Deep learning techniques for prediction of diabetic retinopathy severity

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Outline

1. Research line description
   - Motivation
   - Objectives
   - Mathematical formalization
   - The data
2. Publications
   - A deep learning model for DR image classification (CCAI 2016)
   - QWK: A new loss function for ordinal regression (PRL)
3. Present and future work

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- Diabetic Retinopathy (DR) is a leading disabling chronic disease.
- Main cause of blindness and visual impairment in developed countries for diabetic patients.
- Diagnostic automation can help the physicians to improve the quality of their diagnostics and reduce the cost associated with it.

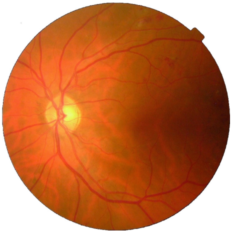

Figure: Image taken with a non-mydriatic fundus camera.

The problem to solve

Diabetic Retinopathy Grade Classification

- Classification of retine images into 5 different categories of increasing disease grade.
- It is a standardized classification defined by ophthalmologists (depending on the number and type of retinal lesions present on the image).

Figure: Five samples of increasing grade. From left to right: 0, no apparent DR; 1, mild non-proliferative (NPDR); 2, moderate NPDR; 3, severe NPDR and 4, proliferative DR

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Objectives of the research

- Design a method for extracting the statistical regularities present in the data that are important for the classification with the minimum human intervention.
- The model should learn alone the important features, not requiring the Computer Scientist to become an expert on the problem that is solving, but only requiring knowledge about the Machine Learning algorithms.
- The model should be self explainable.

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Mathematical formalization

- Find a function f: $\mathbb{R}^{CxHxW} \mapsto \mathbb{R}^n$ that maximizes a objective function (where $CxHxW \gg n$). Optimization.
- Images are high dimensional objects with highly correlated local points. Function proven to exploit this characteristics: a deep convolutional neural network.
- Objective function in neural network argot called cost function.
- Standardized cost function for classification: logarithmic loss (log-loss).
- Evaluation metric: quadratic weighed kappa (QWK).

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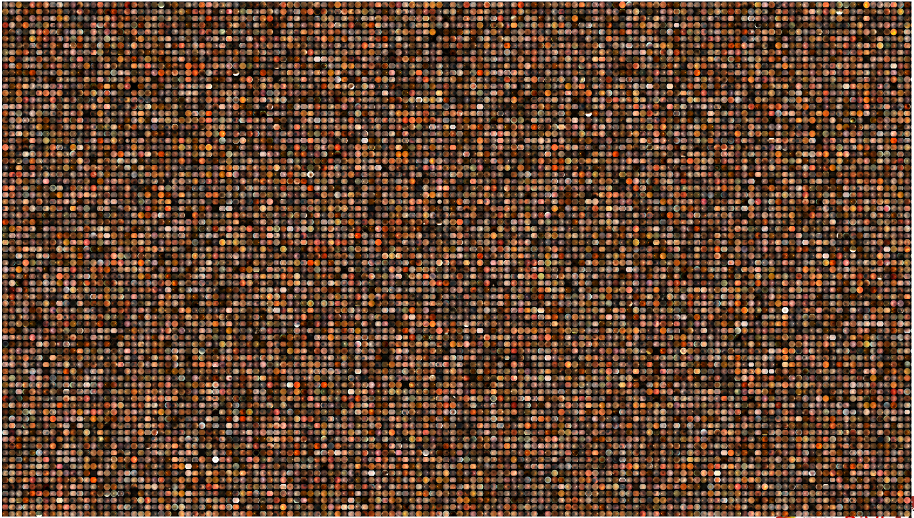
The dataset

Whole dataset of near 85,000 images, 10x10

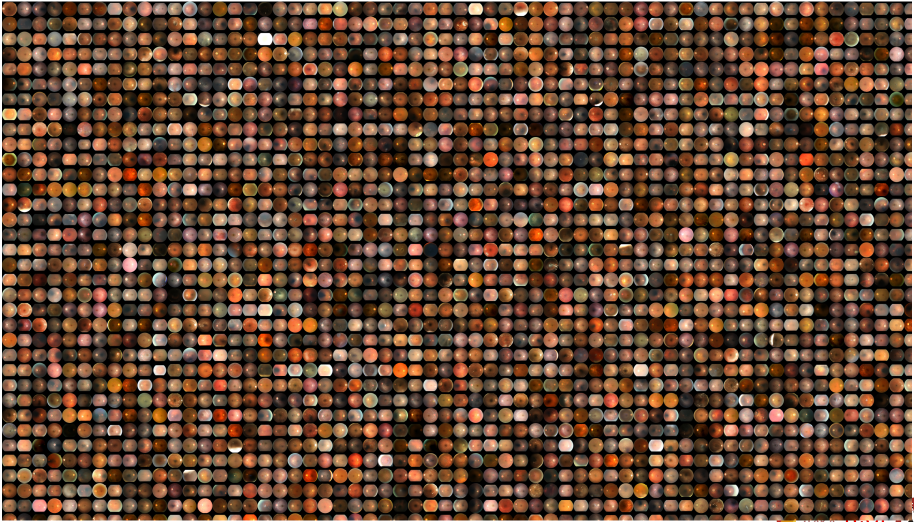
The dataset

10,000 random images, 25x25



The dataset

2,000 random images, 50x50



The dataset

500 random images, 100x100

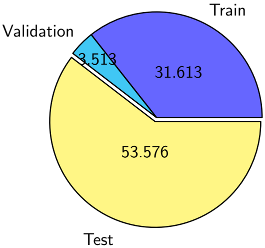


Figure: Dataset conformation

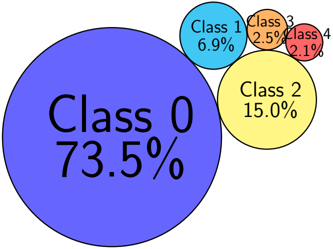


Figure: Dataset class percentage

- Images with differing sizes, illumination conditions, quality.
- For every patient: right and left eye images available.

Data pre-processing

Minimal

Minimal data preprocessing applied (optimization of hardware resources, deep learning optimization methods are computer intensive tasks):

- Remove borders
- Standardization of the image size (downsizing: 128, 256, 512, etc.) depending on the model requirements.

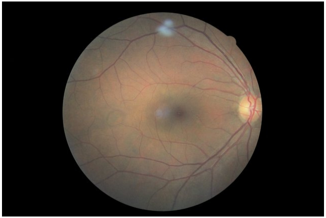


Figure: Original 4752x3168 pixels

Figure: Preprocessed: trimmed + resized

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- Data augmentation techniques were necessary to balance the classes and to increment the generalization capabilities of the model (brightness,contrast, rotations).
- Due to hardware limitations only a part of the input was feeded to the network (about 71% of the useful information), requiring various evaluations and ensembling on test time to increase performance.
- Probabilistic combination of results of both eyes (Bayes rule) helps improve further performance.

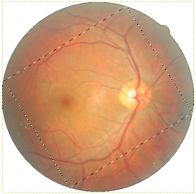

Figure: Input data selection

A deep learning model for DR image classification

Model and training overview (CCIA 2016)

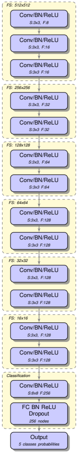

Figure: Model

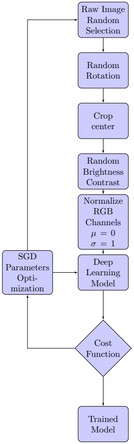

Figure: Training

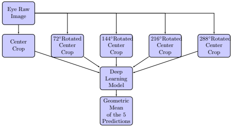

Figure: Evaluation

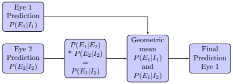

Figure: Combination

Layers	Input size	$\kappa_{test,alone}$	$\kappa_{test,combined}$
12	(3,128,128)	0.488	0.577
14	(3,256,256)	0.636	0.660
16	(3,384,384)	0.668	0.730
16	(3,512,512)	0.725	0.769

Table: Comparison of results obtained with and without probabilistic combination

Outline

QWK: A new loss function for ordinal regression

Mathematical summary of the paper (Pattern Recognition Letters, 2017)

Model function: $p = f(I) \quad where \quad I \in \mathbb{R}^{CxHxW}, \quad p \in \mathbb{R}^n$

Log-loss optimization:

$$min \quad C = \sum_{i=1}^{BS} \sum_{j=1}^{n} t_{i,j} log(p_{i,j})$$

First order derivative:

$$\frac{\partial C}{\partial p_{i,j}} = \frac{t_{i,j}}{p_{i,j}}$$

QWK-loss optimization:

$$max \quad \kappa = \frac{\sum_{i,j} \omega_{i,j} O_{i,j}}{\sum_{i,j} \omega_{i,j} E_{i,j}}$$

$$min \quad C = log(1-\kappa), \quad \omega_{i,j} = \frac{(i-j)^2}{(n-1)^2}$$

First order derivative (check paper for details of the derivation).

- Three different multi-class classification problems using as evaluation metric QWK were trained using QWK-loss and log-loss.
- Different neural networks were tested: a linear classifier, a shallow neural network of 2-3 layers and a deep neural network of up to 16 layers.
- Optimizing QWK reported in all the models and problems increases of performance in the test set of about 5 to 10% over the conventional training method.

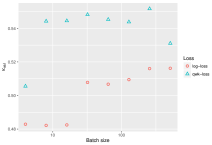

Figure: LC for search results relevance

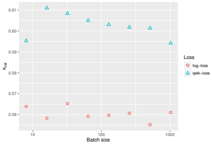

Figure: SNN insurance assessment

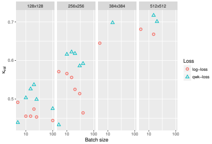

Figure: DCNN for DR classification

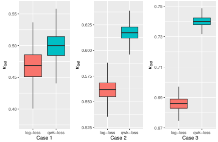

Figure: Confidence intervals (test)

- Deep learning is able to generate models that work very well when trained in a supervised way in the presence of lots of data (thousands of samples per class).
- The drawback of these models is its lack of interpretability. Most of the time act as black boxes.
- Excellent classification performance is a must in medical diagnosis but not enough. Explanation of the reasons behind a result are very important for diagnosis confirmation.
- We are working on improving the interpretability of deep learning in general and of our models in particular.

Summary

- We designed a end to end model for the diagnosis of diabetic retinopathy disease reporting statistical results on the evaluation metric QWK better than human experts.
- Our prediction models are reporting right now QWK values in test set of about 0.844 (Human expert considered with results $QWK \geq 0.80$)
- We proposed the use of a new loss function for the optimization in ordinal regression of neural network based models that report increases of performance of more than a 5%.
- We are working on the interpretability of deep learning models.

Thank you.