TÓMOS ai : Improving CNN performance on reduced tomography datasets

George Prounis

Gabriel M Santos E

Felipe Caballero

TÓMOS ai

Mission To develop ML products that…

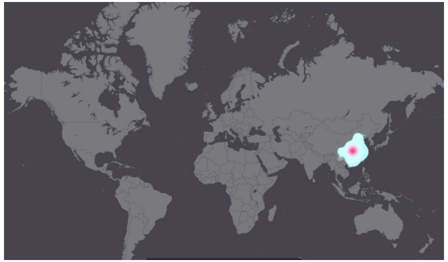
- Perform on **limited medical imaging** data
- Can **adapt** to novel challenges

*Products for the **frontlines…***

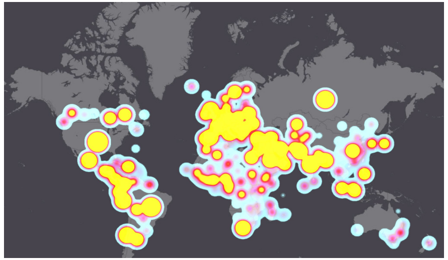
- At early stages of disease discovery
- Using widely available imaging tech (e.g., x-ray tomography)

COVID-19

Normal



COVID-19 cases, January 2020

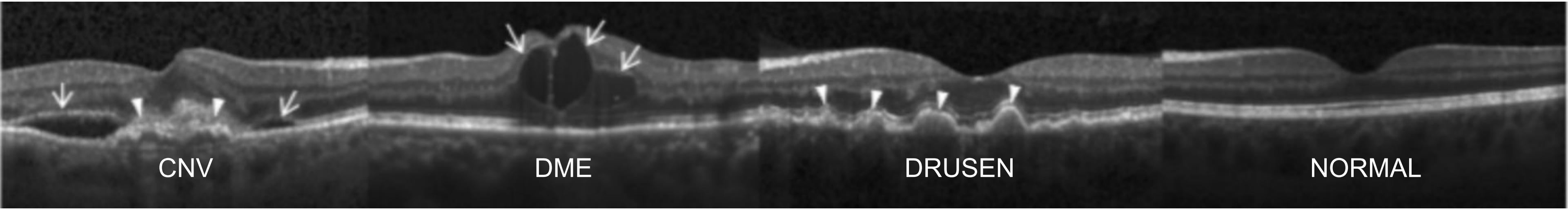


…July 2020

Presentation Outline

- Motivation
- Data overview
- Objective
- Models
    - Baseline: Resnet50
    - Experimental A: Transfer Learning (COVID-19 lung tomography)
    - Experimental B: Semi-supervised Labelling
- Results
- Conclusion & Future Directions

Motivation

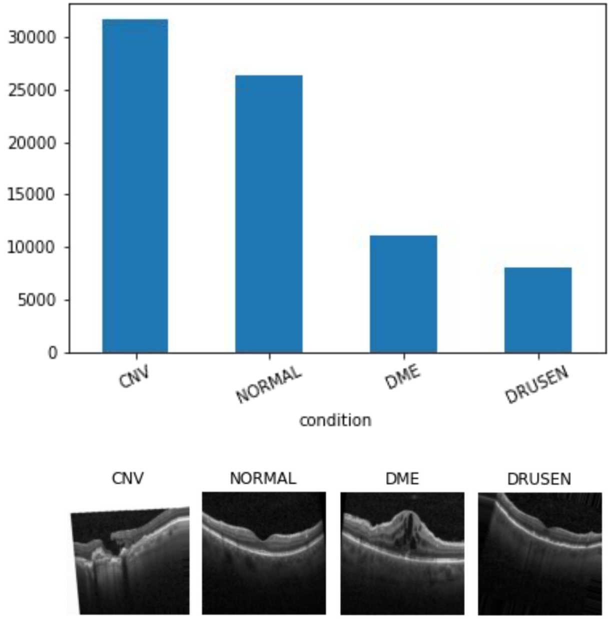


Optical Coherence Tomography (OCT)
- 30 million scans/year
- $1B/year market
- High prevalence:
  - Choroidal neovascularization (CNV): 1.2% adult pop.
  - Diabetic macular edema (DME): 6.6%
  - Drusen: 93% any, 55% medium, 15% large

Machine Learning solutions
- Large amounts of unlabeled data
- Cost-efficient & rapid diagnosis, globally

OCT: Dataset review

- 4 conditions
- Data
  - Total files: 84,484
  - Duplicated files: 7,357
  - Usable files: 77,127
  - We created a pd.dataframe for easier manipulation



Goals and Objectives

Goal

Improve performance on reduced dataset

How?

- Use **similar images** to pre-train - **Covid CT Transfer Learning**
- Generate **more labels** with semi-supervised learning - **Label Spreading**
- Combine **both**

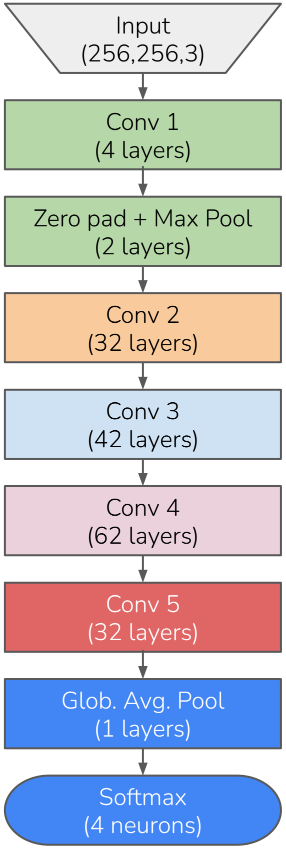
OCT: Model Selection

- 4% of data extracted
- Validation accuracy chosen as target for model selection and tuning
- Best
  - Model = **Resnet50**
  - Optimizer = **Adam**
  - Learning rate = **0.01**
  - Batch_size = **16**
  - Val_Acc = **0.84**

Model	Val_acc	Val_loss	f1_score
Resnet50_.01_Adam_8	0.8396	0.4423	0.734184
Inception_V3_.01_Adam_8	0.8108	0.5646	0.788707
VGG16_.01_Adam_8	0.8234	0.5583	0.825868
Resnet50_.01_SGD_8	0.8126	0.5229	0.769536
Resnet50_.01_Adagrad_8	0.8126	0.5756	0.774433
Resnet50_.1_Adam_8	0.8342	3.7931	0.779204
Resnet50_.001_Adam_8	0.836	0.4436	0.806301
Resnet50_.01_Adam_2	0.836	0.5089	0.767981
Resnet50_.01_Adam_16	0.8414	0.5441	0.770273
Resnet50_.01_Adam_32	0.8342	0.5345	0.773052
Resnet50v2_.01_Adam_16	0.8378	0.4695	0.770538

OCT: Baselines - Resnet50

- Default architecture (177 layers)
- Trainable
- Added last dense layer (4 neurons)
- Data
    - Test set 5%
    - Train set 95%
      20% for validation / training on the rest



OCT: Baselines - Resnet50

- Data augmentation
- Pre processing
- 30 epochs
- Saved best & last model

Model (best in 30 epochs)	Accuracy	Precision	Recall	F1
Resnet 50 / 100% of train set / All trainable	95.38%	95.53%	95.38%	95.40%
Resnet 50 / 5% of train set / All trainable	89.78%	89.85%	89.78%	89.37%
Resnet 50 / 5% of train set / Last 34 layers trainable	92.01%	91.84%	92.01%	91.81%

Experiment A, Transfer Learning / COVID-CTscan Baseline - Resnet50

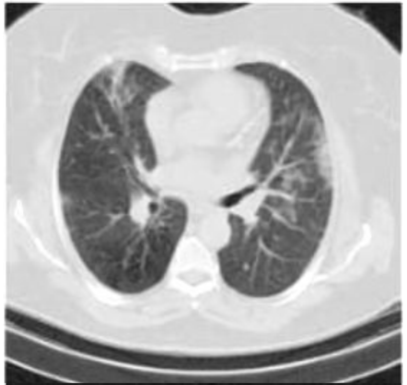
X-ray scans of COVID-19 vs. Normal Lungs

- COVID-19: 2,155 images / 95 patients
- Normal: 9,466 images / 282 patients

Resnet50 baseline model

- Added last dense layer (2 neurons)
- Data
  - 11,621 images
  - 5% test, 20% validation
- Performance
  - 94% testing accuracy

COVID-19



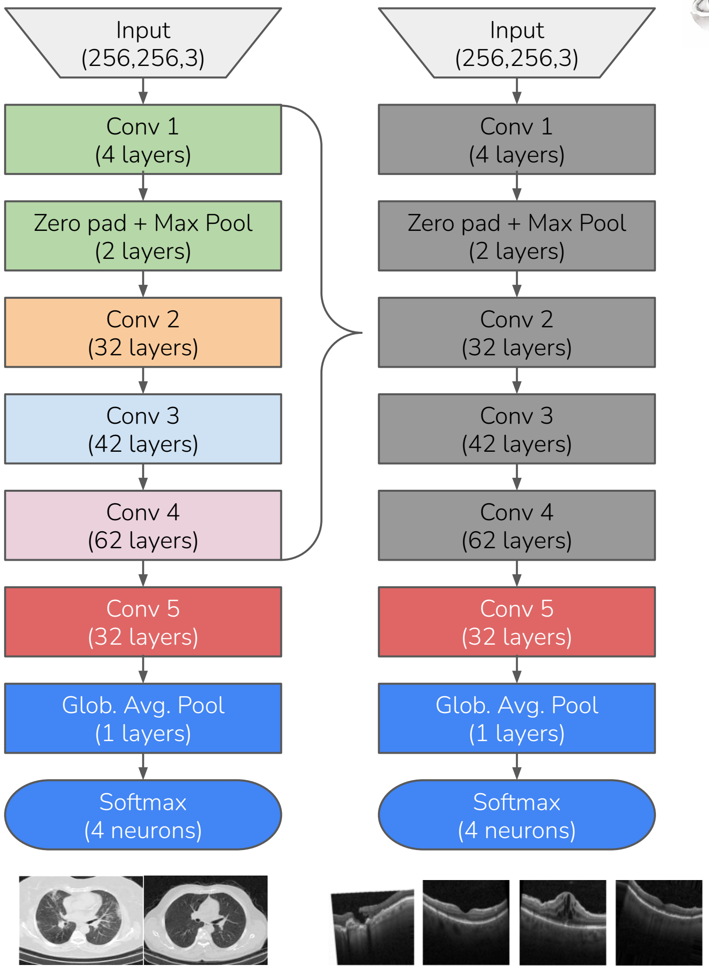
Normal

Experiment A

COVID-CTscan → OCT Model

Transferred weights from COVID-19 Baseline ResNet to all layers of a OCT ResNet model.

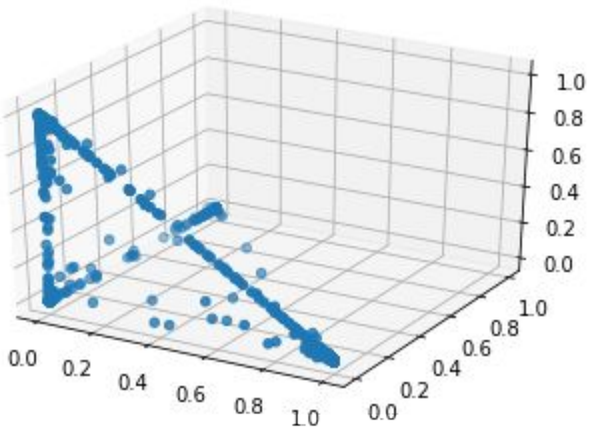
All but last 34 layers are frozen.



TOMOS ai

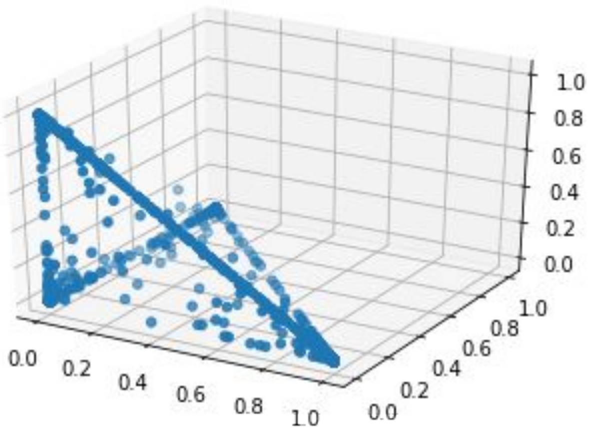
Experiment B
OCT: Semi-Supervised (approach)

- Create unlabelled data set
- Predict new labels
- Fit label spreading model
- Use new labelled data for training



Labelled data probability vector mapping

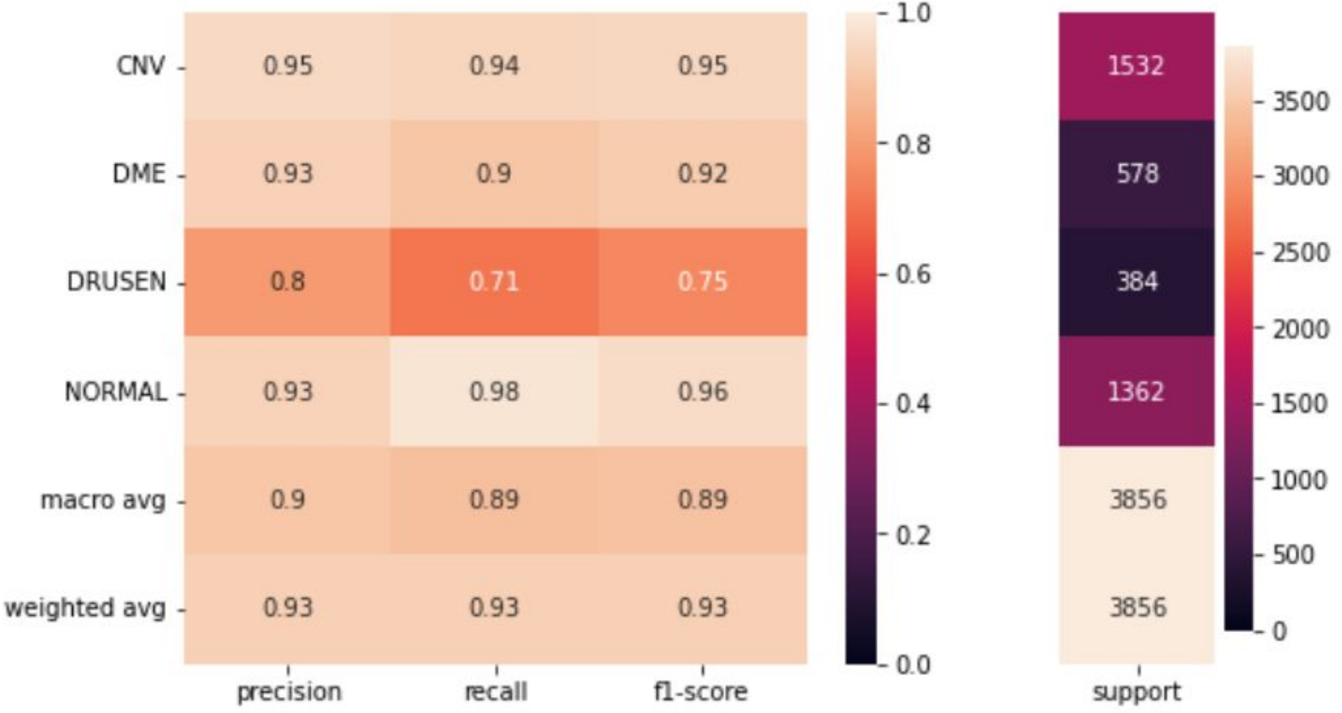
vs



Unlabelled data probability vector mapping

Experiment B

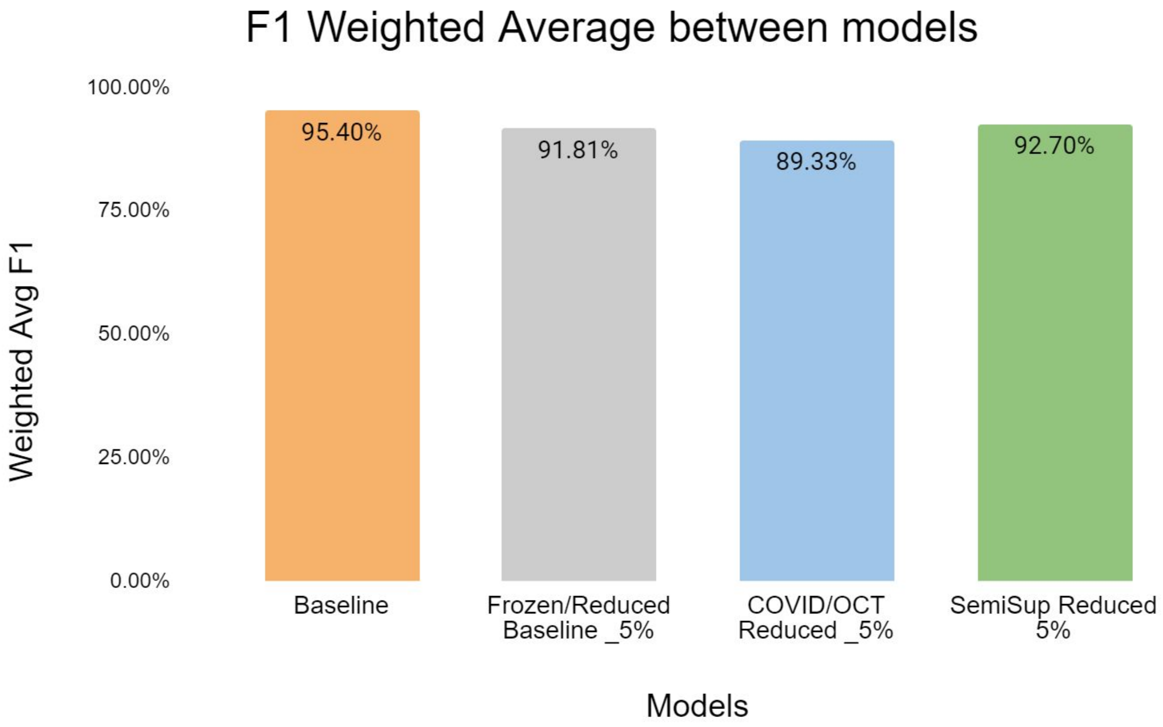
OCT: Semi-Supervised (results)



F1 weighted average = 92.70%

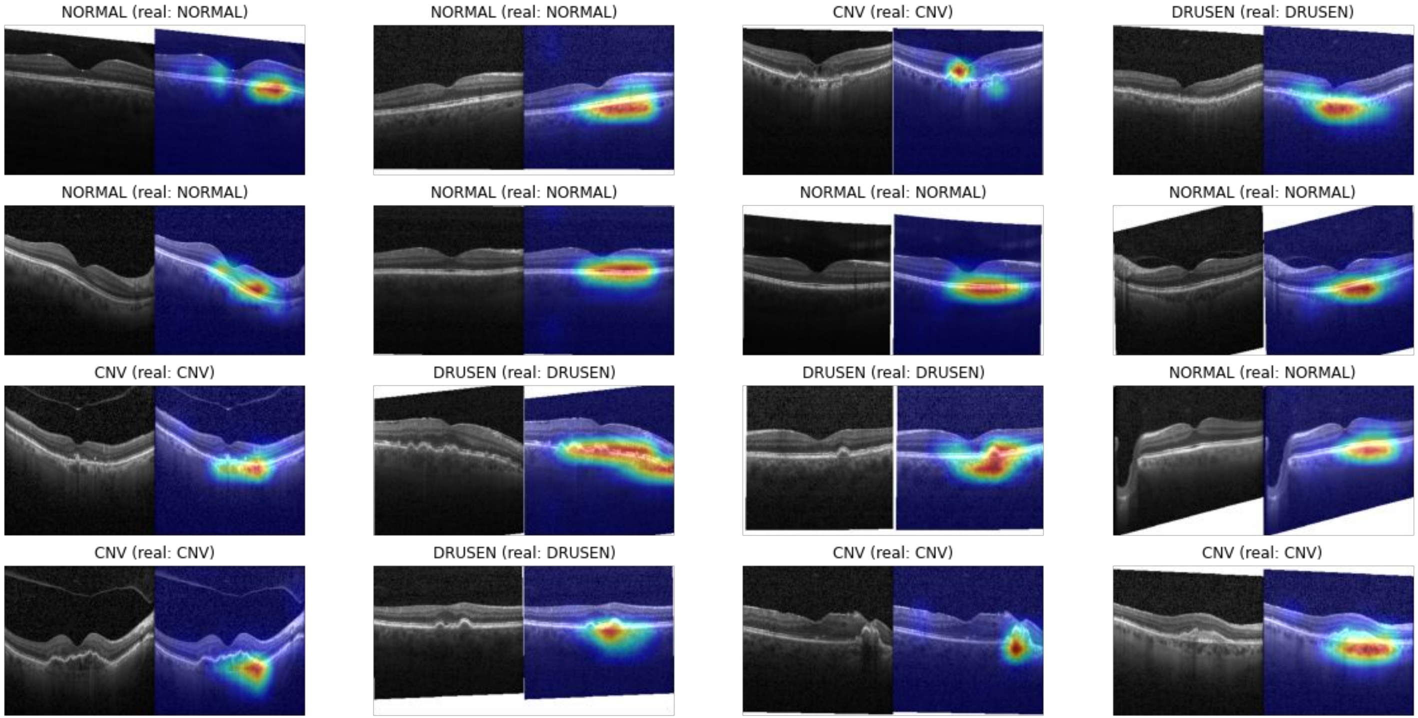
TOMOS ai

Results


F1 Weighted Average between models
100.00%
75.00%
50.00%
25.00%
0.00%
Weighted Avg F1
95.40%
91.81%
89.33%
92.70%
Baseline
Frozen/Reduced Baseline _5%
COVID/OCT Reduced _5%
SemiSup Reduced 5%
Models

Demo time

(try it in this IP: 35.86.237.154)



Classification and heatmaps

Conclusions / Future directions

We improved performance on a limited (5%) labeled dataset with a semi-supervised learning approach (+0.9% F1)

Future directions

- Do co-training
- Reduce data further
- Try VGG16
- Experimenting with which layers get frozen during transfer learning

What did we learn?

We learned how to take a specific Dataset, run it through a Machine Learning pipeline specific to that data and improve the performance catering the pipeline to the data.

Questions?

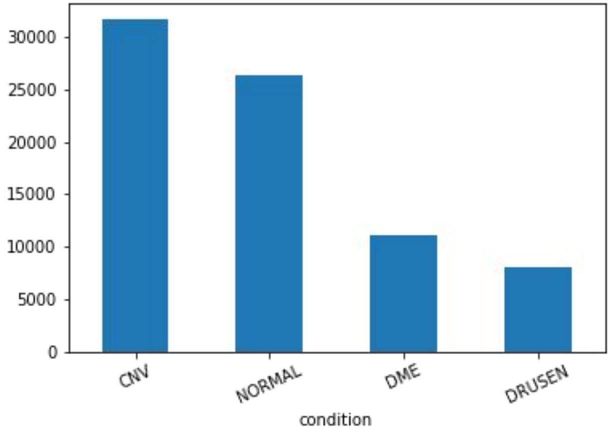
TÓMOS ai

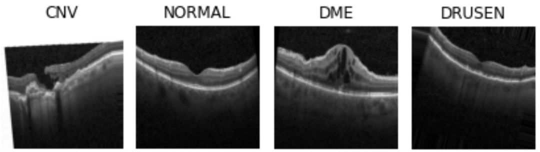
Felipe Caballero felipe@caballero.co	George Prounis george.prounis@gmail.com	Gabriel Santos-Elizondo g.santose4@gmail.com

Backslides

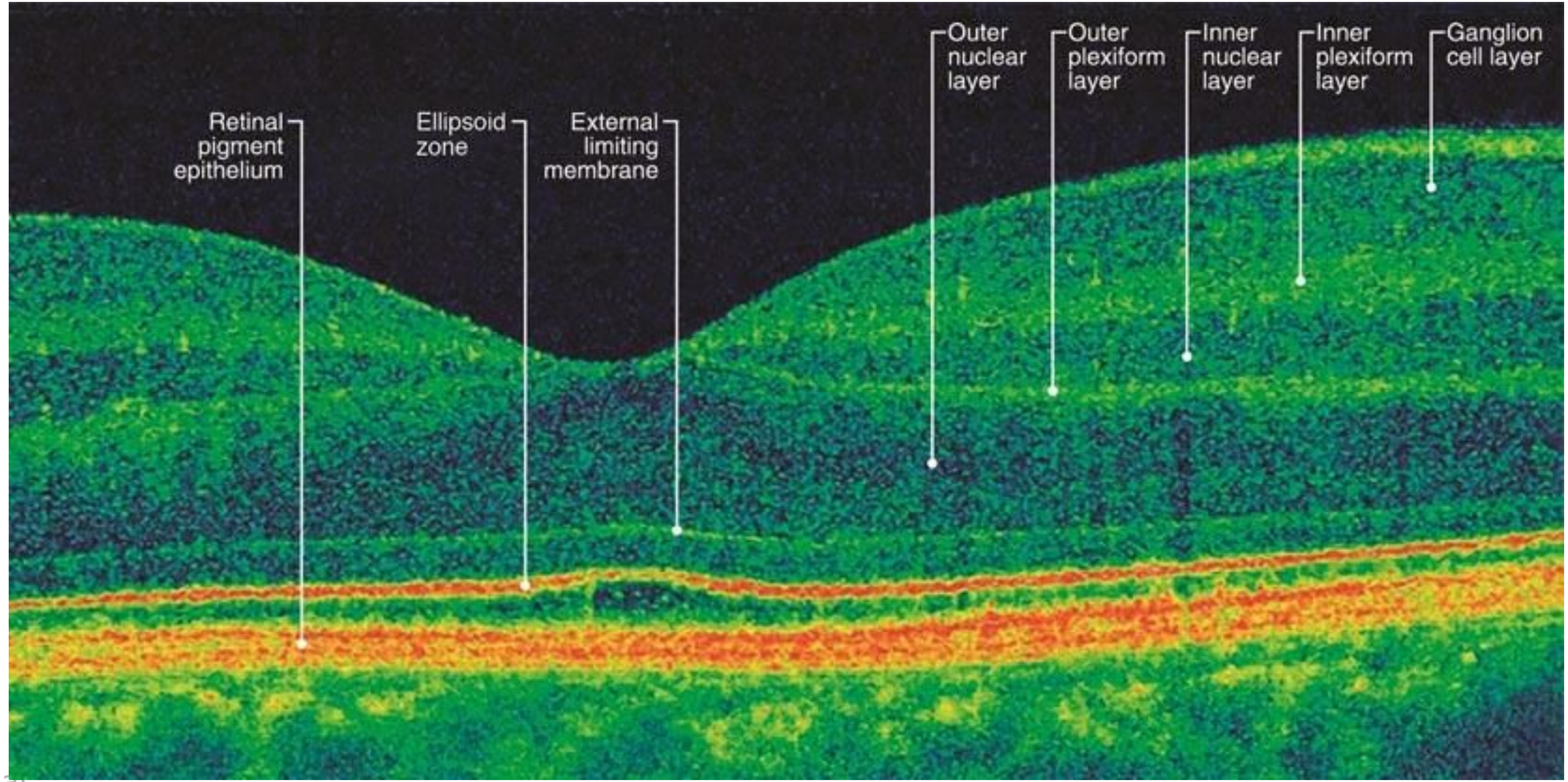
OCT: Dataset review

- Two datasets: *Kaggle* and *Mendeley*
- We use the *Mendeley* one
- Data
    - Total files: 84.484
    - Duplicated files: 7.357
      (duplicates are considered when md5 and condition are the same)
    - Usable files: 77.127
    - We created a pd.dataframe for easier manipulation

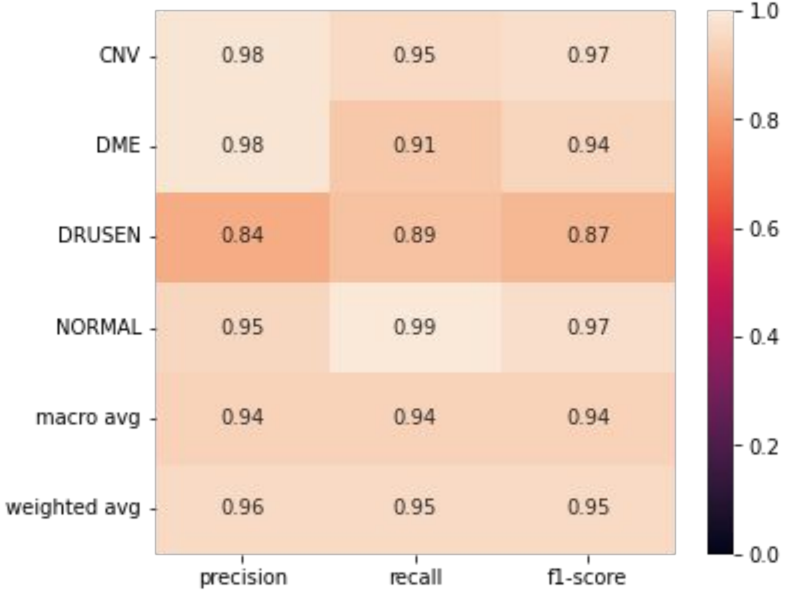


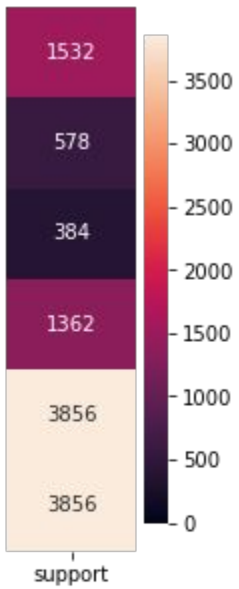


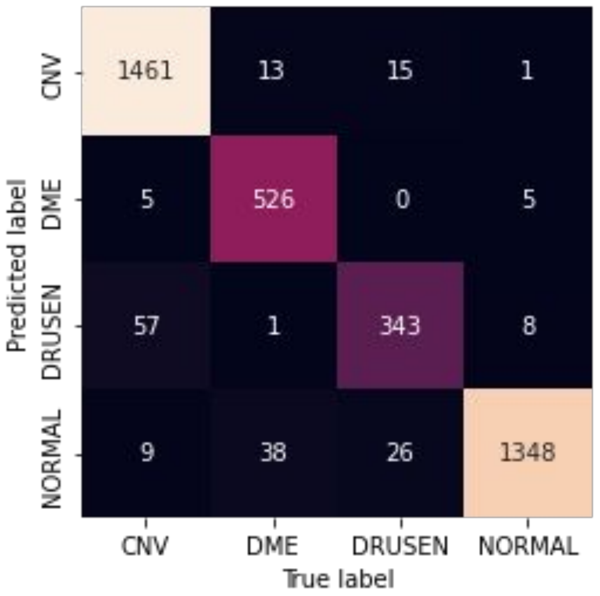
OCT: Dataset review, image description



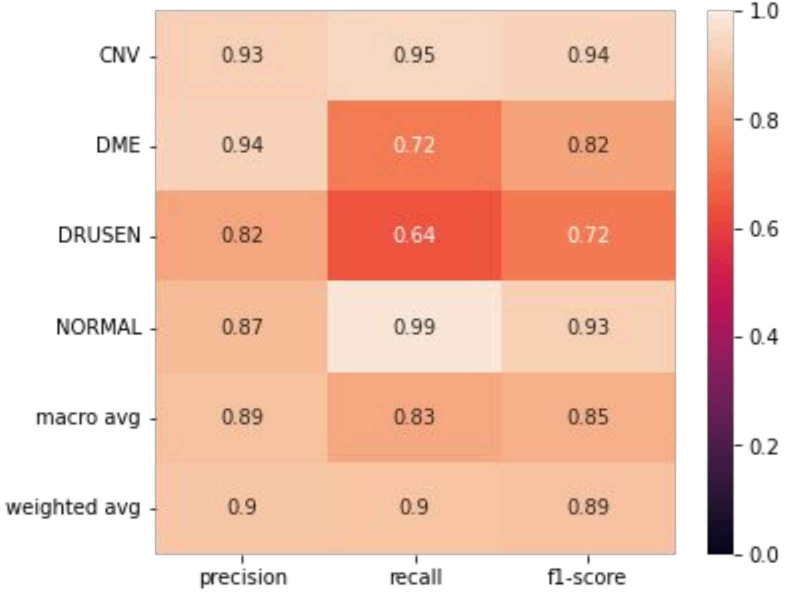
Baseline - Resnet 50 / 100% of train set / All trainable

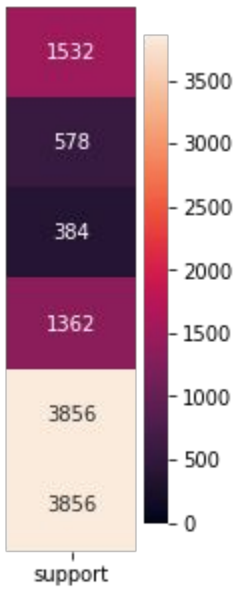


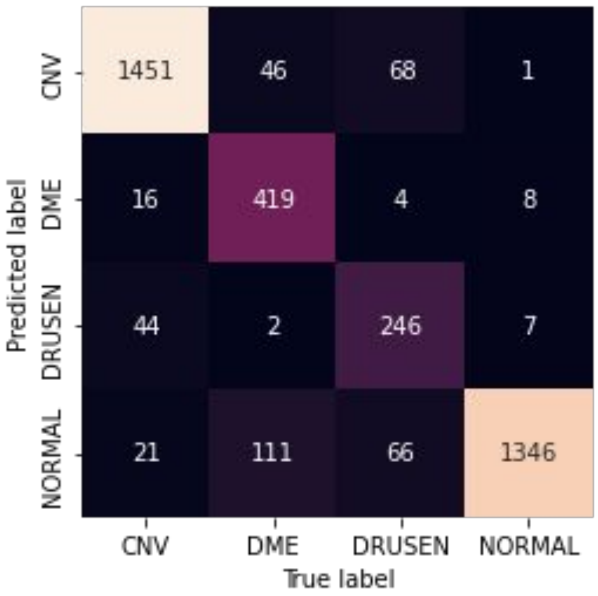




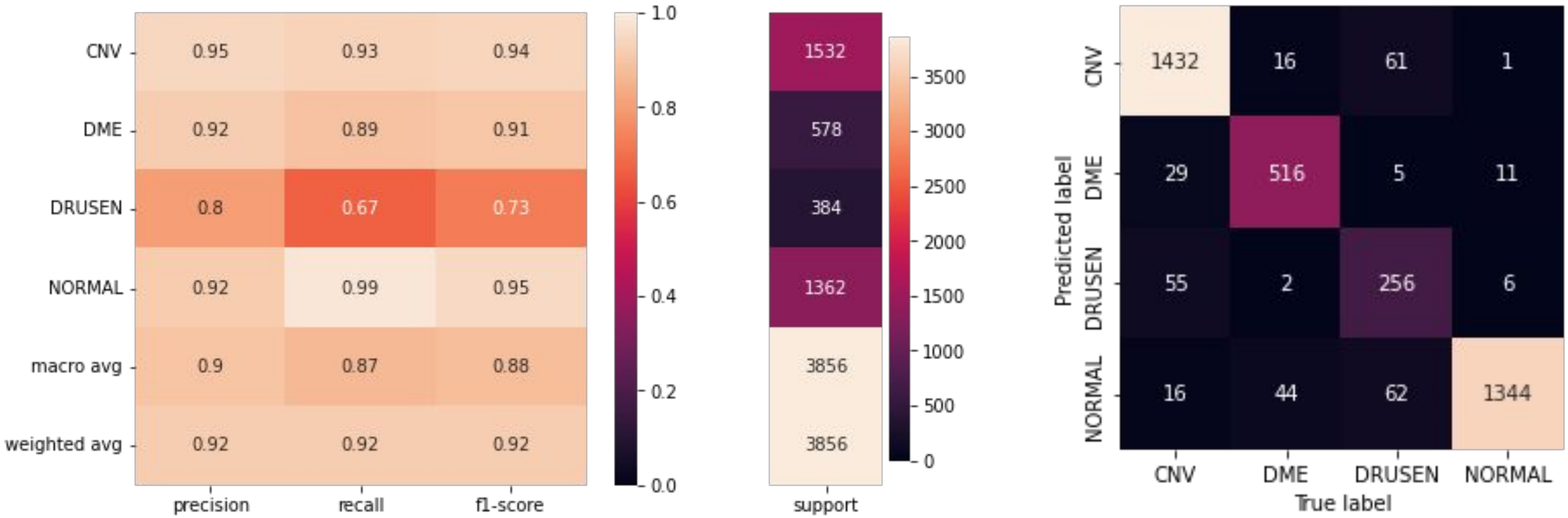
Baseline - Resnet 50 / 5% of train set / All trainable







Baseline - Resnet 50 / 5% of train set / Last 34 layers trainable



COVID-OCT-Resnet 50 / 5% of train set / Last 34 layers trainable