

# Stain Based Contrastive Co-training for Histopathological Image Analysis

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## Introduction

- Deep learning models are widely used in histopathology image classification.
- Expert annotation at tile level for providing labels in model training has very high cost and is infeasible beyond a small number of whole slide images (WSIs).
- Semi-supervised learning (SSL) utilizes unlabeled data in training combined with limited amount of labeled data.
- Co-training approach to SSL achieves excellent results when multiple conditionally independent views of each sample are available, and each view is able to support accurate classification on its own.
- We explored if H&E slides can be color deconvoluted to Hematoxylin (H) and Eosin (E) stain images to fulfill co-training's view requirements.
- A novel contrastive co-training model with H and E views was tested on a clear cell renal cell carcinoma (ccRCC) dataset and a prostate cancer dataset.
- Our co-training model always had the best performance over other state-of-the-art SSL methods in both datasets, including consistency regularization, MixMatch and FixMatch.

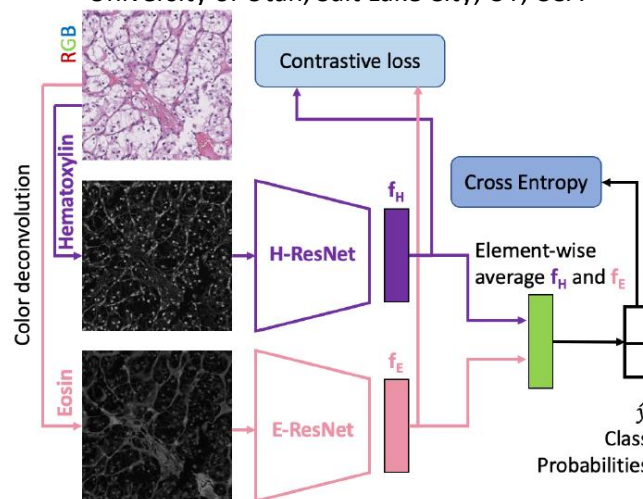
## Model design

$$\text{Stain separation: } \begin{bmatrix} H \\ E \end{bmatrix} = \begin{bmatrix} 1.838 & 0.034 & -0.760 \\ -1.373 & 0.772 & 1.215 \end{bmatrix} \begin{bmatrix} \log_{10} 255/R \\ \log_{10} 255/G \\ \log_{10} 255/B \end{bmatrix}$$

Contrastive loss:

$$\mathcal{L}_{c.t.}(x_i) = \max(\|f_H(x_i) - f_E(x_i)\|_2 - \|f_H(x_i) - f_E(x_k)\|_2 + m, 0)$$

$$\text{Total loss: } \mathcal{L} = \sum_{x_j \in L} y_j \log \hat{y}_j + \lambda \sum_{x_i \in L \cup U} \mathcal{L}_{c.t.}(x_i)$$



## Experiment settings

- In clear cell renal cell carcinoma (ccRCC) dataset\*:
  - ✓ Histologic growth pattern (HGP) tiles were cropped from expert annotated polygons from 53 WSIs.
  - ✓ Tiles from same patient are only in same set.
  - ✓ 10% tiles set as labeled data from training polygons in SSL.
  - ✓ Performed nested vs. diffuse (non-nested) classification and compared with other SSL models.
- In prostate cancer dataset\*:
  - ✓ 5% tiles set as labeled data from training polygons in SSL.
  - ✓ Performed benign vs. cancer classification and compared with other SSL models.
- Randomly selected labeled data 5 times to calculate mean and standard deviation of classification accuracies.

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## Experiment results

| ccRCC Model             | Test Accuracy      | Prostate Model          | Test Accuracy      |
|-------------------------|--------------------|-------------------------|--------------------|
| 100% label RGB ResNet   | 84.8 ± 2.4%        | 100% label RGB ResNet   | 77.5 ± 2.5%        |
| 100% label H/E co-train | <b>92.0 ± 2.6%</b> | 100% label H/E co-train | <b>79.1 ± 2.0%</b> |
| 10% label RGB ResNet    | 76.9 ± 5.9%        | 5% label RGB ResNet     | 73.4 ± 1.0%        |
| 10% label RGB consis    | 86.8 ± 3.3%        | 5% label RGB consis     | 74.7 ± 1.3%        |
| 10% label RGB MixMatch  | 85.9 ± 5.7%        | 5% label RGB MixMatch   | 73.7 ± 5.0%        |
| 10% label RGB FixMatch  | 88.3 ± 3.8%        | 5% label RGB FixMatch   | 78.2 ± 3.8%        |
| 10% label H/E co-train  | <b>92.3 ± 2.1%</b> | 5% label H/E co-train   | <b>78.7 ± 1.9%</b> |

H-only and E-only models' test accuracy for the ccRCC dataset to show each view (H or E) can do classification alone:

| Model               | Accuracy    | Model              | Accuracy    |
|---------------------|-------------|--------------------|-------------|
| 100% label H ResNet | 79.4 ± 3.7% | 10% label H ResNet | 73.5 ± 4.0% |
| 100% label E ResNet | 94.0 ± 1.4% | 10% label E ResNet | 82.3 ± 7.0% |

Coefficient of determination ( $R^2$ ) of image mapping between various channels on ccRCC validation set to show independence between channels:

| Experiments       | $R^2$ value | Experiments       | $R^2$ value |
|-------------------|-------------|-------------------|-------------|
| H $\Rightarrow$ E | 0.5223      | E $\Rightarrow$ H | 0.4613      |
| R $\Rightarrow$ G | 0.8464      | G $\Rightarrow$ R | 0.7833      |
| R $\Rightarrow$ B | 0.8207      | B $\Rightarrow$ R | 0.7713      |
| G $\Rightarrow$ B | 0.8522      | B $\Rightarrow$ G | 0.8824      |

Ablation study on ccRCC (Test set accuracy of ResNet and co-training models taking only 2 channels from RGB as input with 10% labeled data in training):

| Model        | Accuracy    | Model        | Accuracy    | Model        | Accuracy    |
|--------------|-------------|--------------|-------------|--------------|-------------|
| RB ResNet    | 77.5 ± 6.6% | RG ResNet    | 80.2 ± 6.4% | GB ResNet    | 78.4 ± 9.7% |
| R/B co-train | 78.2 ± 4.5% | R/G co-train | 79.8 ± 5.6% | G/B co-train | 76.6 ± 7.3% |

## Conclusion

- The experiments show that our model outperforms all other tested state-of-the-art semi-supervised learning methods in both datasets.
- The experiments prove that the benefit of our model is due to contrastive co-training loss on hidden features combined with more independent H and E view selection.