

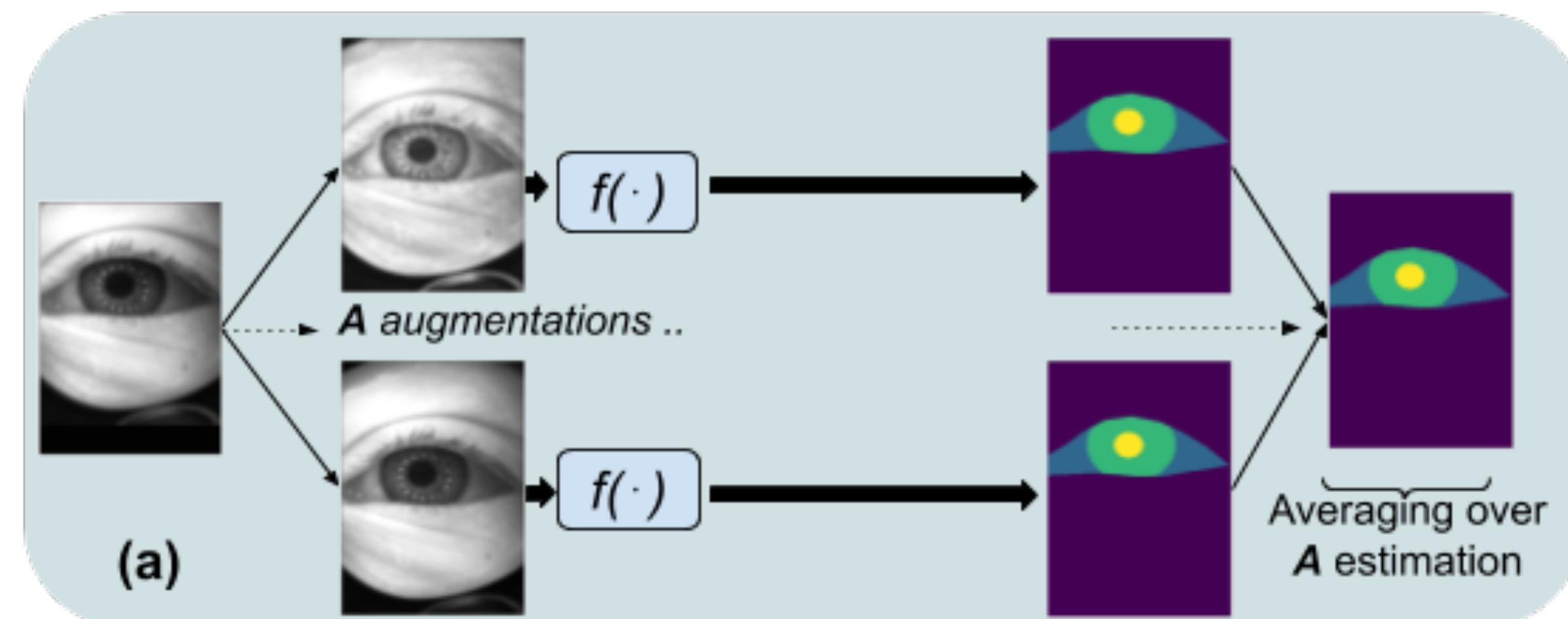
## Overview

- Labeling **large** dataset is **tedious**, requires expertise [leads to] bias and inconsistency
- Semi-supervised learning (SSL) : Exploit **hidden relationships** within data to predict labels for **unlabeled** images
- Network **Consistency** : **Same label prediction** to image even after **perturbation** (mostly used in **classification** task)
- For **semantic segmentation** assumption of network consistency is **violated**

## Proposed Method

### SSL with domain-specific augmentation (SSL<sub>D</sub>)

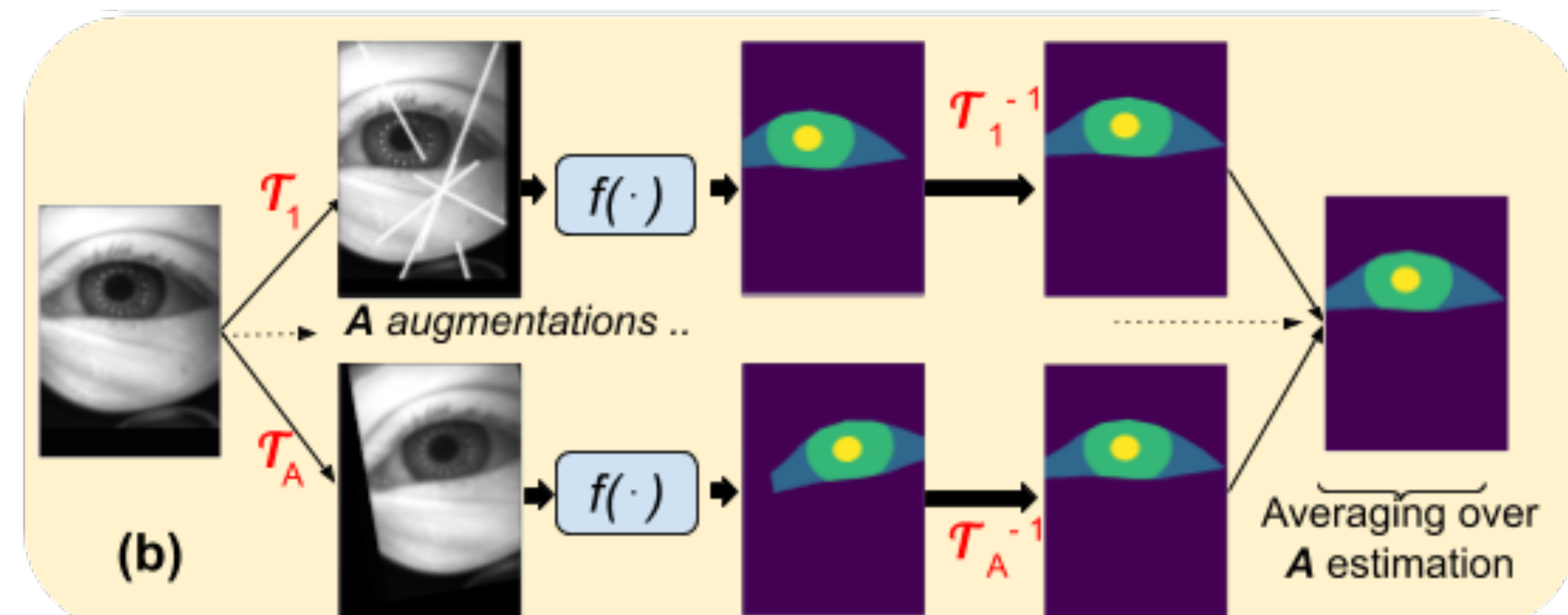
- Vary **contrast & luminance** of eye images
- CLAHE & Gamma correction**



For each unlabeled image, labels are guessed for  $A$  separate copies generated via proposed SSL with domain-specific augmentation

### SSL with self-supervised Learning (SSL<sub>SS</sub>)

- Pretext learning task** -> predicting image from inversion of the transformed image
- Account for **translation / rotation** of images



For each unlabeled image, labels are guessed for  $A$  separate copies generated via proposed SSL with a self-supervised approach

## Objective function

$$\text{Total loss} = \text{Supervised loss} + \lambda_u \times \text{unsupervised loss} + \lambda_{ss} \times \text{self-supervised loss}$$

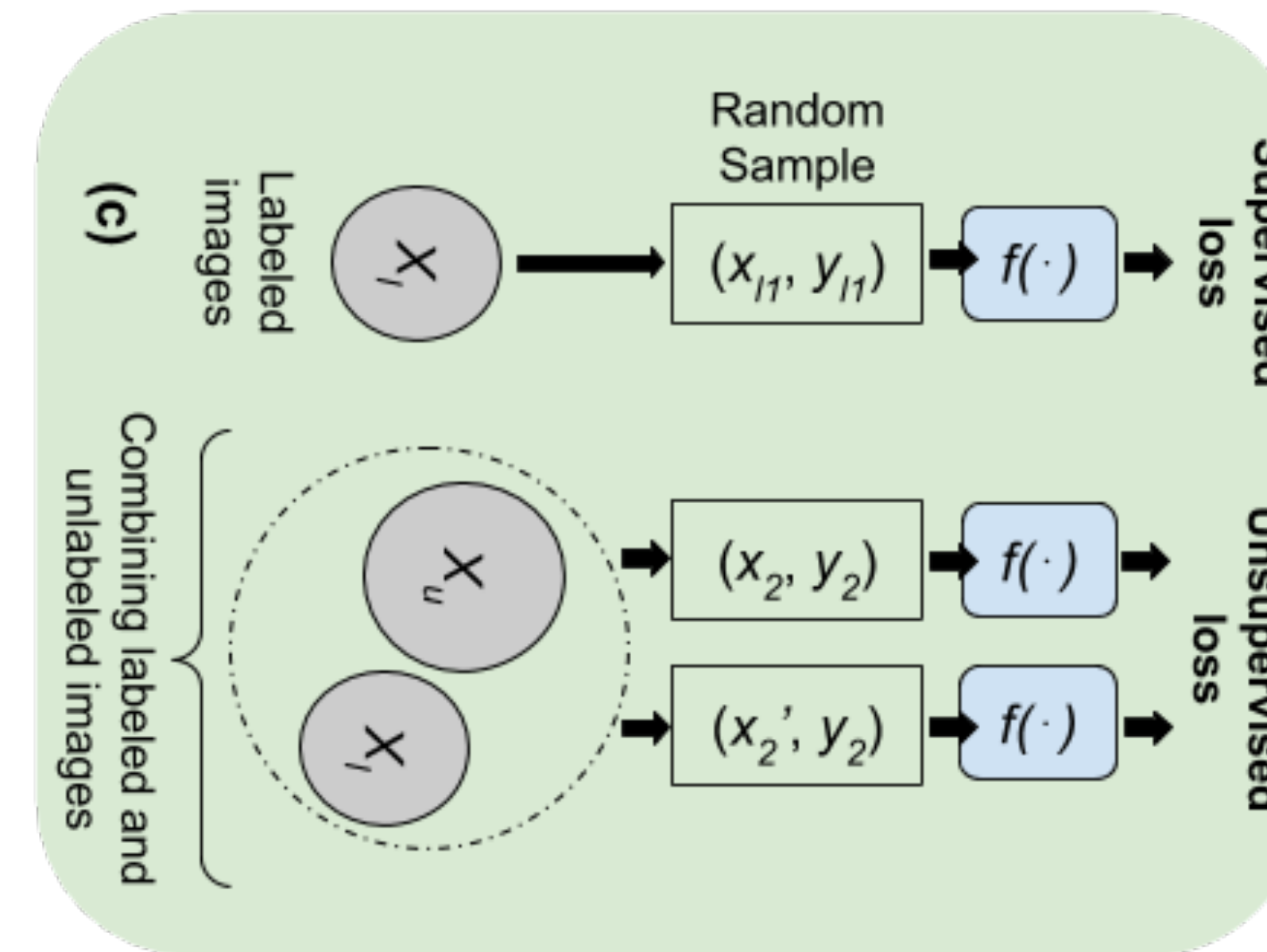


Fig: Supervised loss and unsupervised loss are computed separately for labeled and a combination of labeled and unlabeled data set in both types of SSL methods.

## Results

### Training with multiple subjects

- fixed unlabeled images (8916 images)
- for  $X_l = 8916$  images,  $S_L$  achieved 94.80% whereas we obtained **94.73% with SSL<sub>SS</sub>** for  $X_l = 940$  images only.

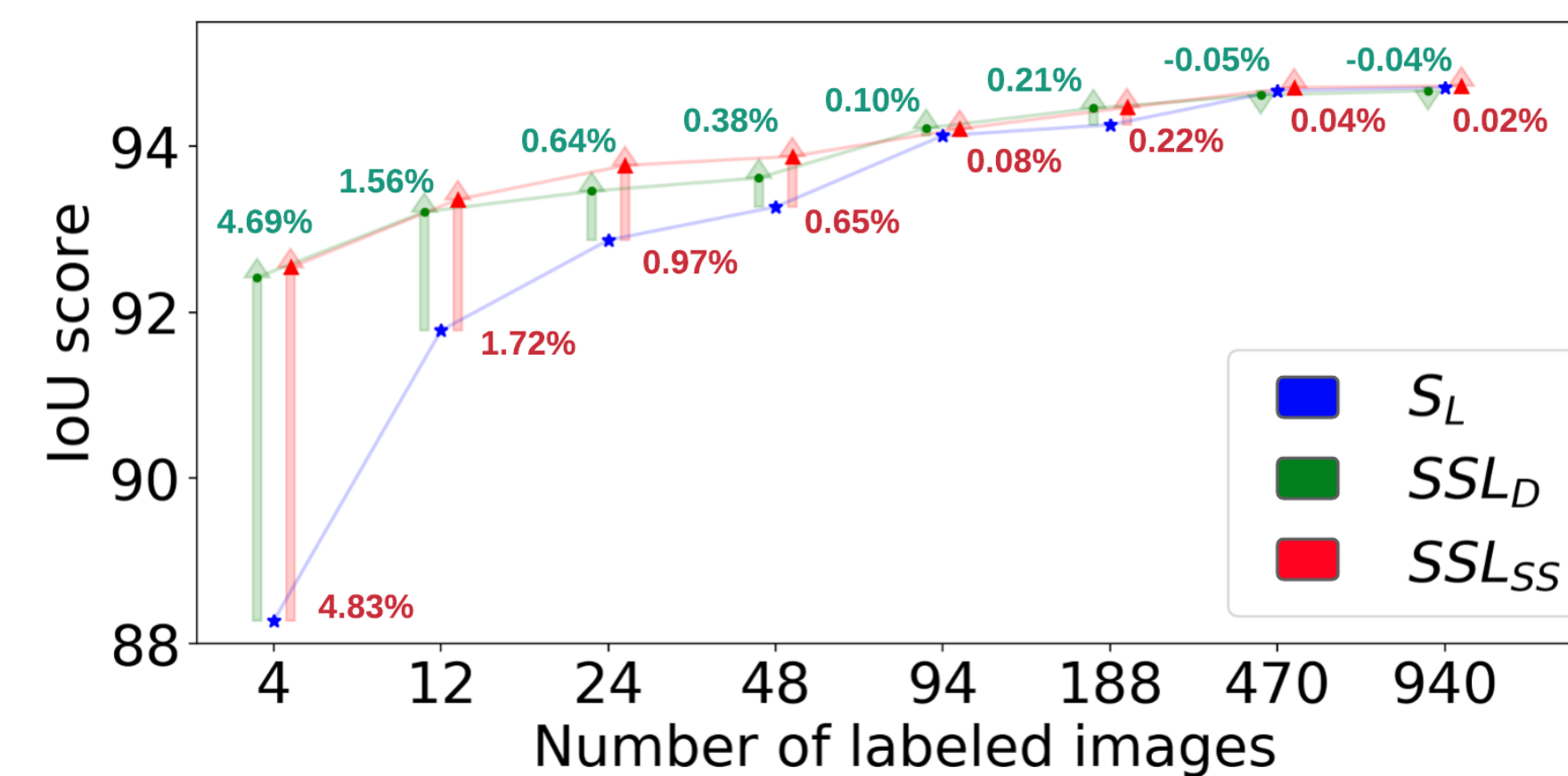


Fig: IoU score for three cases ( $S_L$ : blue,  $SSL_D$ : green, and  $SSL_{SS}$ : red) are shown with varying numbers of  $X_l$  and fixed  $X_u$ . The number alongside arrows indicate respective improvement (in %) over  $S_L$ .

### Our Presence at ETRA 2021

- Enhancing the precision of remote eye-tracking using iris velocity estimation (Short Paper)
- Privacy-Preserving Eye Videos using Rubber Sheet Model (Short Paper)
- RIT-Eyes, realistically rendered eye images for eye tracking applications (Video)

### Training with single subject

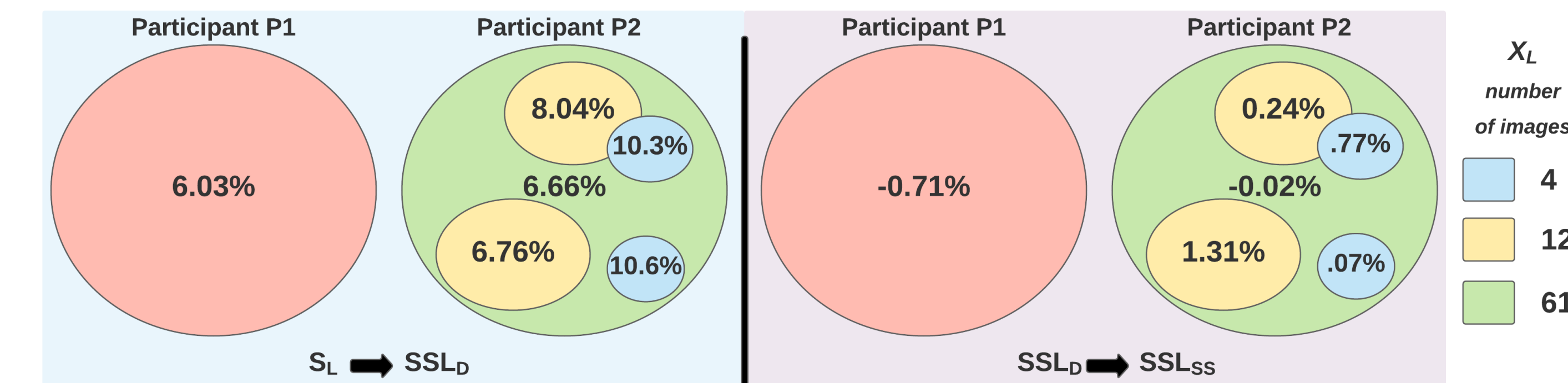


Fig: Demonstration of improvement (in %) for cases  $S_L$  to  $SSL_D$  (left) and  $SSL_D$  to  $SSL_{SS}$  (right) when models are trained on two subjects (red and green). For P2 (green), we further test the change in model performance for various subsets of  $X_l$ .

### Eye part Segmentation

$X_l$	4	12	24	48	4 (P1)	12 (P1)	61 (P1)
% change	4.08 (4.48)	0.85 (1.37)	0.54 (0.99)	0.44 (0.78)	4.40 (7.32)	4.50 (6.12)	2.13 (4.09)

Fig: Comparison of % change of pupil and iris (inside parenthesis) class IoU scores for cases from  $S_L$  to  $SSL_{SS}$  for varying number of  $X_l$  and fixed number of  $X_u$ . P1 indicates samples from a single subject.

### Qualitative Results

- As the number of images increases, the confidence in prediction and unwanted spurious patches are reduced when models are trained on  $S_L$ .
- For SSL approaches, the confidence in prediction is more even when a small number of  $X_l$  are used.
- No significant difference is visible for the two SSL approaches, which vary mostly in **finer details**.

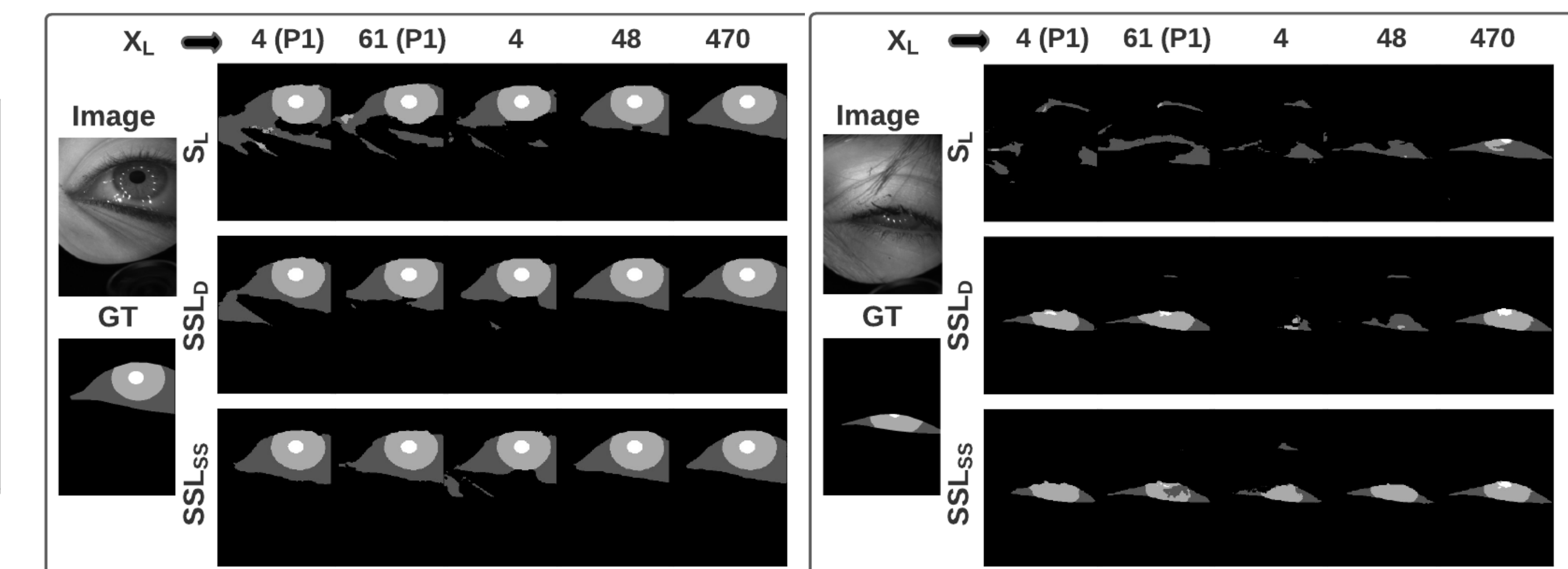


Fig: Two samples of the test set with its corresponding ground-truth and network predictions for the number of cases are shown in adjacent blocks.

## Conclusion

- Frameworks to leverage **domain specific** augmentations and **novel spatially varying image transformations**
- Trained on just 4 and 48 labeled images, improvement by at least 4.7% and 0.4% respectively, in segmentation performance
- Future Work - Investigate the effect of curating labeled datasets (e.g., **considering eye position and blinks**) instead of random selection