

## 1 Description

<b>Dataset name</b>	Retinal Fundus Multi-Disease Image Dataset (RFMiD)
<b>Link</b>	<a href="#">Grand Challenge</a>
<b>License</b>	-
<b>Medical discipline</b>	Ophtalmology
<b>Medical procedure</b>	Microscopy
<b>Multi-class problem</b>	✓
<b>Multi-label problem</b>	✓

This dataset was created for [RIADD](#)'s classification sub-challenge. Classes that can be found are:

- DR
- ARMD
- MH
- DN
- MYA
- BRVO
- TSLN
- ERM
- LS
- MS
- CSR
- ODC
- CRVO
- TV
- AH
- ODP
- ODE
- ST
- AION
- PT
- RT
- RS
- CRS
- EDN
- RPEC
- MHL
- RP
- OTHER
- NORMAL

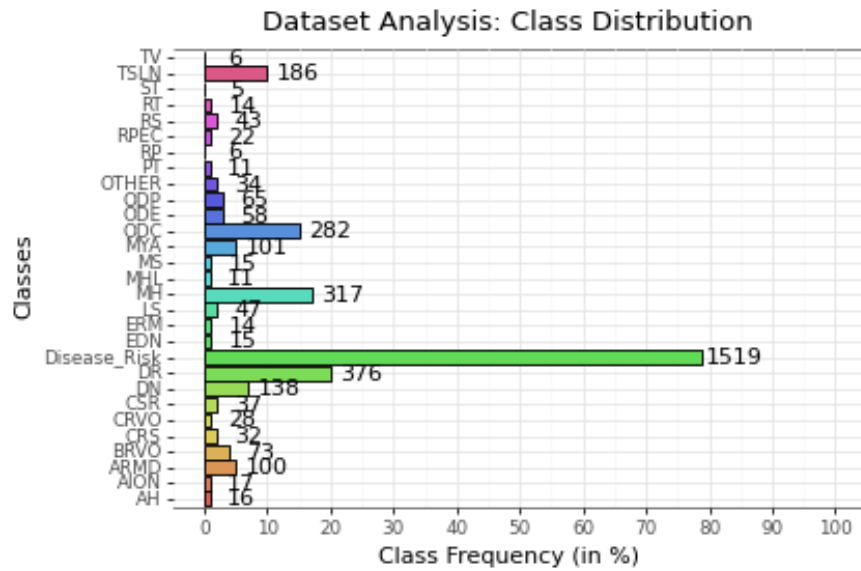


Figure 1: Class distribution: Retinal Fundus Multi-Disease Image Dataset (RFMiD)

## 2 Pre-processing

No pre-processing was done.

## 3 Training

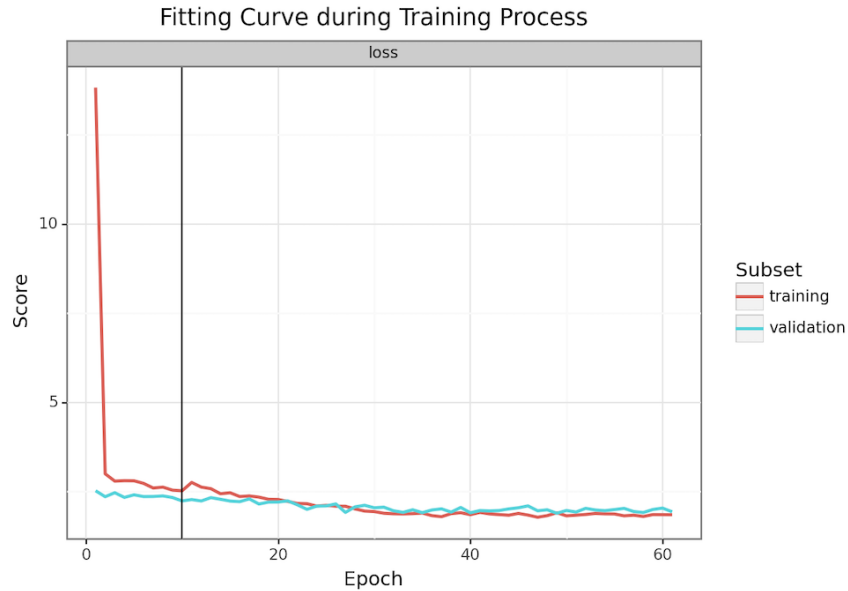


Figure 2: Training: Retinal Fundus Multi-Disease Image Dataset (RFMiD)

The training curve shows the training progress beautifully. Both the training and validation loss curve are fairly smooth, despite the imbalance within the dataset (see figure 1). Validation loss seems to increase after episode 40, indicating a slight tendency to overfit.

## 4 Results

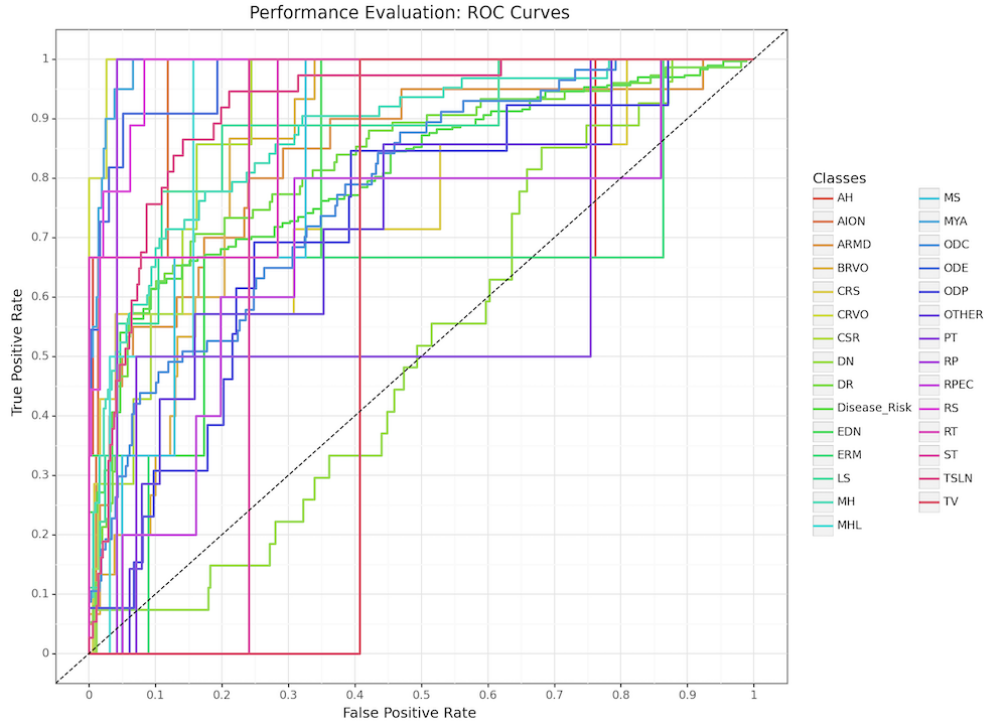


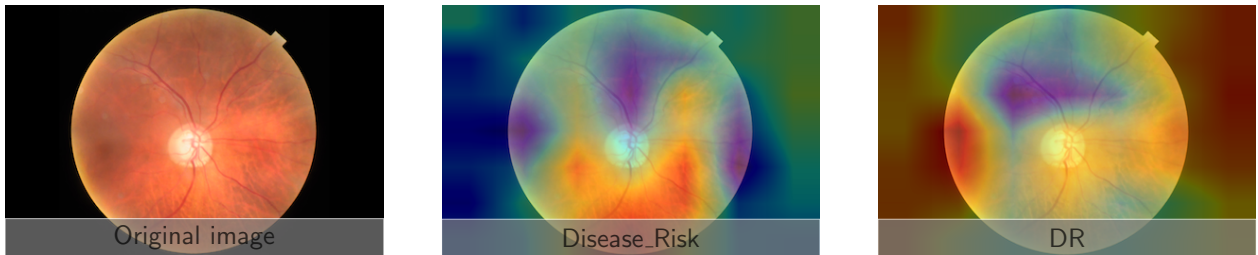
Figure 3: ROC curve: Retinal Fundus Multi-Disease Image Dataset (RFMiD)

Given the complexity of a multi-label classification task, ROC curves in figure 3 are acceptable. It appears that classes with only a few samples, for instance TV (6 samples), ST (5 samples) and RP (5 samples), generate ROC curves with very noticeable, big steps and hardly achieve a high true positive rate.

## 5 XAI

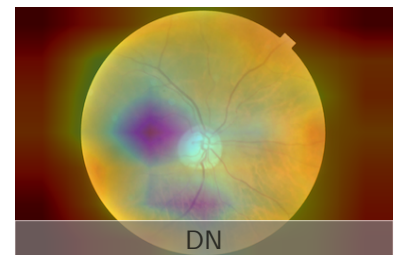
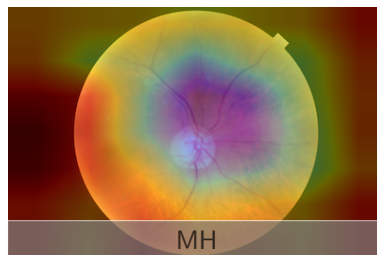
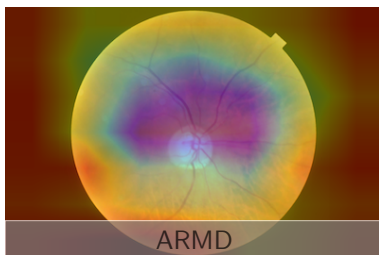
As opposed to a simple multi-class problem, in case of a multi-label problem, we need to inspect one sample and check probabilities for all possible labels. We analyse image **700.png**, that is assigned the labels Disease\_Risk, ODC and TSLN. Table 1 contains all available labels and the probability, our model predicted for them in descending order. The three before-mentioned true labels are among the four most likely labels. Obviously, MYA is a false positive, if we assume the classification threshold to be lower than 21 %.

In any of the Grad-CAM images at hand, the optic disc, the light point where the veins are originating, is not considered relevant. The images show us, that the veins seem to be of interest to our model. The Grad-CAM mark-up for the optic disc coloboma (ODC) class is very distinct: Two wings right and left to the optic disc seem to be relevant for the decision.



Class	Truth	Probability (%)
Disease.Risk	✓	47.1
MYA		21.4
ODC	✓	20.9
TSLN	✓	14.2
MH		7.1
DR		4.7
ODP		4.4
DN		3.9
OTHER		3.1
ARMD		2.7
BRVO		2.1
LS		1.0
ODE		0.5
CRVO		0.4
MHL		0.4
ST		0.3
EDN		0.3
ERM		0.3
PT		0.3
AH		0.2
AION		0.2
RPEC		0.1
CSR		0.1
RS		0.1
RT		0.1
MS		0.1
CRS		0.0
TV		0.0
RP		0.0

Table 1: Probabilities per label for sample 700.png



## 6 Summary

Assigning multiple labels to a single sample is a complex problem to solve. Despite our simple pipeline, the results at hand are solid: Three out of the four most probable labels were correct.

Grad-CAM images are helpful in trying to understand the assignment of a label. In this particular instance, the images highlight the veins, instead of the optic disc itself. That may help shed new perspectives on diagnosing eye-related diseases.

