19-11-2024

H. Pillory Diagnosis

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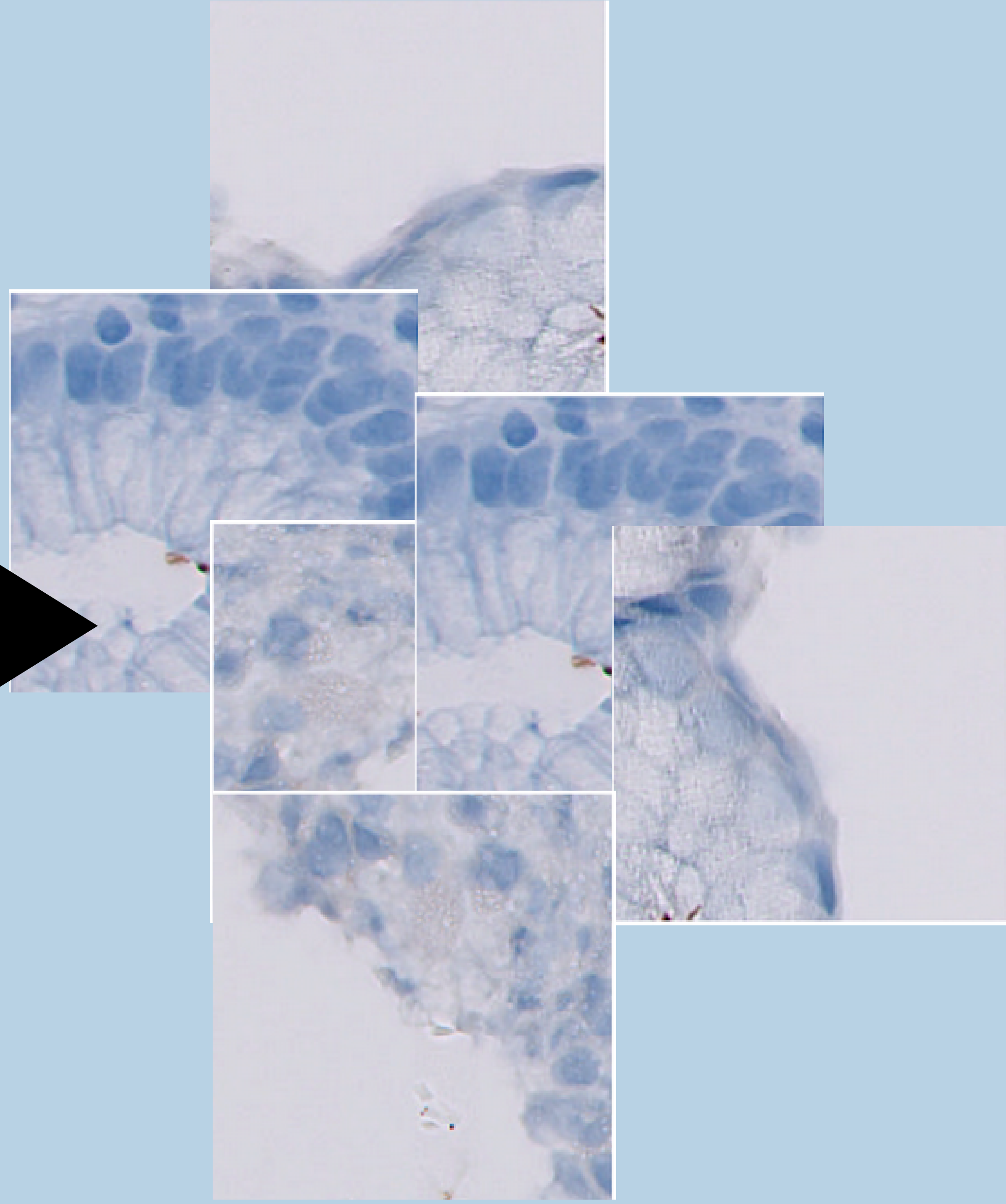
Vision & Learning

Introduction



A. Detection/Classifier

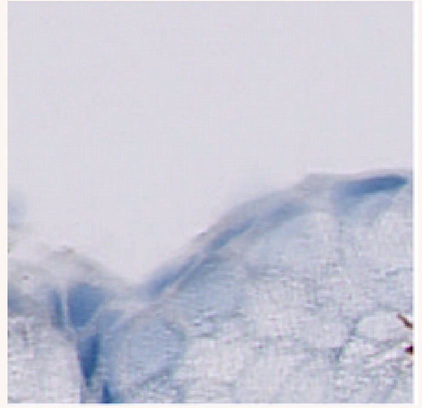
Patch Classification
Patient Diagnosis

Attention/Adaptive
Thresholding...

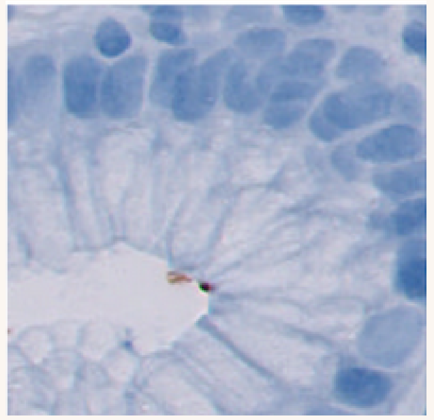
Methodology

Patch classification

Patient X

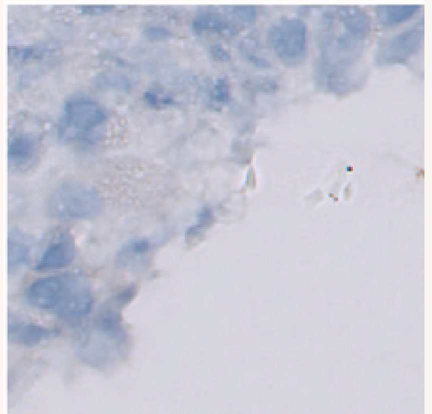


Negative



Positive

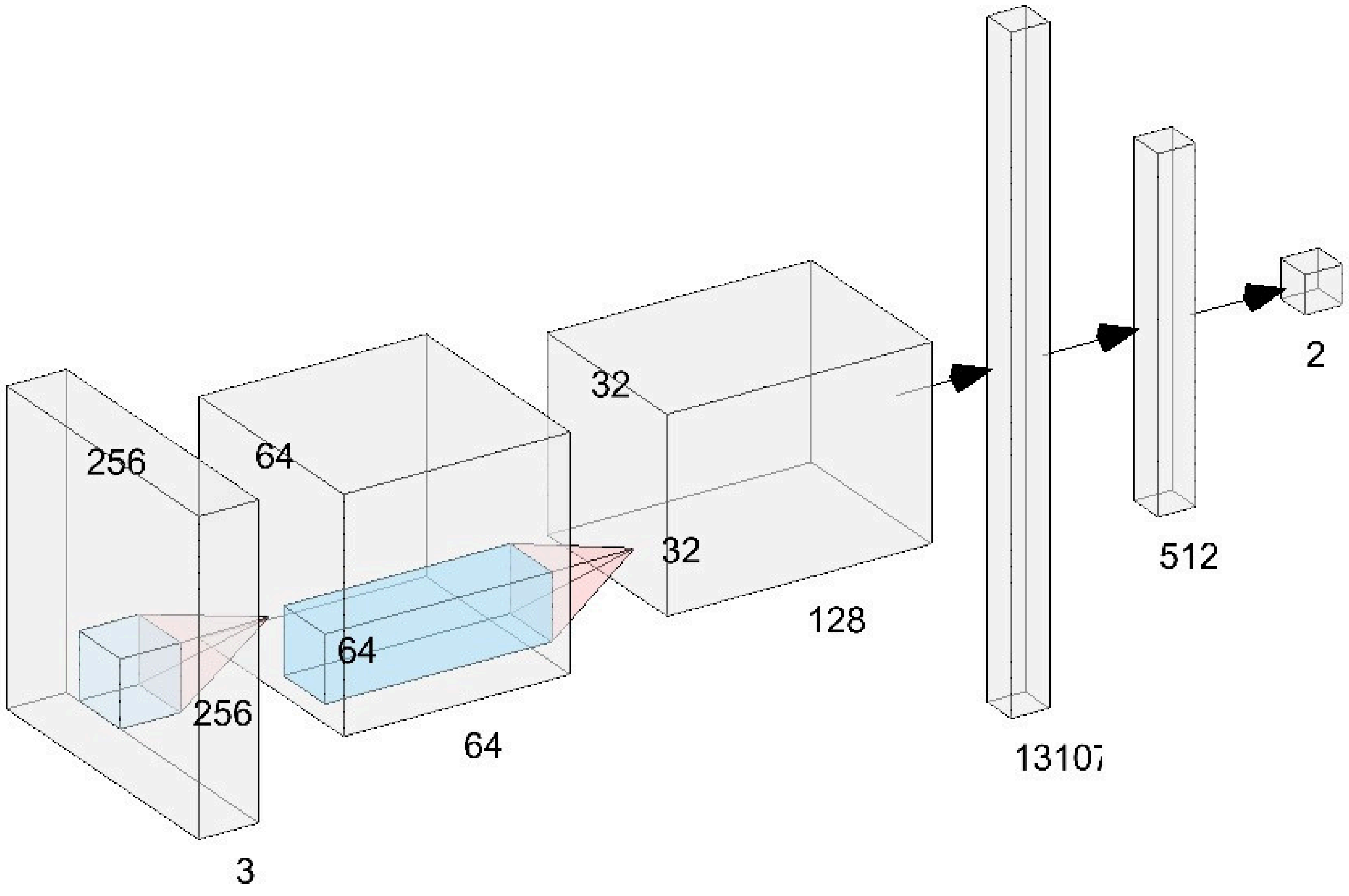
...



Negative

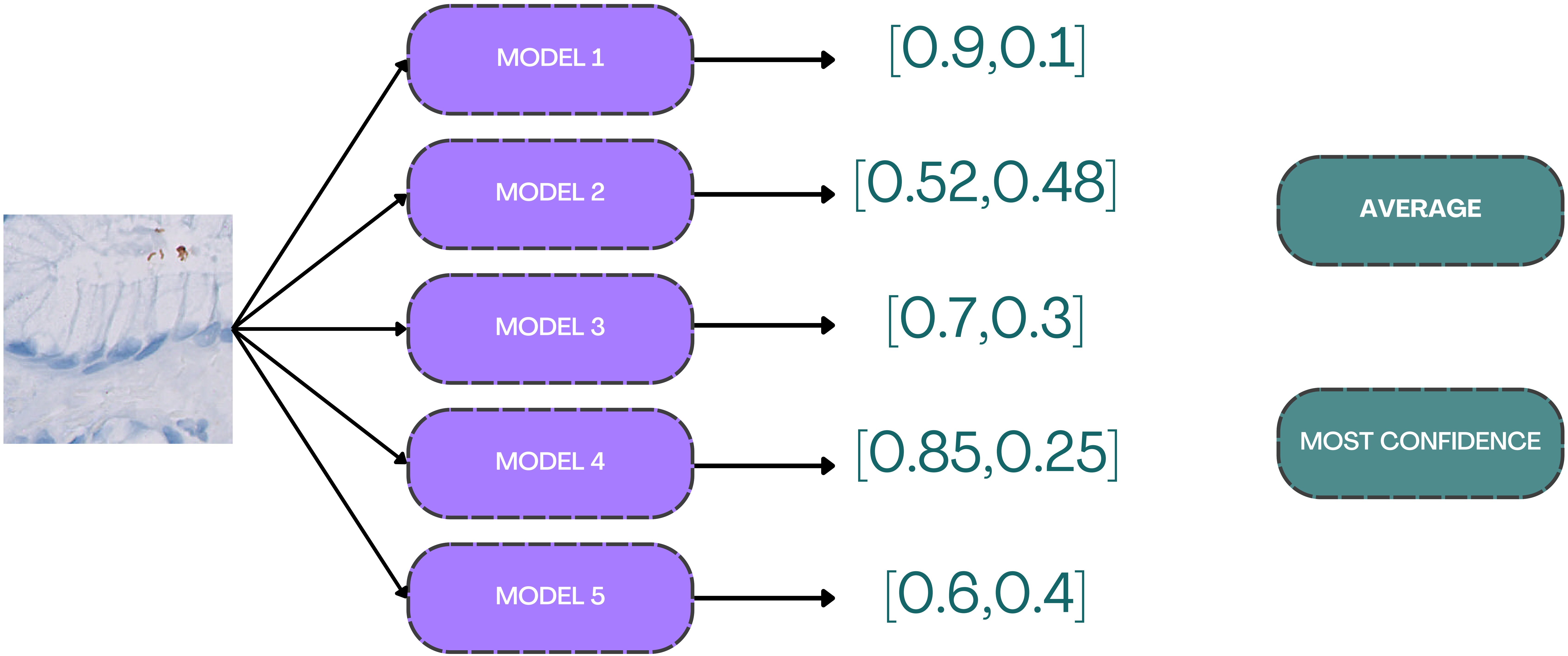
Binary Classification

Classification model
Patch classification



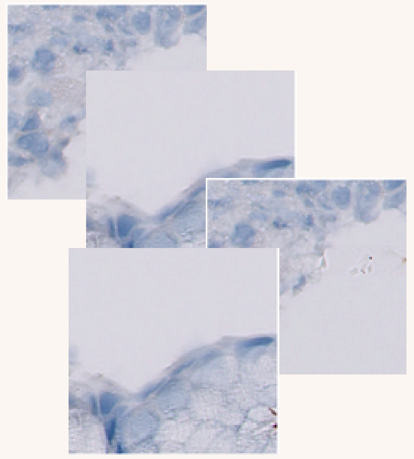
Architecture

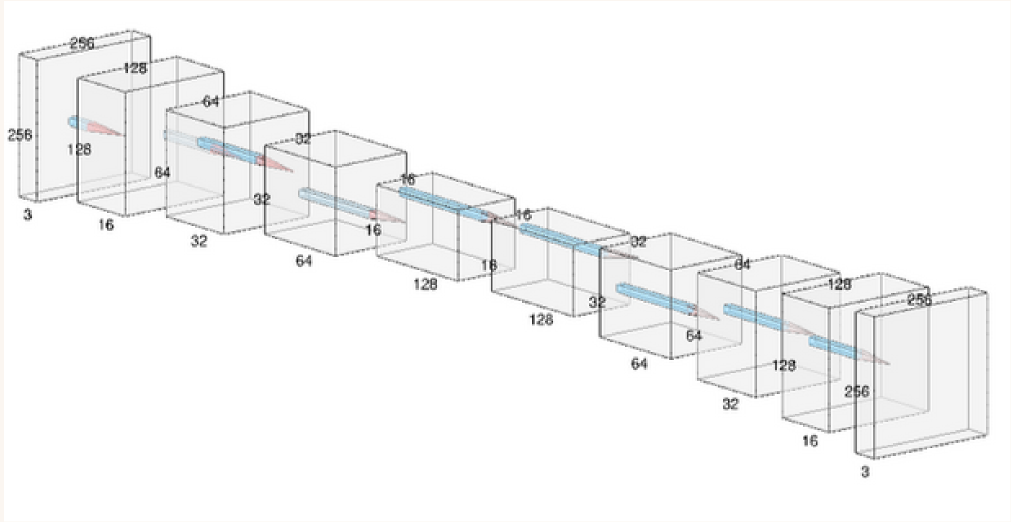
Classification model
Patient Diagnosis



Anomaly Detection:
Patch Classification

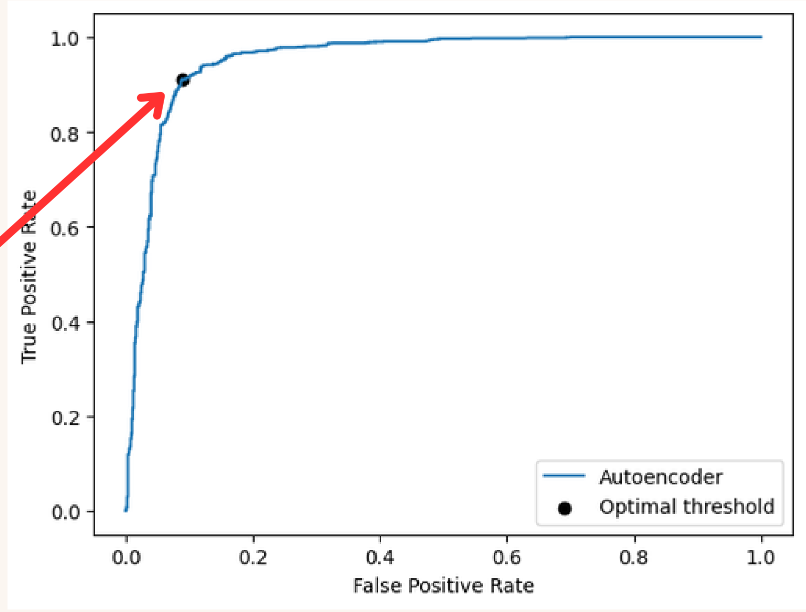
1. Train AE on patches of Negative Diagnosis



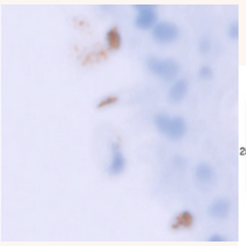


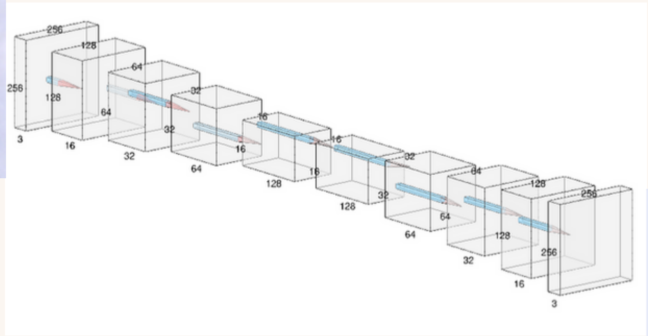
3. Find Optimal Threshold in ROC curve

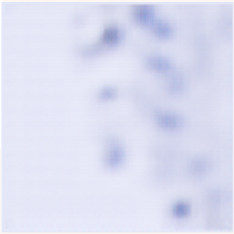
0.34
0.92
– 1.5
4.7
30.1
30.7
+ 32.2
40.2



2. Compute Red Fraction (in HSV)

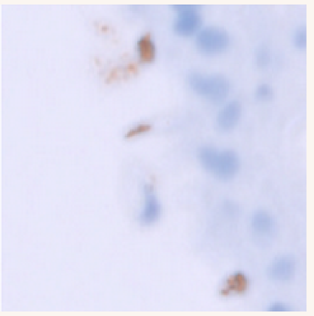
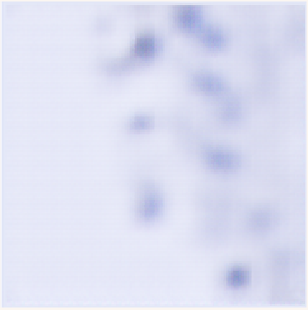






$$F_{red} = \frac{\#\{(i,j) \text{ with } -20 < H_{Ori}(i,j) < 20\}}{\#\{(i,j) \text{ with } -20 < H_{Rec}(i,j) < 20\}}$$

4. Classify

 / 

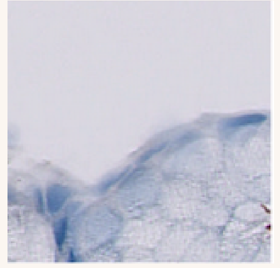
= 31.2 > 30.7

↓

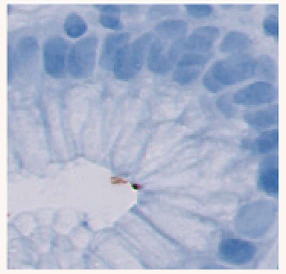
Positive

Anomaly Detection:
Patient Diagnosis

Patient X

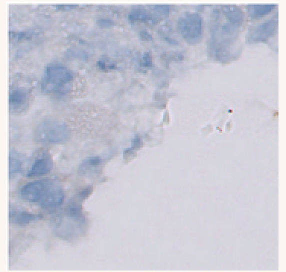


Negative



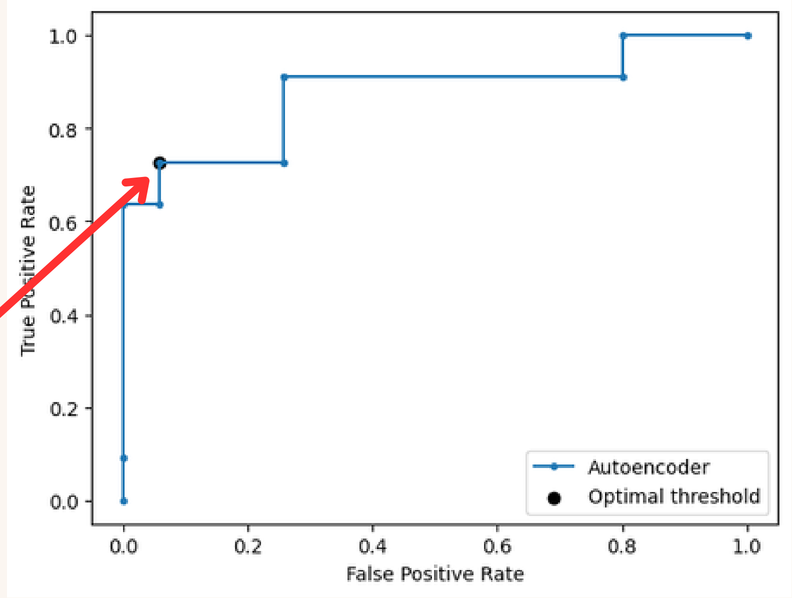
Positive

...



Negative

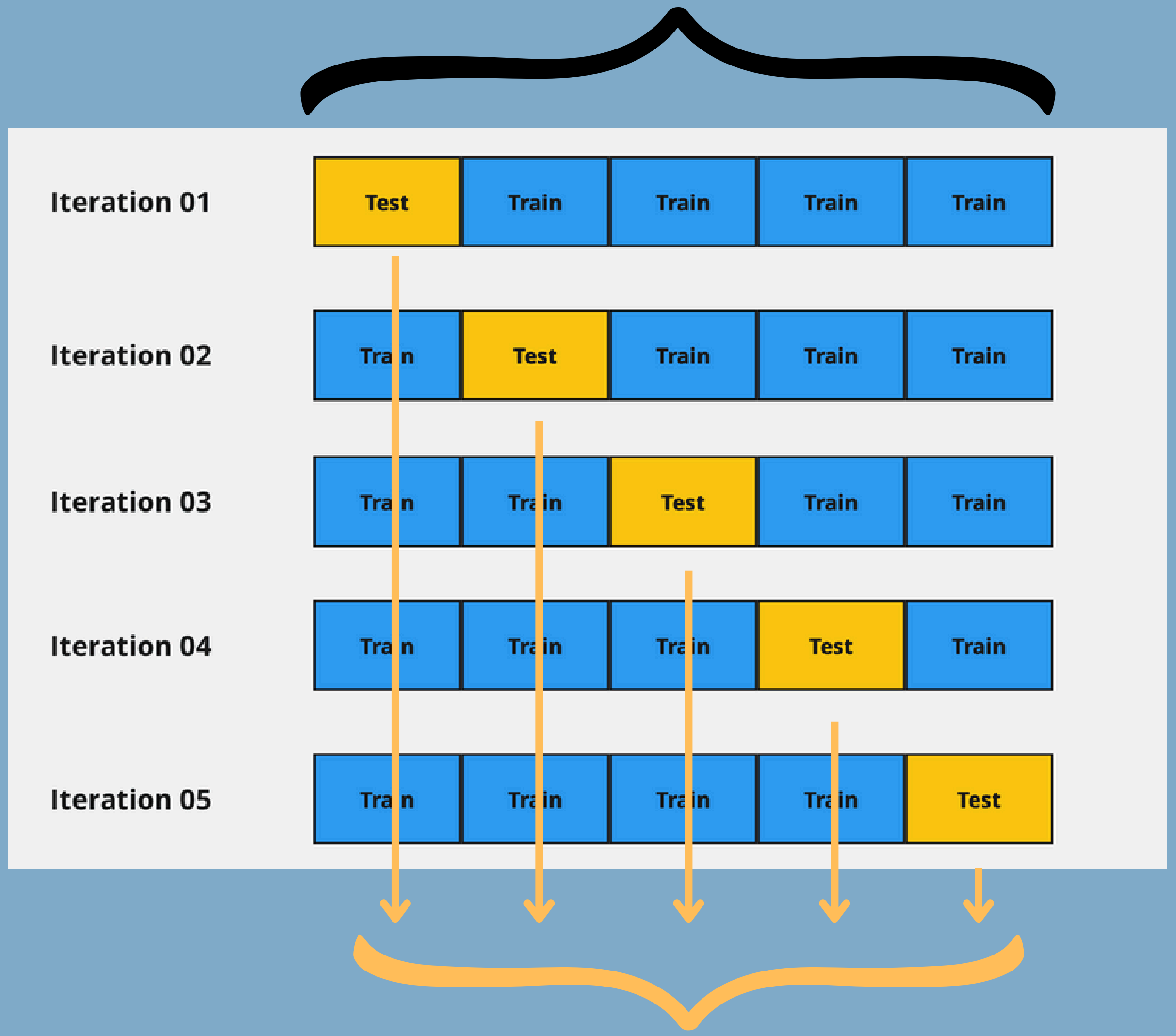
1.22
2.03
– 14.92
16.32
16.90
22.29
+ 23.80
30.17



Experimental design

K-fold Cross Validation

Total Patients in “CrossValidation” set



Aggregate

Evaluate Patch Classification

Evaluate Patient Diagnosis

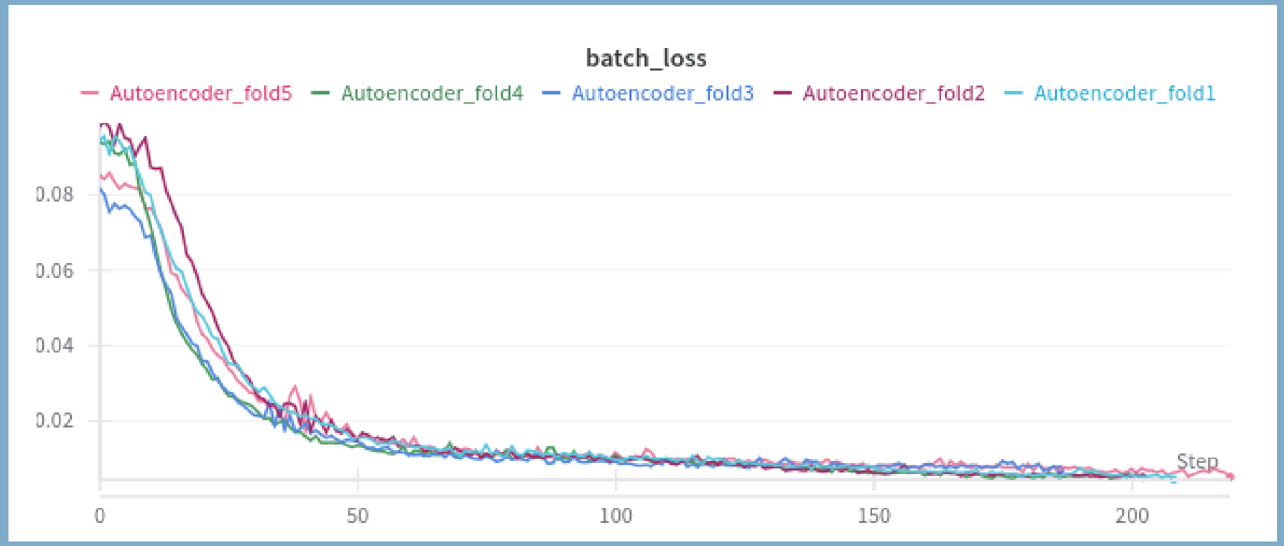
Train model

+

Classify patches

+

Diagnose patients



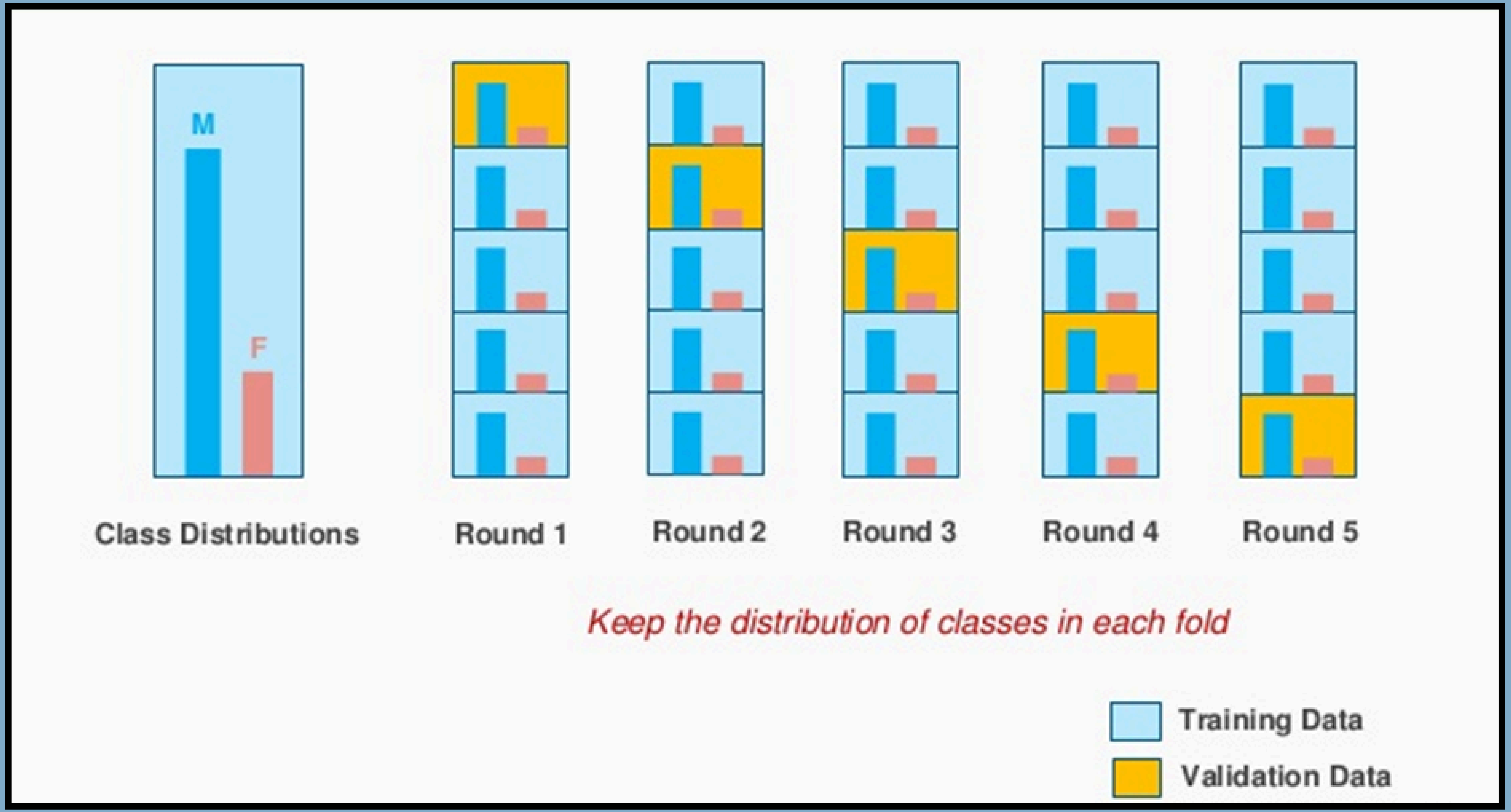
Classifier Training

- Trained on 2080 images
- Parameters:

  Epochs 40 (EarlyStopping)

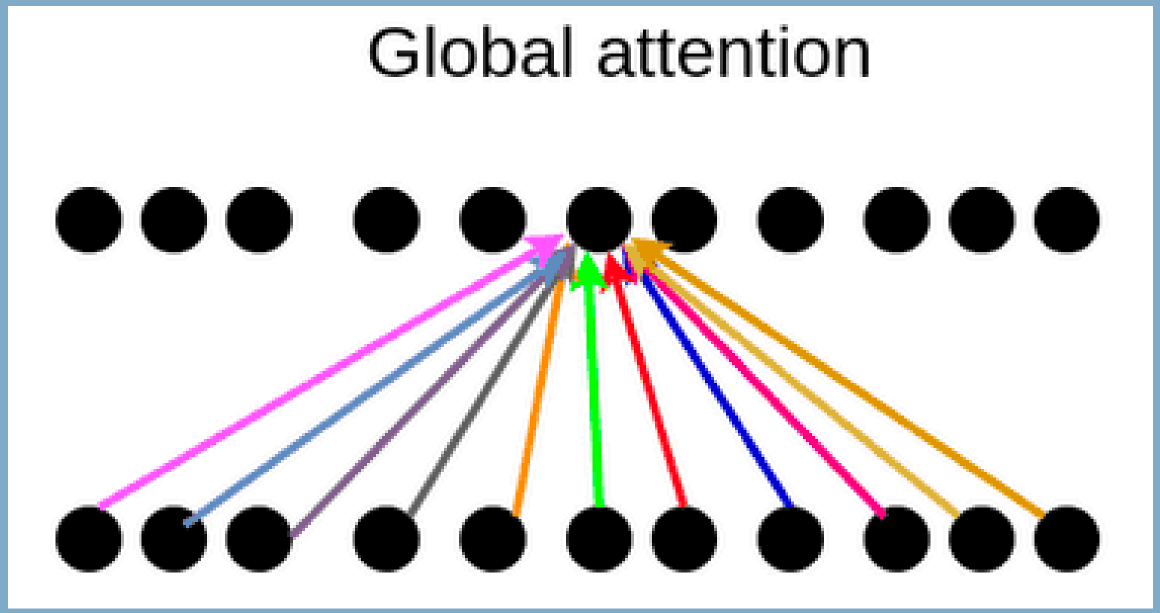
  Learning Rate: 0.001

  Batch Size: 256
- Taking into account PatientX do not appear in train and validation at the same time.



Attention Mechanisms

All built on Classifier Patch Classification



Overfitting!!!

-Introducing more trainable params

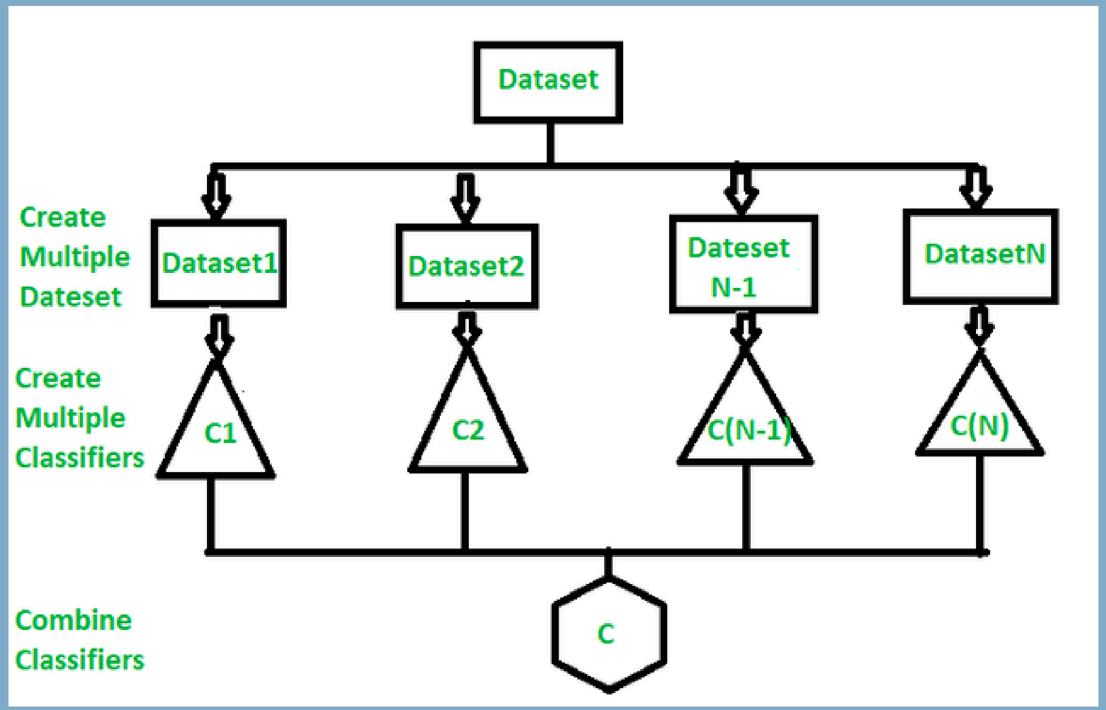
-No regularization

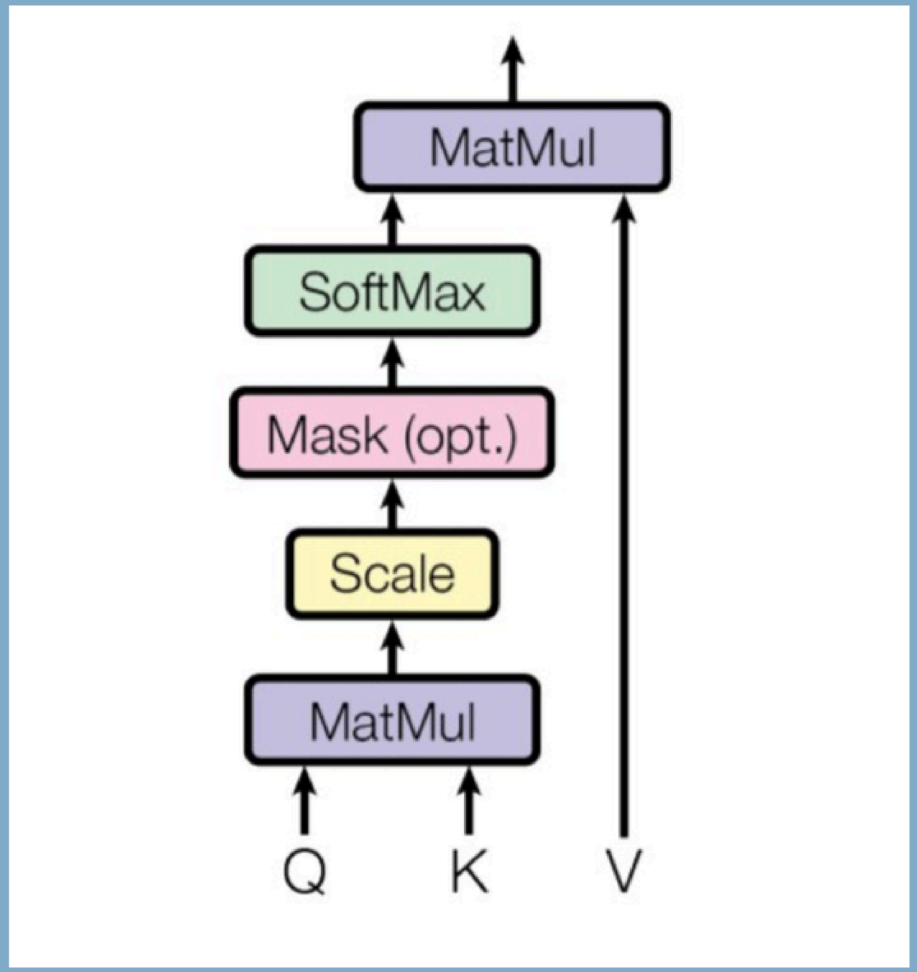
-Complex feature extraction

Attention Mechanisms

Soft attention + learned weight mechanism -> Dot-product attention

Combination of ensembles model per fold (aggregation)





+ No overfitting
+ Better overall results to other attention method

Results

Results
Patch Classification: **Classifier**

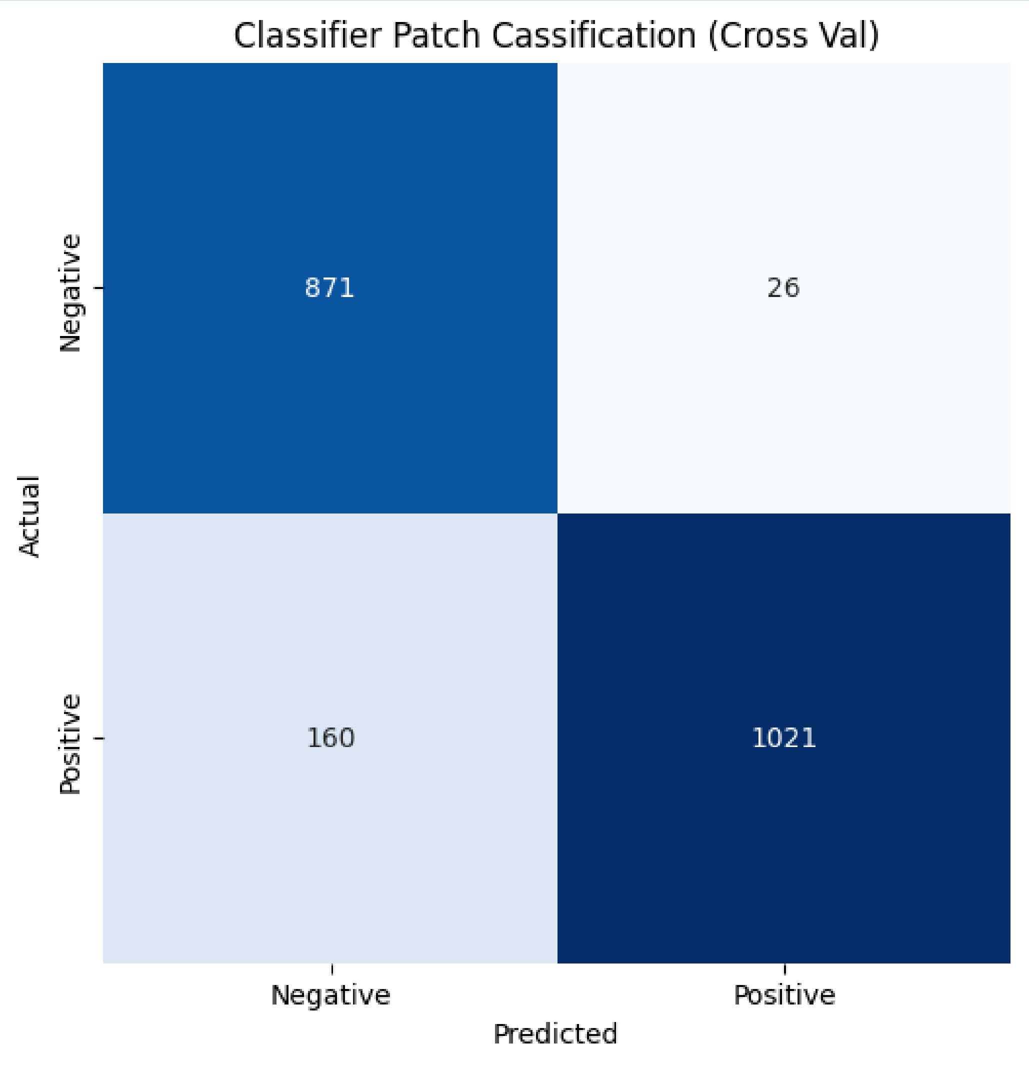
Cross Validation

Accuracy: **0.91**

Precision: **0.97**

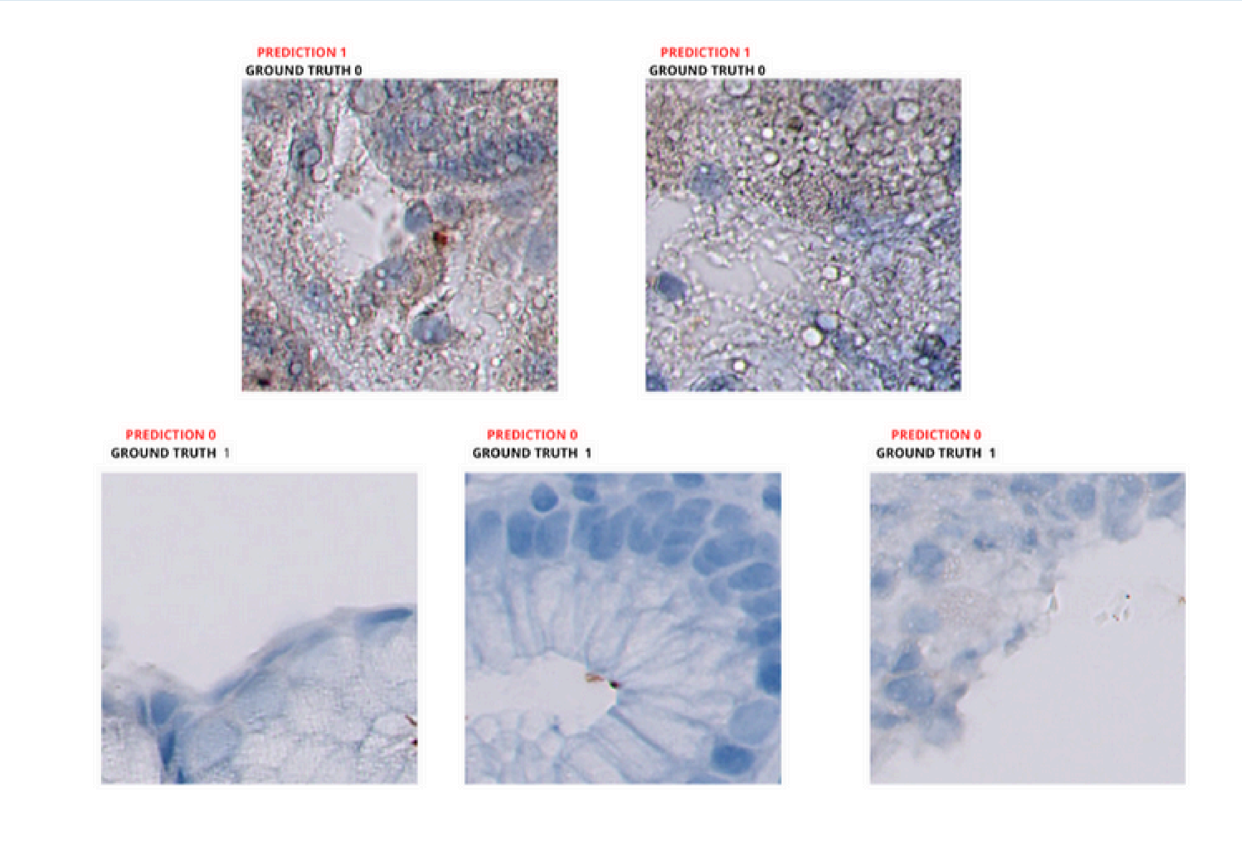
Recall: **0.86**

F1: **0.91**



Fold	Train Label Distribution	Validation Label Distribution	Epoch	Loss	Validation Loss	Accuracy (%)	Confusion Matrix	Loss Improvement
0	1: 945, 0: 719	1: 236, 0: 180	6	0.305	0.269	87.5	[[176 4], [48 188]]	0.3347 to 0.2699
1	1: 945, 0: 719	1: 236, 0: 180	7	0.189	0.268	90.625	[[176 4], [35 201]]	0.2931 to 0.2689
2	1: 945, 0: 719	1: 236, 0: 180	9	0.325	0.436	88.701	[[172 8], [39 197]]	0.4503 to 0.4365
3	1: 945, 0: 719	1: 236, 0: 180	6	0.202	0.245	90.865	[[176 4], [34 202]]	0.2604 to 0.2450
4	1: 944, 0: 720	1: 237, 0: 179	8	0.240	0.229	92.307	[[174 5], [27 210]]	0.2855 to 0.2294

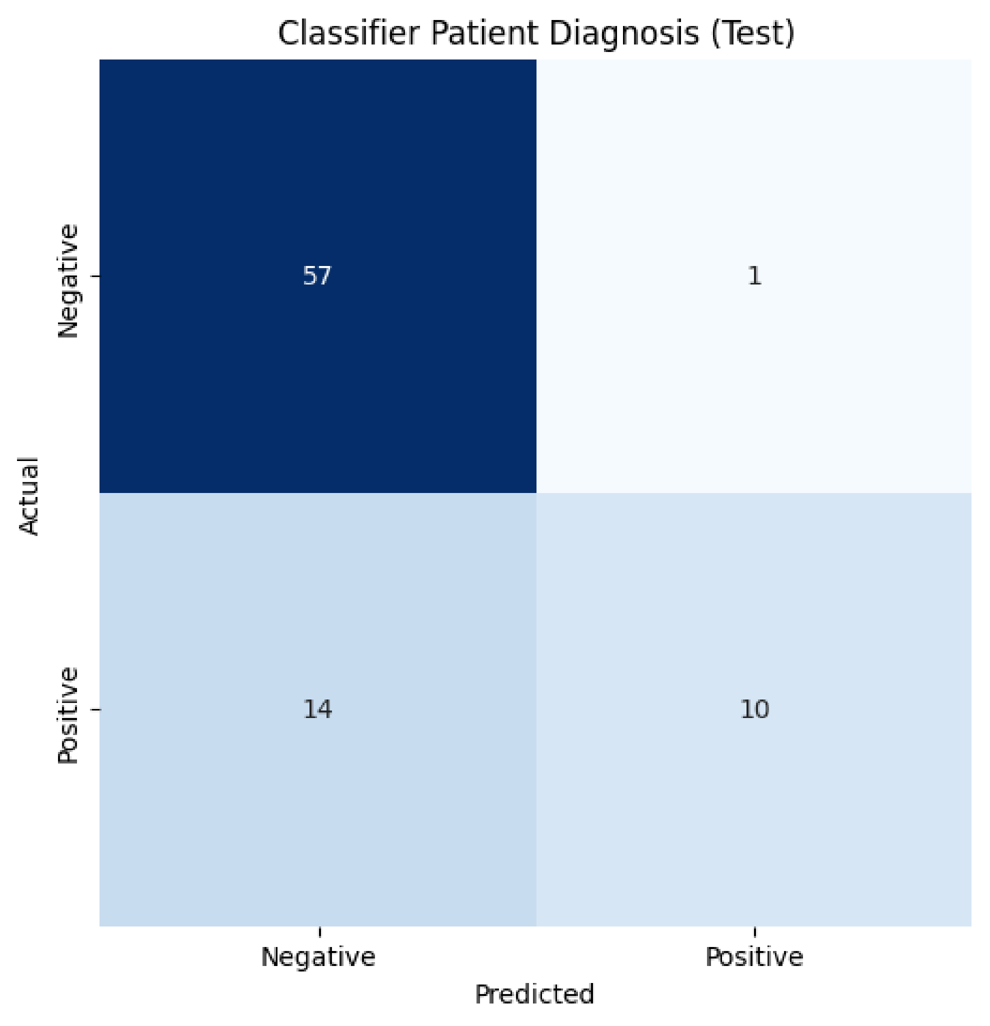
Table 1:Training Performance Across Folds



Results
Patient Diagnosis: **Classifier**

Test (Holdout)

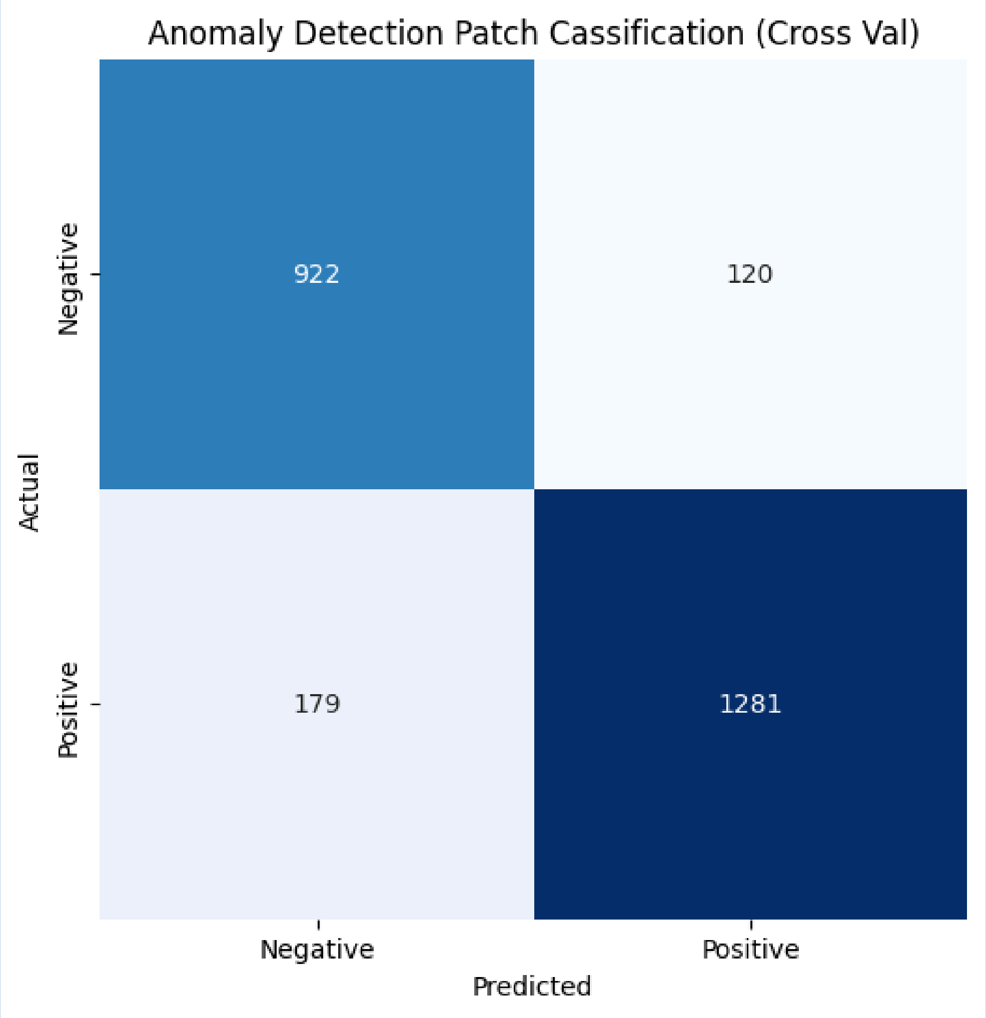
Accuracy: **0.81**
Precision: **0.90**
Recall: **0.41**
F1: **0.57**



Results
Patch Classification: **Anomaly Detection**

Optimal Red Fraction threshold: **38.0**
Accuracy: **0.88**
Precision: **0.91**
Recall: **0.87**
F1: **0.89**
ROC AUC: **0.94**

Cross Validation



Results

Patient Diagnosis: **Anomaly Detection**

Optimal %Positive Patches Threshold: **7.90**

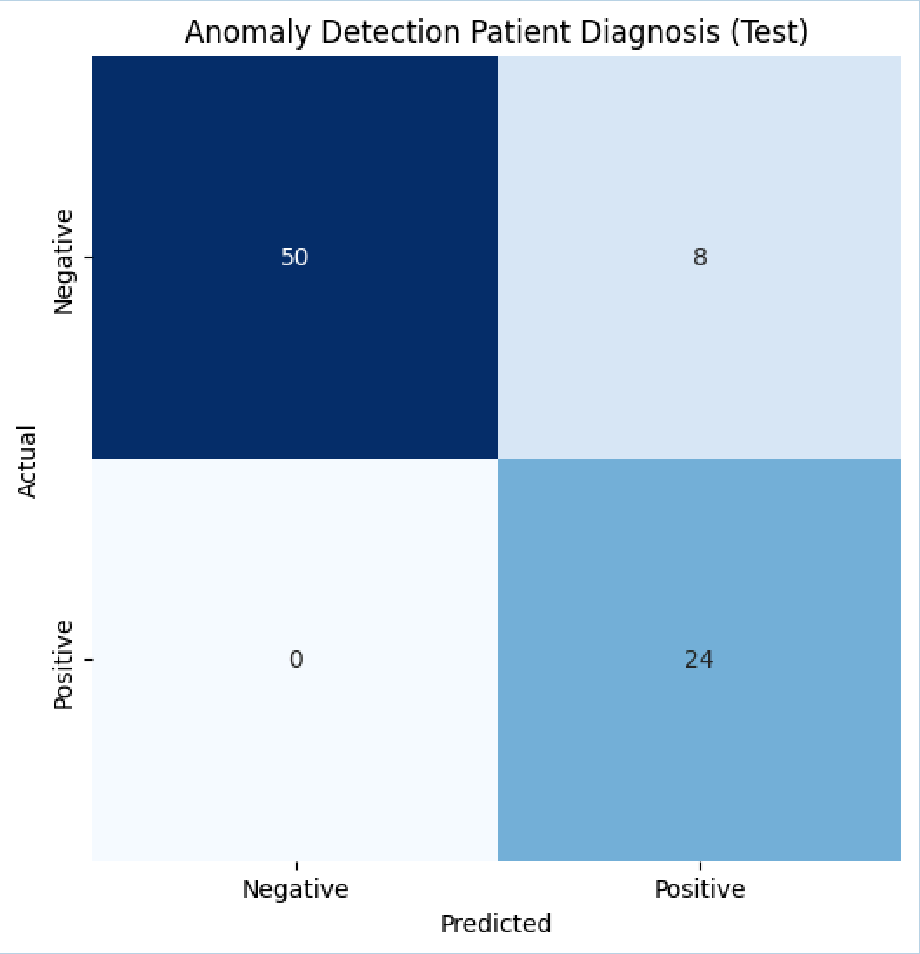
Accuracy: **0.90**

Precision: **0.75**

Recall: **1.00**

F1: **0.85**

Test (Holdout)



Conclusions & Things to Improve

Sum up:

1. *Two approaches for Patch classification*
2. *Two approaches for Patient Diagnosis*
3. *K-fold Cross Validation*
4. *Final test on Holdout*
5. *Additional Experiments (Attention)*

Low Recall: failing to report cases of H.Pillory

Increase Dataset Size
Address Class Imbalance: SMOTE
More Data Augmentation
Threshold Optimization
Feature Engineering

If we had more time?

+ Grid search for best parameters

+ More exploration on Attention

+ ML Classifier for Patient Diagnosis
based on Patch Classifications

Thank you very much!