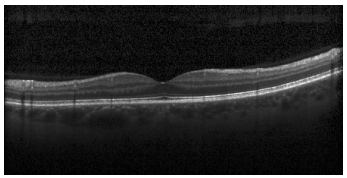
- Test: 1000 images (250 for each category)

Kermany et.al (2018) - Inception V3

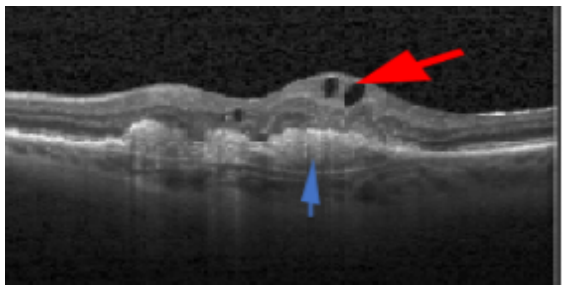


Accuracy 96.6

Typical aspect

Normal OCT 

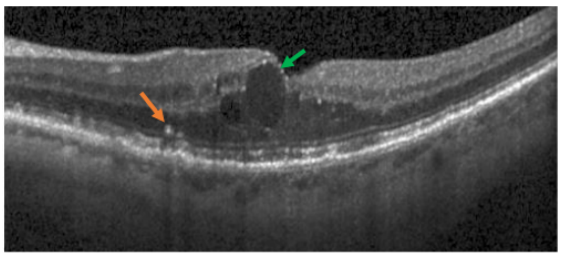
Choroidal neovascularisation (CNV)



fibrous plaque (typical for this class)

cyst-like empty optical spaces - (typical for DME, but can appear in CNV 3)

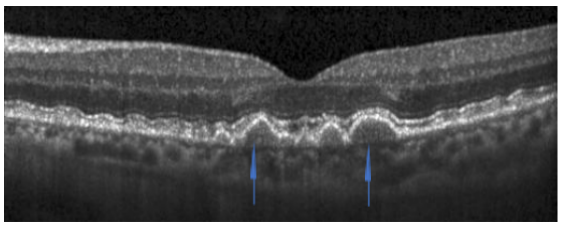
Diabetic macular edema (DME)



the cyst-like empty optical spaces cystoid-macular oedema

hyperreflective dots-hard exudates

DRUSEN



wavelets in the RPE with average reflectivity content

with no fluid or fibrosis

What we trained?

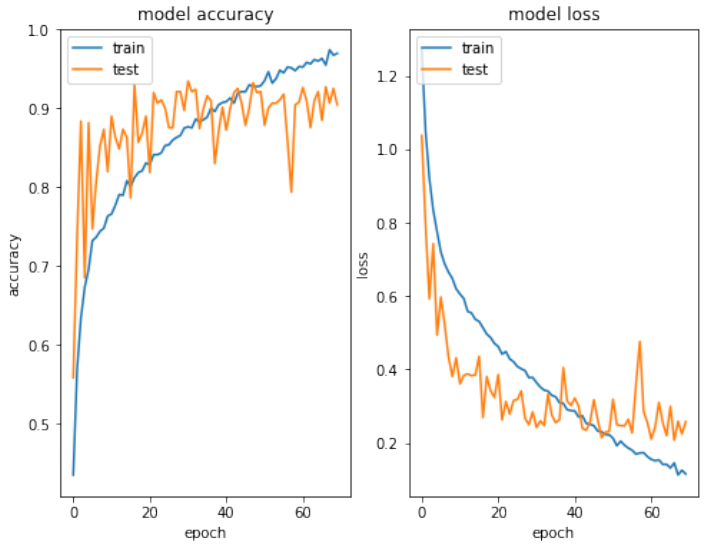
- With transfer knowledge: VGG-16 +
  - Conv 1024 5×5 + MaxPooling + Flatten + Dropout+ Dense 64 + Dense 4
  - Total params: $19 * 10^6$, Trainable: $5 * 10^6$
- Without pretrained: SqueezeNet (achieved AlexNet-level accuracy on ImageNet with 50x fewer parameters)
  - Total params: $76,059$, Trainable: $76,059$

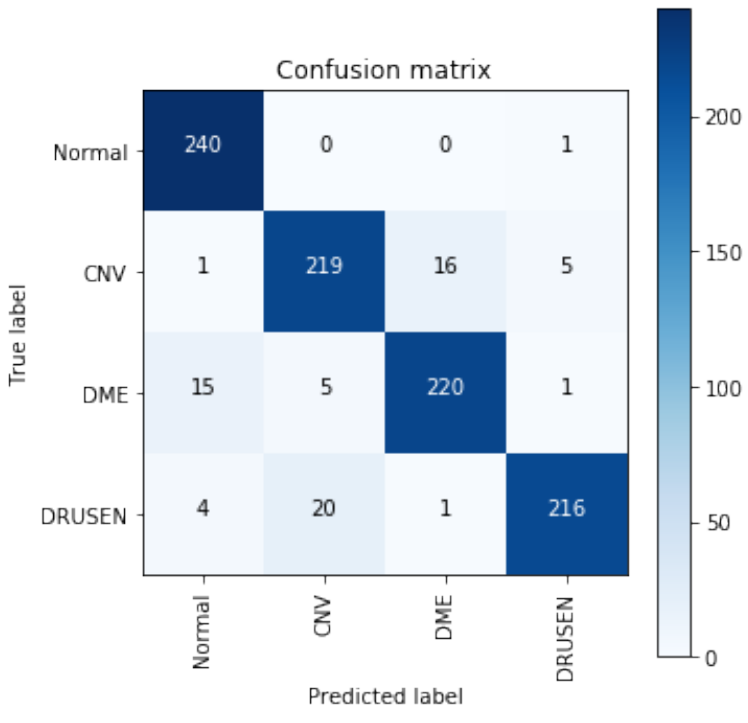
Quantitative results

- Training on 1399 Normal images, 790 CNV, 712 DME, respectively 708 DRUSEN, meaning aproximately 5% of the entire train set.
- Testing on 241 images for each category

Quantitative results - VGG-16 based network

- learns very fast
- overfits after 50 epochs - small training set





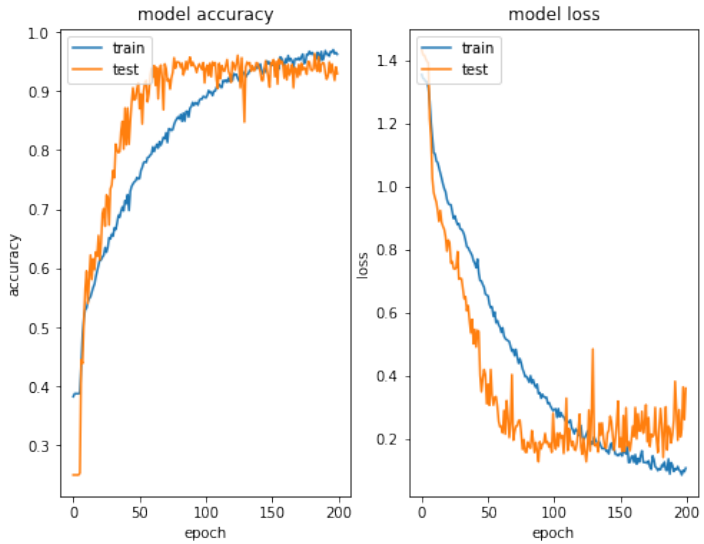
	Precision	Recall	F1-score	Support
Normal	0.92	1.00	0.96	
CNV	0.90	0.91	0.90	
DME	0.93	0.91	0.92	
DRUSEN	0.97	0.90	0.93	
accuracy			0.93	

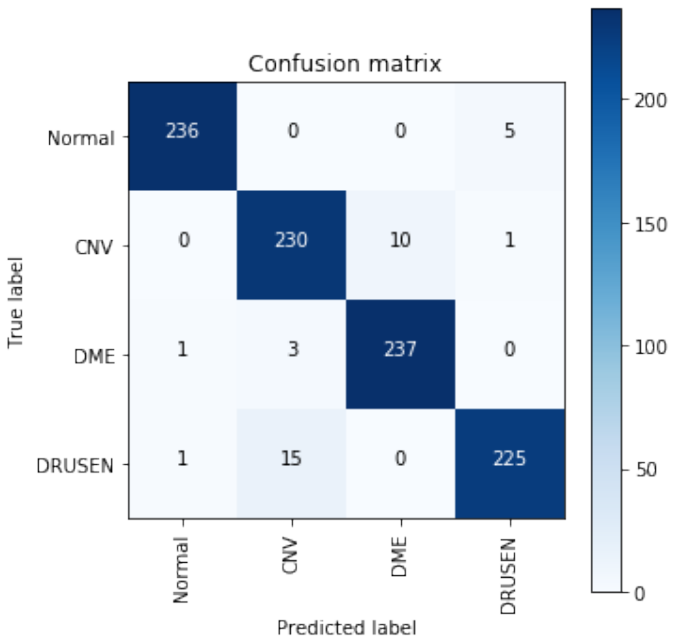
- many abnormals included in normal

- many non-CNV included in CNV
- very precise for DRUSEN

Quantitative results - SqueezeNet network

- learns slowly
- the effect of overfitting appears at lower values of loss
- it reaches higher values for accuracy





	Precision	Recall	F1-score
Normal	.99	.98	.99
CNV	.93	.95	.94
DME	.96	.98	.97
DRUSEN	.97	.93	.95
accuracy			0.96

- normal OCT more precise
- CNV as DME
- DRUSEN as CNV

1. Interpretation of the results obtained with SqueezeNet

Features which can belong to two conditions are present in the image, DL identifies both classes, but the wrong class has higher probability

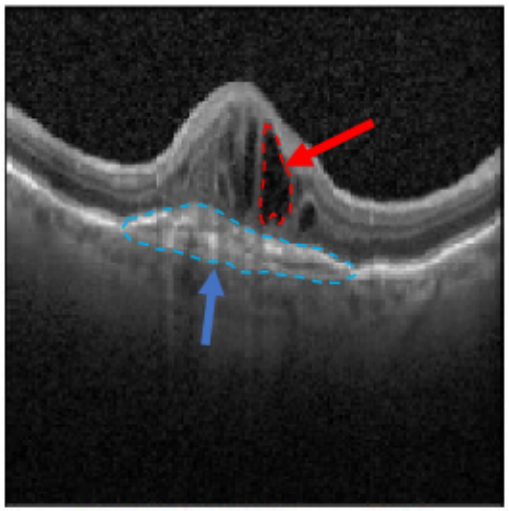


image:20
NO: 0
CNV: .27
DME: .73
DR: 0

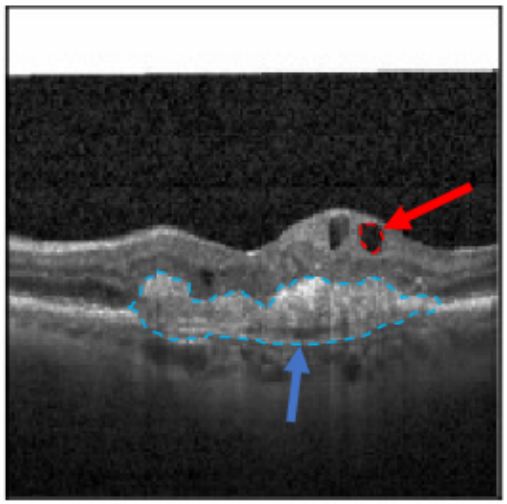


image:66
NO: 0
CNV: .13
DME: .87
DR: 0

Subretinal fibrous plaque is a sign of CNV, the cyst-like empty optical spaces are more typical for DME, but it can also appear in CNV type 3. However, seeing the fibrous plaque associated with the cysts, CNV type 3 should be the most probable diagnostic.

1. Interpretation of the results obtained with SqueezeNet

Features which can belong to two conditions are present in the image, DL identifies the correct class with a probability close to 1

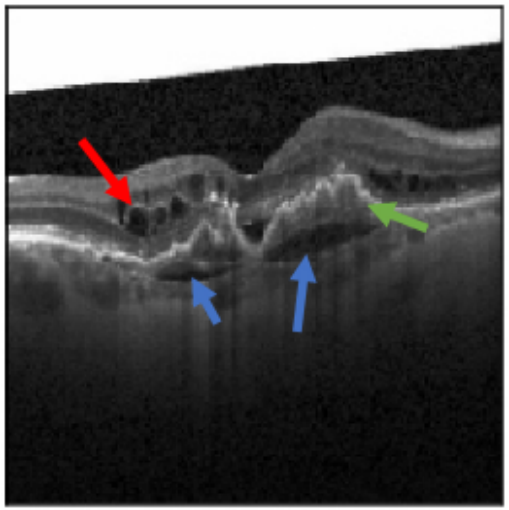


image:116
NO: 0
CNV: .99
DME: .01
DR: 0

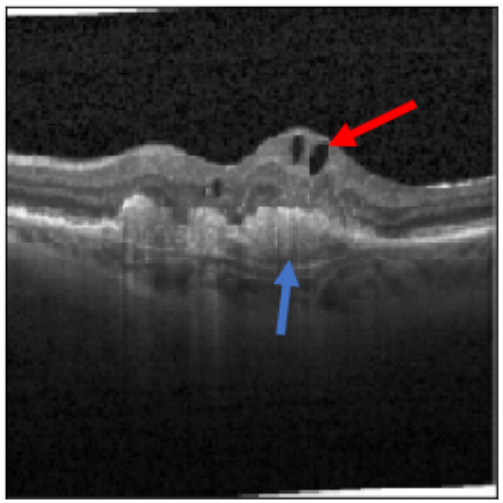


image:106
NO: 0
CNV: 1
DME: 0
DR: 0

There is subretinal fluid - sign of CNV and also pigment epithelium detachment associated with CNV . Even though there are cyst-like empty optical spaces. the probability for DME is 0. This comes in contrast with image 66 which is quite similar with image 106 and yet, it is classified as DME.

1. Interpretation of the results obtained with SqueezeNet

Features which can belong to two conditions are present in the image, DL identifies the wrong class with probability close to 1

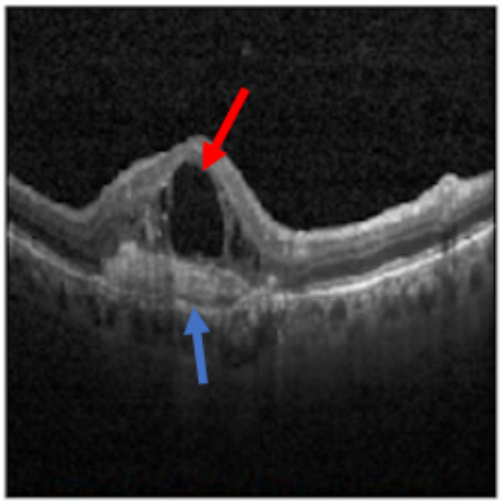


image:223
NO: 0
CNV: .02
DME: .98
DR: 0

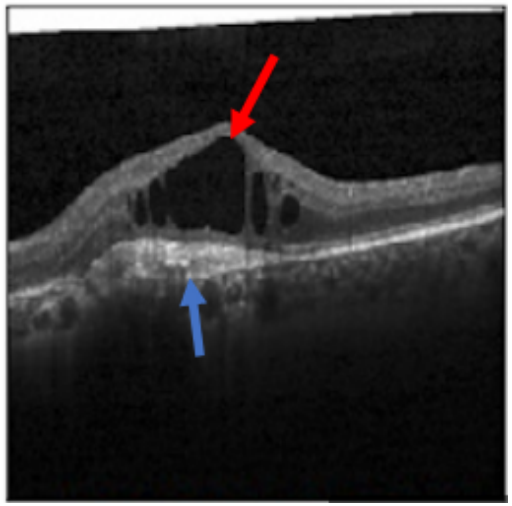
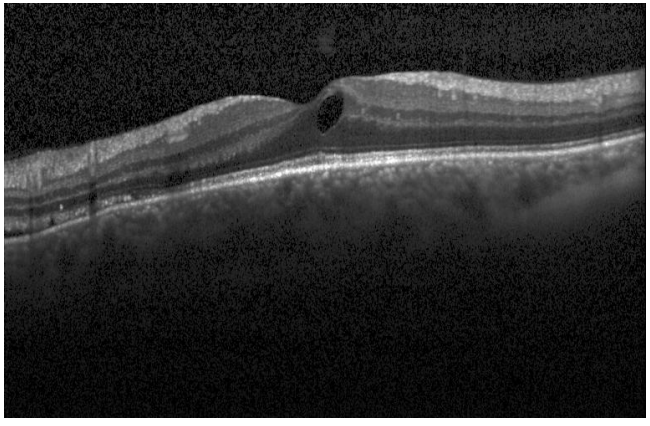


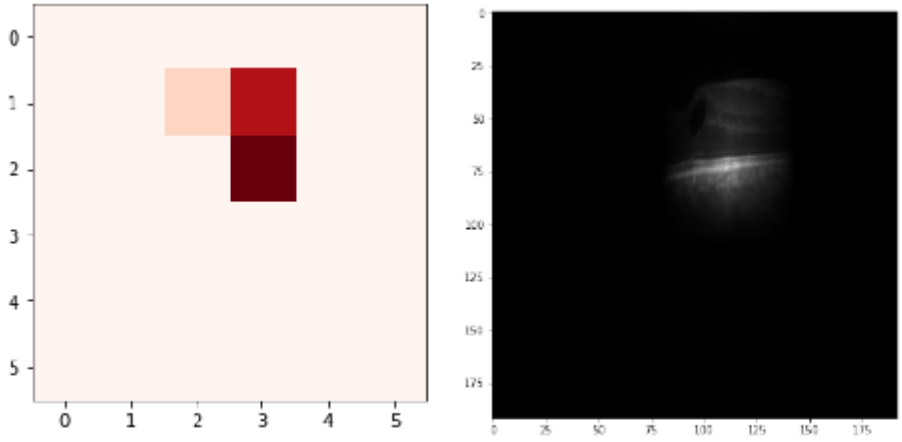
image:226
NO: 0
CNV: .00
DME: 1
DR: 0

The subretinal fibrous plaque associated with cyst indicates CNV type 3. A possible explanation for the wrong classification as DME might be the size of the cysts.

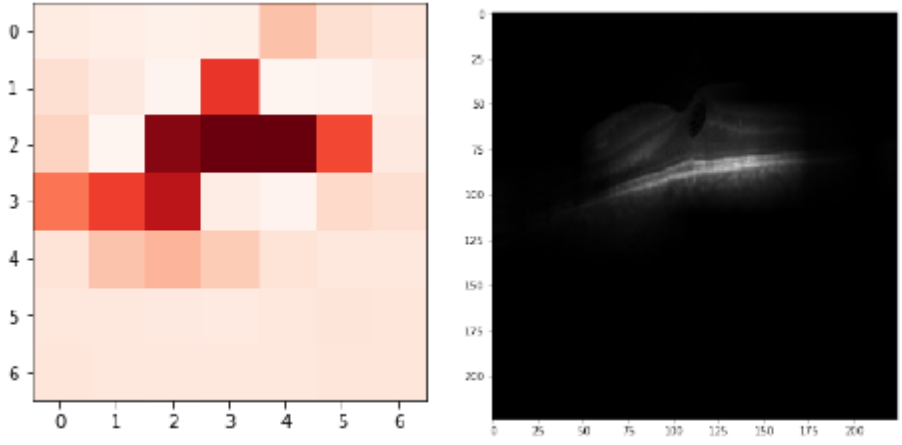
2. Are the features of interest identified by the DL?

Occlusion test: correct classified image DME





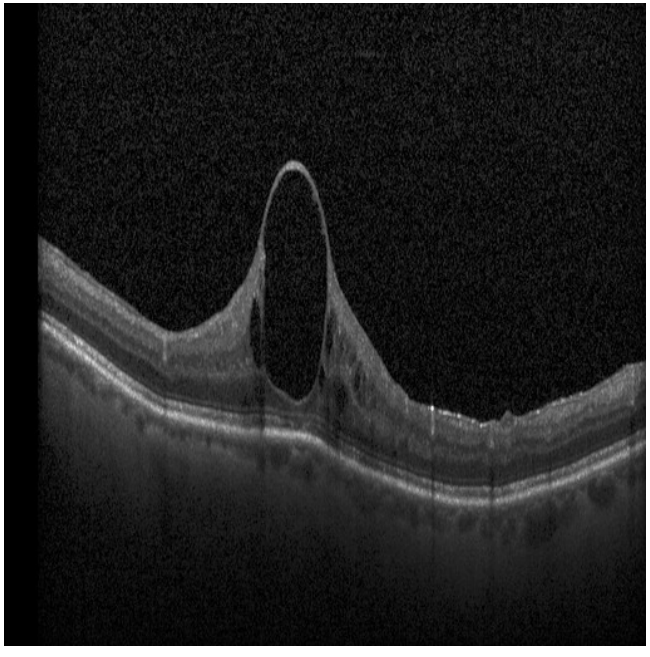
b) SqueezeNet is more specific in identifying cyst-like empty optical space DME specific feature

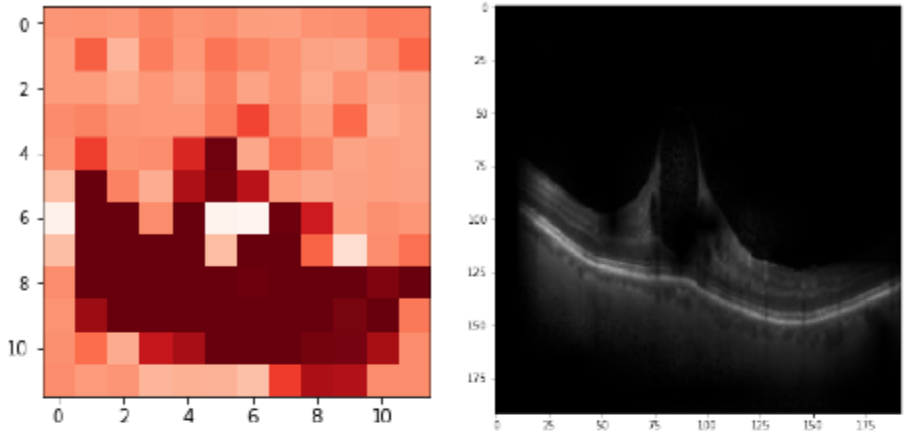


(c) VGG16 considers a larger area

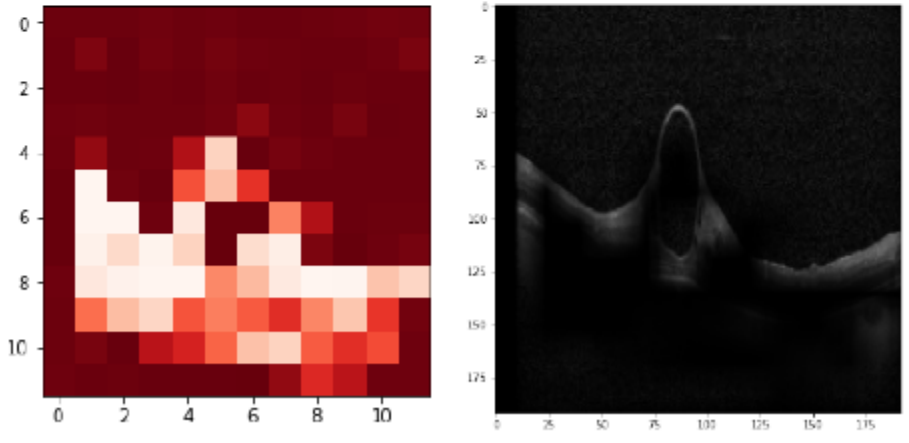
2. Are the features of interest identified by the DL?

Occlusion test: DME wrongly classified as Normal





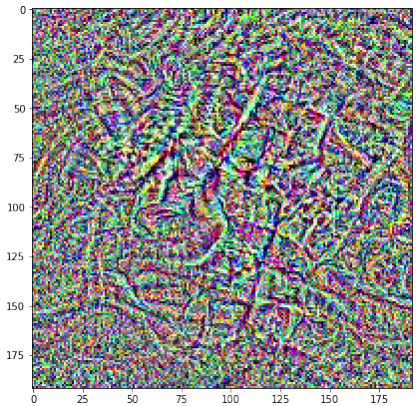
(b) Heatmap obtained for the class NORMAL (which is wrongly predicted)



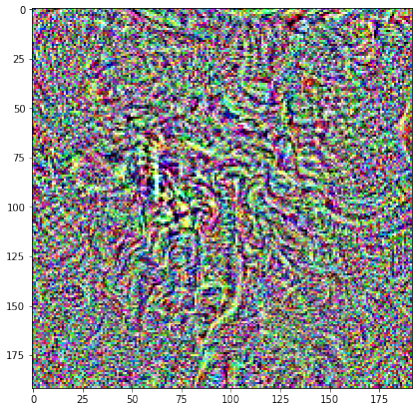
(c) Heatmap obtained for maximization of positive variance in DME and negative variance in NORMAL

3. Finding images that maximizes a specific class

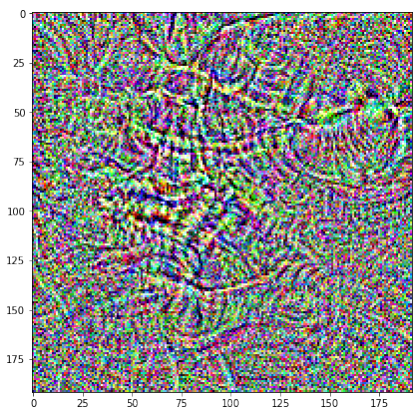
Gradient ascent for VGG-16 based network



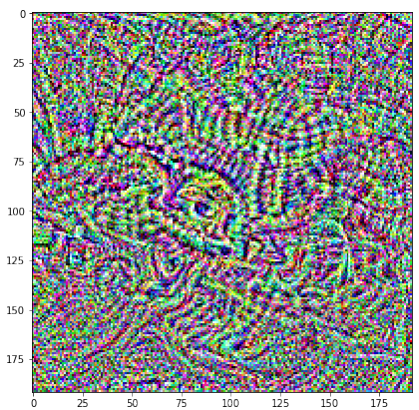
Normal



CNV



DME



DRUSEN

Classified by SqueezeNet with almost 1 in CNV

Conclusions

- Deep Neural Network are capable of representing OCT images - at least for classification
  - small training set is enough in both approaches: with transfer knowledge & without transfer knowledge but with smaller network
  - the network without transfer knowledge appears to be better suited - an explanation could be the particularities of the medical domain compared to ImageNet
- Are the OCT specific features captured by the networks? Current conclusion: areas containing relevant OCT features are important for the networks

Future work:

- continue investigation towards understanding what the network learns
- use NN representation for the analysis of evolution of AMD