UNIVERSITAT POLITÈCNICA
DE CATALUNYA
BARCELONATECH

RETINAL LESIONS SEGMENTATION USING CNNS AND ADVERSARIAL TRAINING

In partial fulfilment of the requirements for the degree in Telecommunications Technologies and Services Engineering

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INTRODUCTION

Problem statement

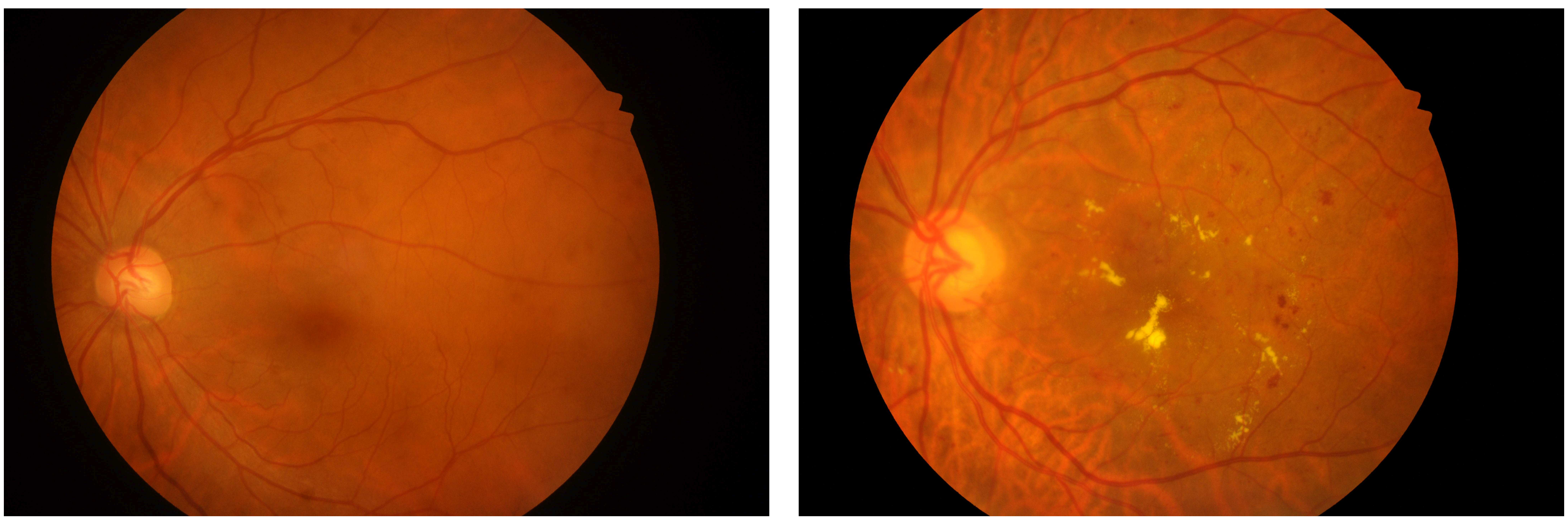
- Interpretations of medical data are done by experts
- Problem: cost of these interpretations very high
- Solution: deep learning techniques to help experts

Medical interpretations made by experts

INTRODUCTION

Diabetic retinopathy

- Leading cause of blindness among working-age adults
- It affects people with diabetes and the damage occurs in the retina



Funduscopy images. Left: healthy retina. Right: retina with lesions

INTRODUCTION

Project overview

- Objectives: apply deep learning techniques to detect and segment retinal lesions
- Convolutional Neural Networks (CNNs) will be used
- Adversarial training will be added to the previous CNN to improve its results
- Dataset: *Indian Diabetic Retinopathy Image Dataset* (IDRiD) from the *Diabetic Retinopathy: Segmentation and Grading Challenge*

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STATE OF THE ART

Semantic segmentation

- Convolutional Neural Networks:
    - One of the models with successful results: U-Net
- Adversarial training

Automation of Diabetic Retinopathy diagnostics

- Most work: classification into different stages of DR
- Low accuracy on retinal lesions segmentation
- Relevant work on detecting anatomical structures of blood vessels, fovea and optic disk

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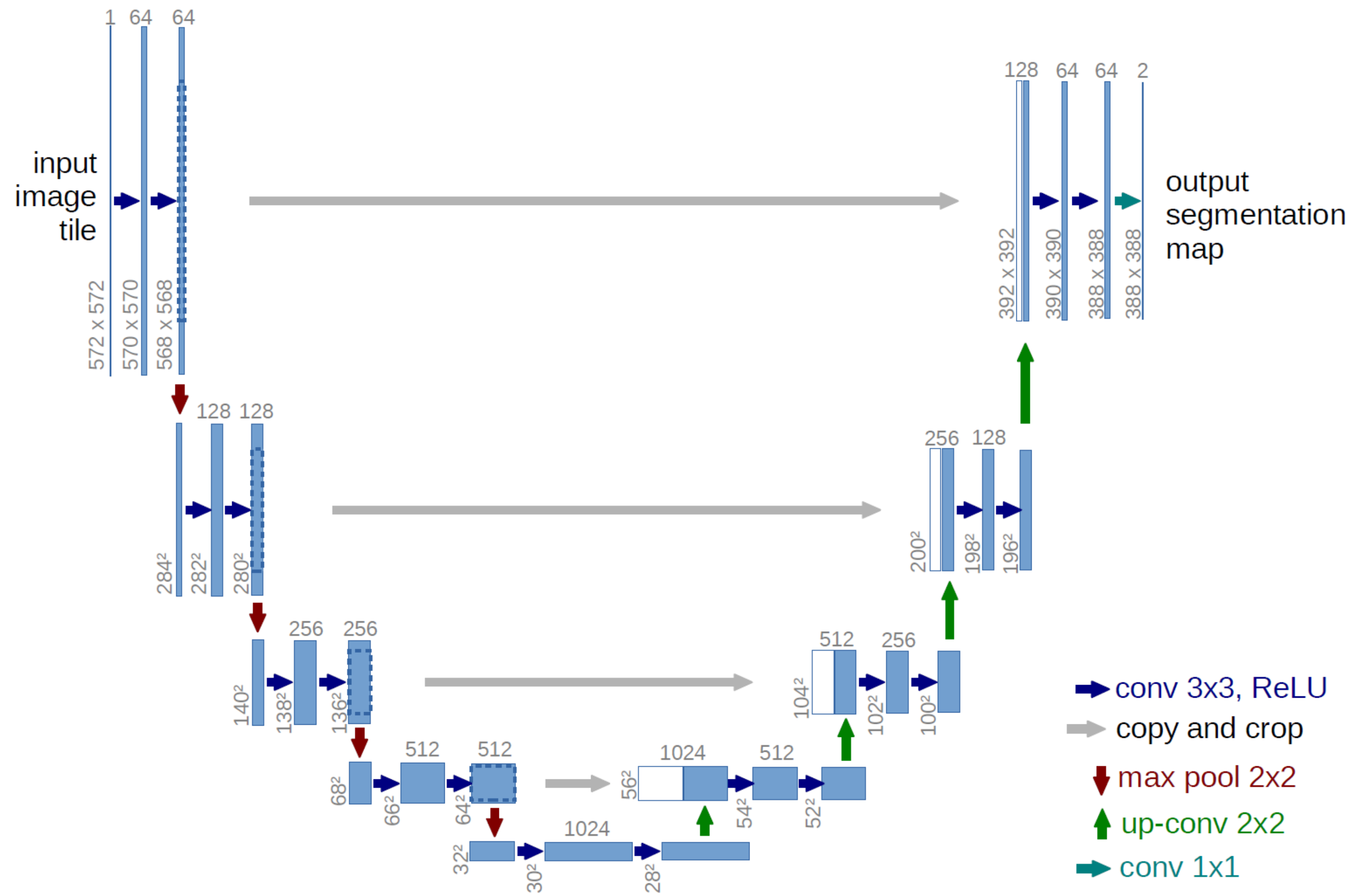
METHODOLOGY

U-Net

- CNN used to segment images
- Structure: contracting path + expansive path

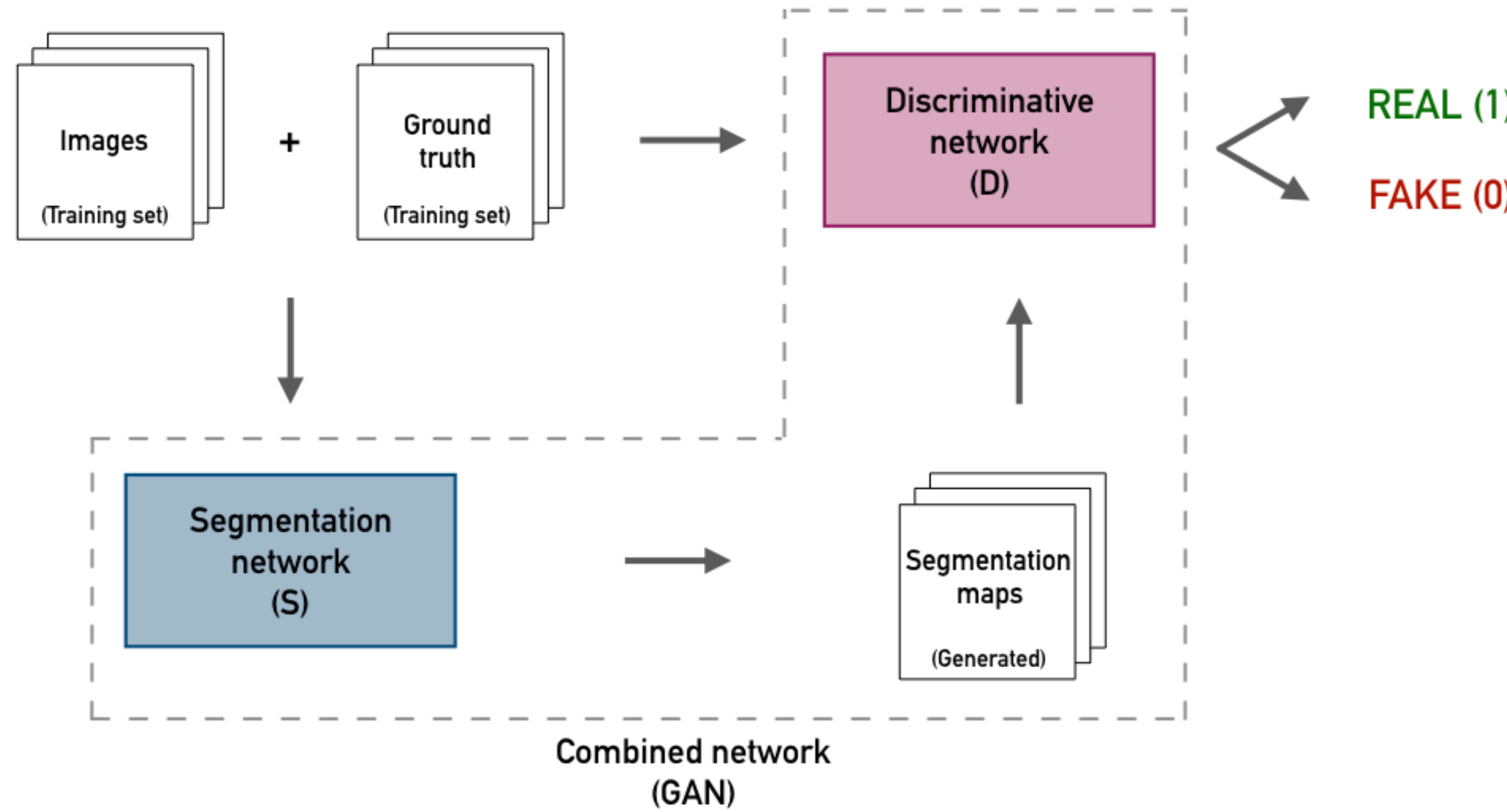


U-Net structure

METHODOLOGY

Adversarial training

- Idea used by GANs applied to train segmentation models
- Structure: two networks pitting one against the other
- Adversarial training procedure is a two-player minimax game:



Architecture used with adversarial training

$$\min_S \max_D V(S,D) = \mathbb{E}_{x,y\sim p_{data}(x,y)}[\log D(x,y)] + \mathbb{E}_{x\sim p_{data}(x)}[\log(1 - D(x, S(x)))]$$

METHODOLOGY

Loss functions

- U-Net:
  - Categorical cross-entropy
  - Dice coefficient
  - Generalised dice coefficient
- Adversarial training:
  - Discriminator:
    - Binary cross-entropy
    - Mean squared error
  - Segmentation network:
    - $L_{GAN} = \lambda \cdot L_{ADV} + L_{SEG}$

METHODOLOGY

Metrics

- To evaluate the models, we used the dice score:

$$D = \frac{2|P \cap G|}{|P| + |G|} = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

P: Predicted labels, G: Ground truth

TP: True Positives, FP: False Positives, FN: False Negatives

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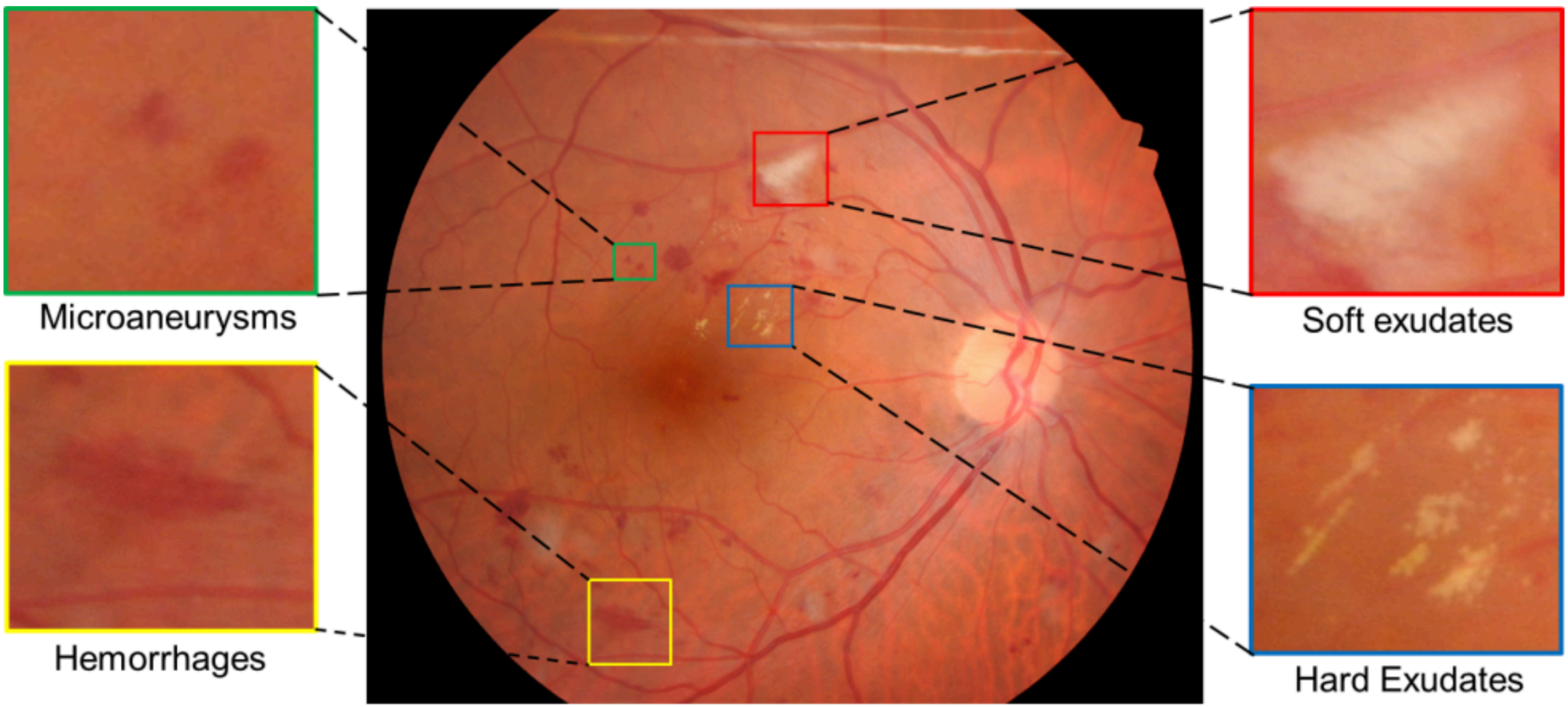
EXPERIMENTS AND RESULTS

Dataset

- *Indian Diabetic Retinopathy Image Dataset* (IDRiD) from the *Diabetic Retinopathy: Segmentation and Grading Challenge*
- 54 images with different retinal lesions:
    - Microaneurysms (MA)
    - Haemorrhages (HE)
    - Soft Exudates (SE)
    - Hard Exudates (EX)
- Dataset is divided in: 80 % train, 10% validation and 10% test
- Images are divided in patches to fit in memory

EXPERIMENTS AND RESULTS



Retinal lesions in dataset images

EXPERIMENTS AND RESULTS

U-Net

- 19 convolutional layers
- Batch normalization
- Learning rate: 0.0001
- Batch size: 8

Optimizer	DA	Loss function	EX	HE	MA	SE
Adam	False	Categorical cross-entropy	0.579	0.365	0.374	0.281
Adam	False	Dice coefficient	**0.727**	0.429	0.423	0.0
Adam	True	Generalised dice coefficient	0.694	**0.458**	**0.477**	**0.351**

Results using U-Net with dice score metric

EXPERIMENTS AND RESULTS

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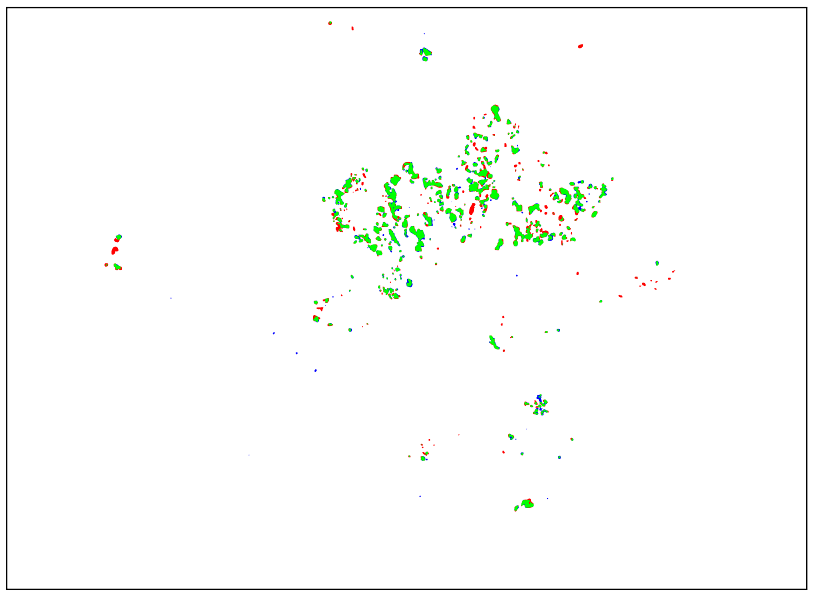
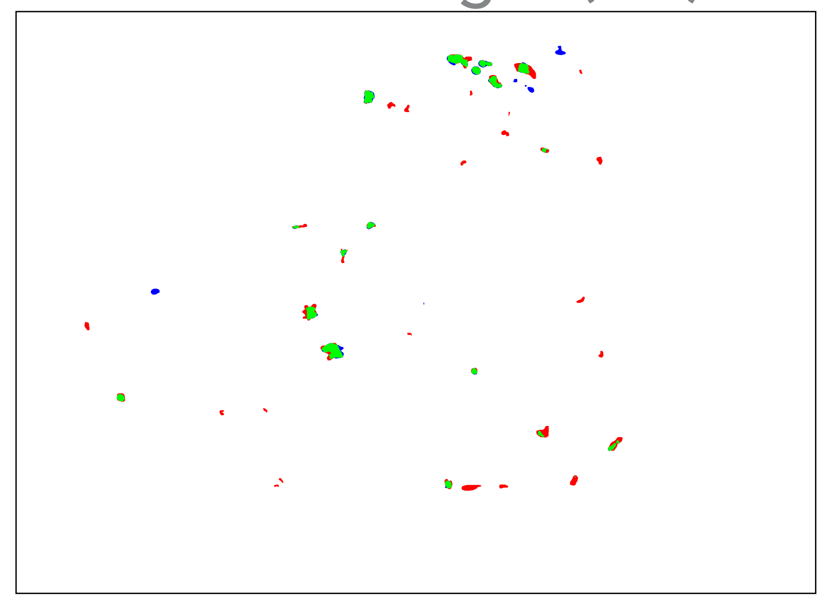
EXPERIMENTS AND RESULTS **U-Net**

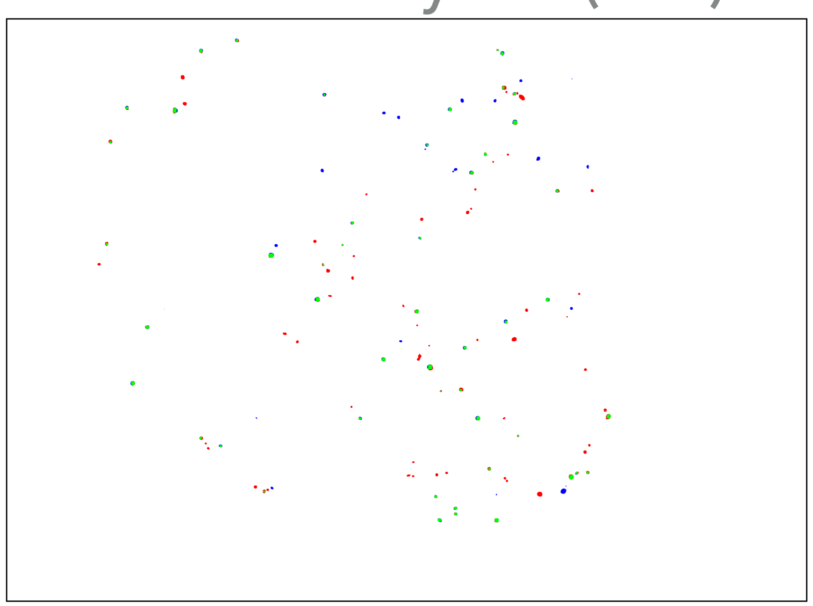
Hard Exudates (EX)



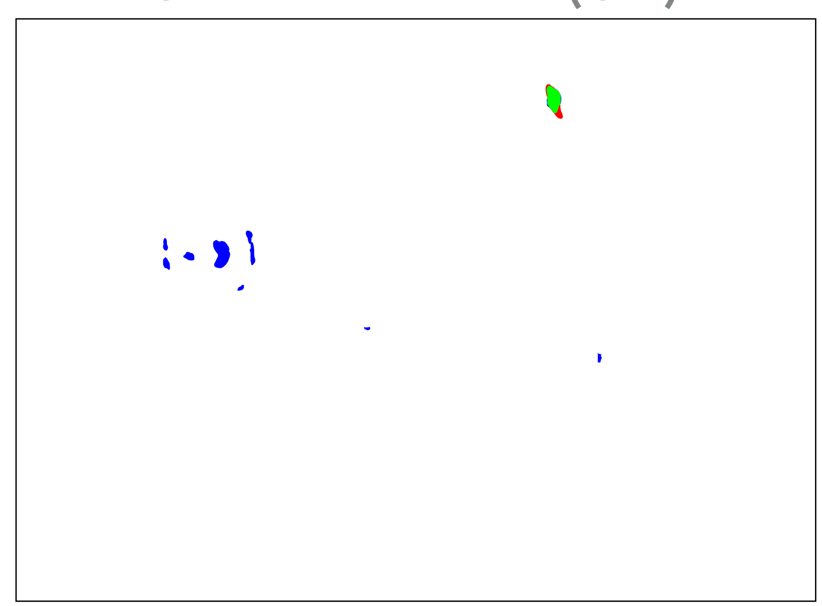
Haemorrhages (HE)



Microaneurysms (MA)



Soft Exudates (SE)



Difference maps. Green: true positives, Red: false negatives, Blue: false positives

EXPERIMENTS AND RESULTS

Adversarial training

$$L_{GAN} = \lambda \cdot L_{ADV} + L_{SEG}$$

$$L_{SEG} = \text{Generalised dice coefficient}$$

L_{ADV}	λ	EX	HE	MA	SE
Binary cross-entropy	0.05	**0.734**	0.458	0.423	0.415
Binary cross-entropy	0.07	0.713	0.439	0.454	**0.470**
Mean Squared Error	0.05	0.707	**0.476**	**0.462**	0.405
Mean Squared Error	0.07	0.722	0.472	0.447	0.364

Results using U-Net with adversarial training with dice score metric

EXPERIMENTS AND RESULTS

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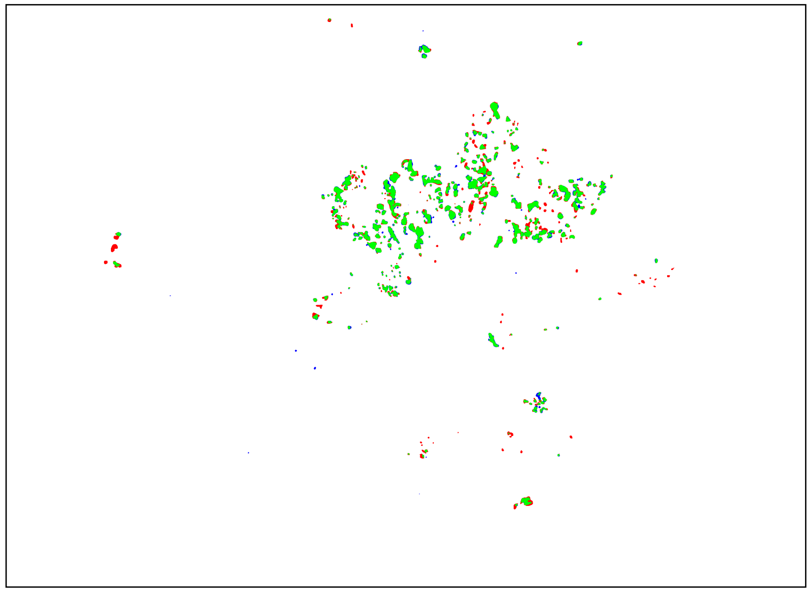
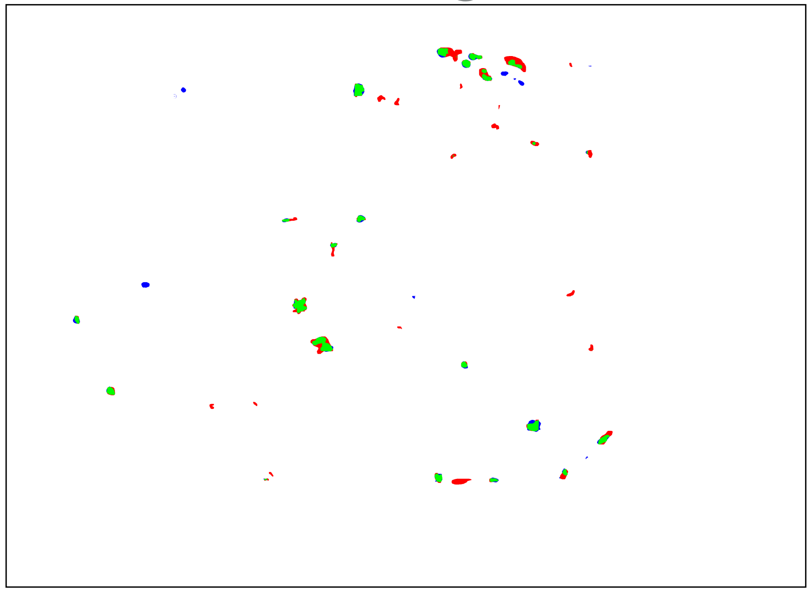
Results using U-Net with adversarial training with dice score metric

EXPERIMENTS AND RESULTS **Adversarial training**

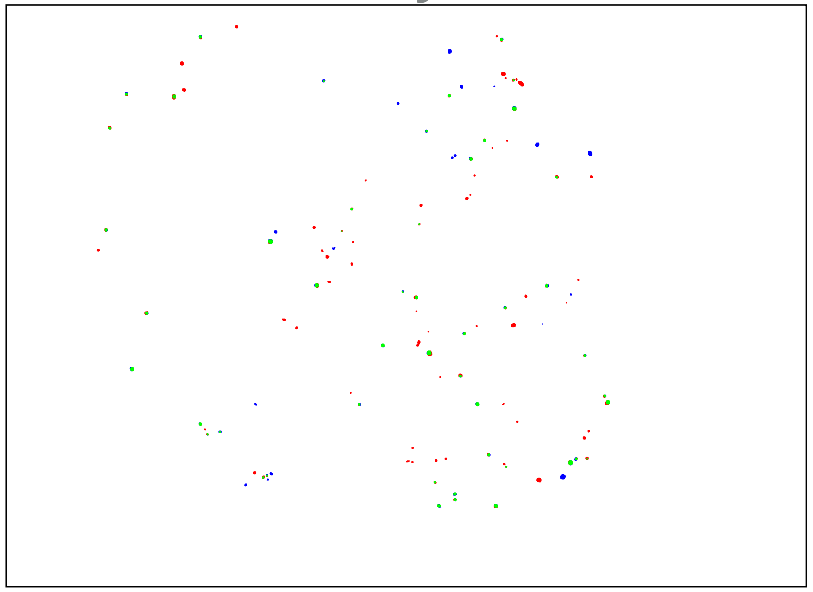
Hard Exudates (EX)



Haemorrhages (HE)



Microaneurysms (MA)



Soft Exudates (SE)

Difference maps. Green: true positives, Red: false negatives, Blue: false positives

EXPERIMENTS AND RESULTS

Discussion

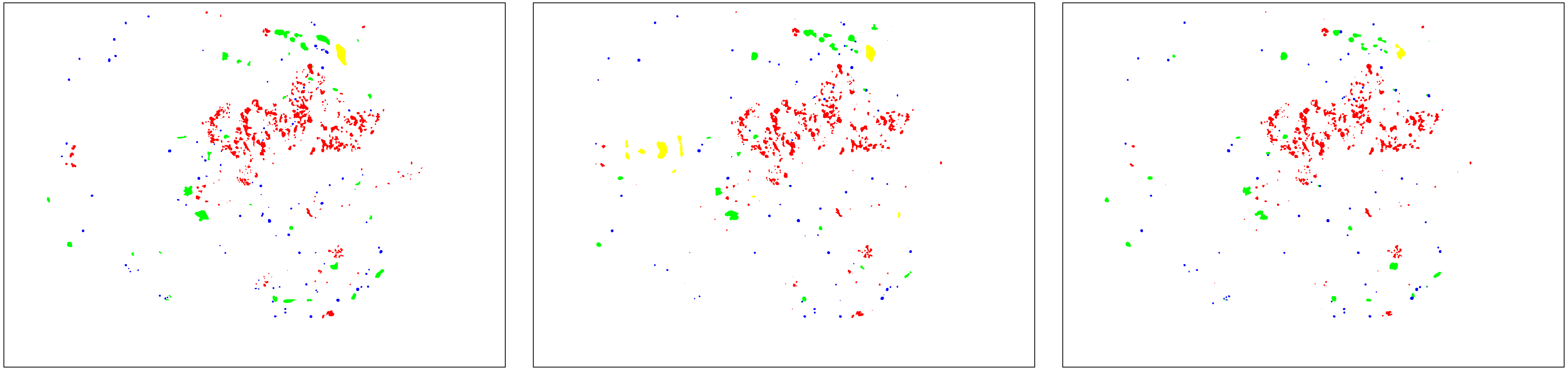
- Criteria to rank the results: we focused on class HE
- The addition of adversarial training improve the results

Architecture	EX	HE	MA	SE
U-Net without adversarial training	0.694	0.458	0.477	0.351
U-Net with adversarial training	0.707	0.476	0.462	0.405

Comparison of the addition of adversarial training using dice score metric

EXPERIMENTS AND RESULTS

Ground truth | Predicted labels without adv. training | Predicted labels with adv. training



Red: class Hard Exudates (EX), Blue: class Microaneurysms (MA),
Green: class Haemorrhages (HE), Yellow: class Soft Exudates (SE)

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CONCLUSIONS AND FUTURE DEVELOPMENT

- We proved that adversarial training applied to a segmentation network improved its performance
- The architecture's configuration must take into account the high-imbalance between classes
- Results are not comparable to the ones from the challenge due to the metric used

CONCLUSIONS AND FUTURE DEVELOPMENT

- As future development, a more robust estimate of the model's performance could be done
- The use of an architecture with dilated convolutions instead of U-Net to avoid pooling operations
- The use of an adaptive sampling scheme would also be interesting to tackle the high-imbalance between classes

THANK YOU FOR YOUR ATTENTION

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