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Learning Self-Supervised Representations for Label Efficient Cross-Domain Knowledge Transfer on Diabetic Retinopathy Fundus Images

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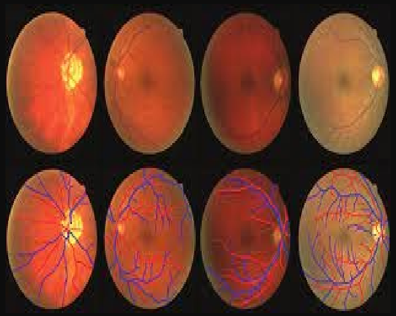
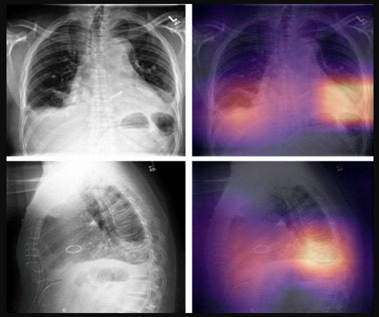
Vision & Medical Imaging Domain

- Labeled scarcity
- Effectiveness of transfer learning
- Distinct visual concepts

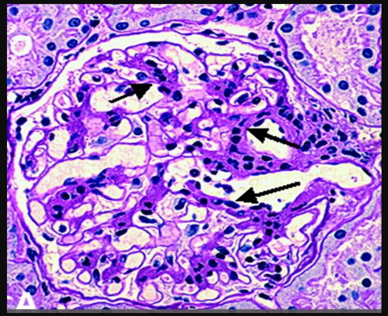
Retina DR dataset



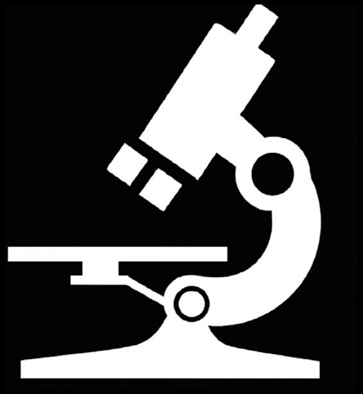
CheXpert dataset



Breakhis histopathology

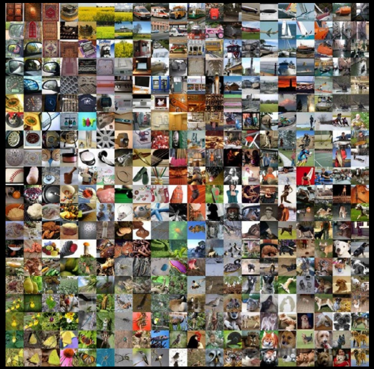


Why Label Scarcity?

Annotation by experts	High human error	Device dependance	Privacy concerns
			

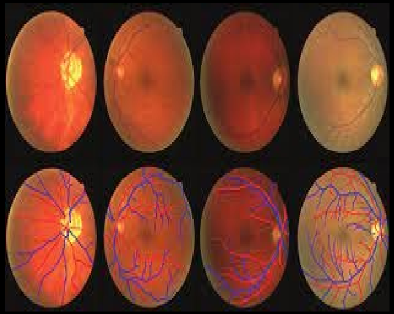
Jacob, Joseph, et al. "Disentangling Human Error from the Ground Truth in Segmentation of Medical Images." ACL, 2021.
Waheed, Summaiya, et al. "The impact of dependence on advanced imaging techniques on the current radiology practice." Annals of Medicine and Surgery 78 (2022): 103708.

Transfer Learning from ImageNet?

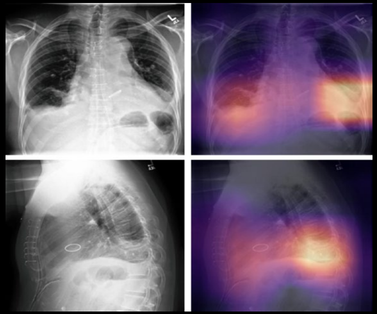


(Supervised) Transfer learning

Retina DR dataset



CheXpert dataset



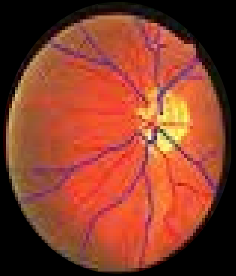
ImageNet transfer learning does not significantly affect performance on medical imaging tasks[1]

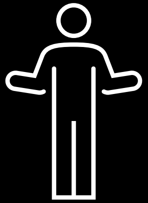
- Task specific learning - only initial layers with low-level features are useful

[1] *Raghu, M., Zhang, C., Kleinberg, J., & Bengio, S. (2019). Transfusion: Understanding transfer learning for medical imaging. Advances in neural information processing systems, 32.*

Visual Concepts in Medical Imaging

Vs.





Vs.

Retina

Retina

Limited human understanding

- Due to Lack of interpretation for domain specific properties

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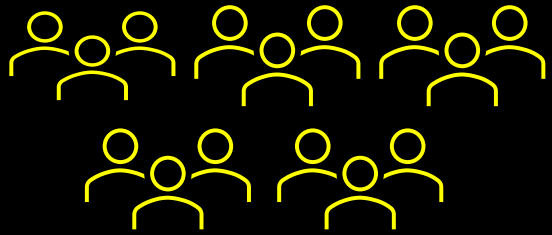
Why Diabetic Retinopathy Diagnosis is Important?

diabetic retinopathy is the leading cause of blindness in the working-age population of the developed world. It is estimated to affect over 93 million people.



Need Knowledge Transfer Method – Pretraining?

- ✓ Efficient
- ✓ Less human supervision
- ✓ Effective representations

Self-supervised Representation Learning (SSL) Approach

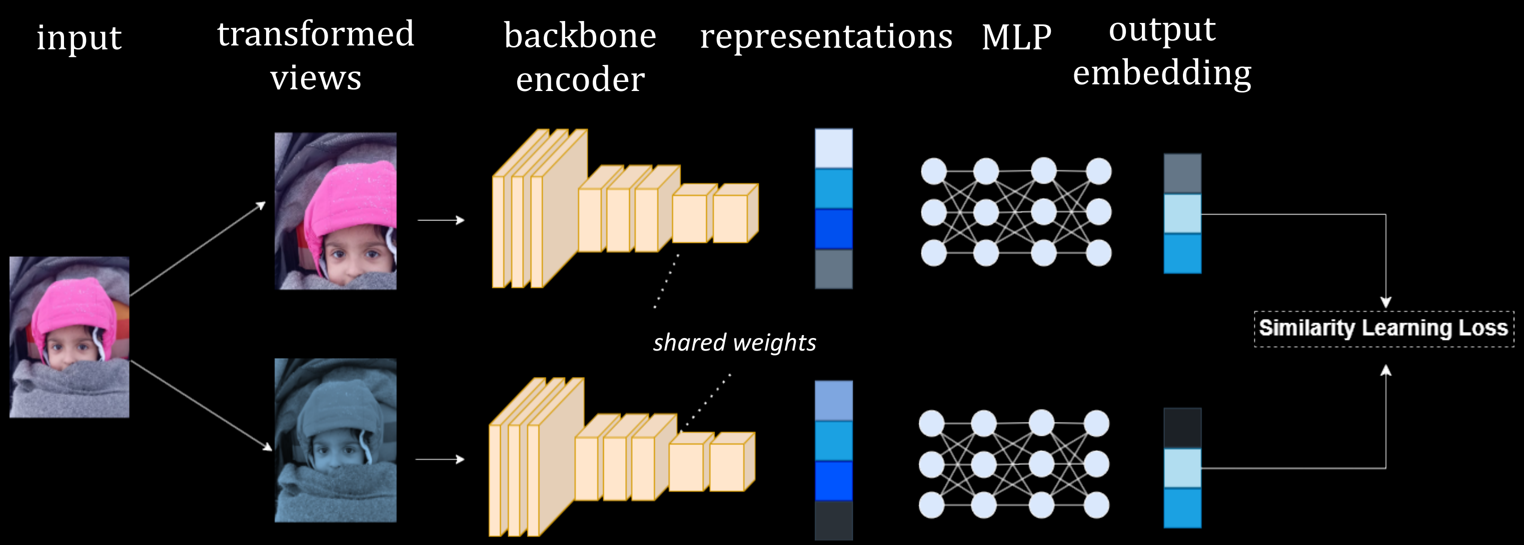


Figure Inspired : Chhipa, Prakash Chandra. "Self-supervised Representation Learning for Visual Domains Beyond Natural Scenes." Licentiate Thesis, Luleå tekniska universitet (2023).

Adapting SSL on Diabetic Retinopathy

- ✓ Contrastive Self-Supervision
  - SimCLR[1]
  - learn similarity for positive pair
  - learn dissimilarity otherwise
  - ResNet-50 backbone

- ✓ Pretraining Dataset
  - EyePACS[2] - diabetic retinopathy (DR)
  - 35,126 training images

[1]Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." International conference on machine learning. PMLR, 2020

[2]Diabetic Retinopathy Detection Dataset, https://www.kaggle.com/c/diabetic-retinopathy-detection/data

Adapting SSL on Diabetic Retinopathy

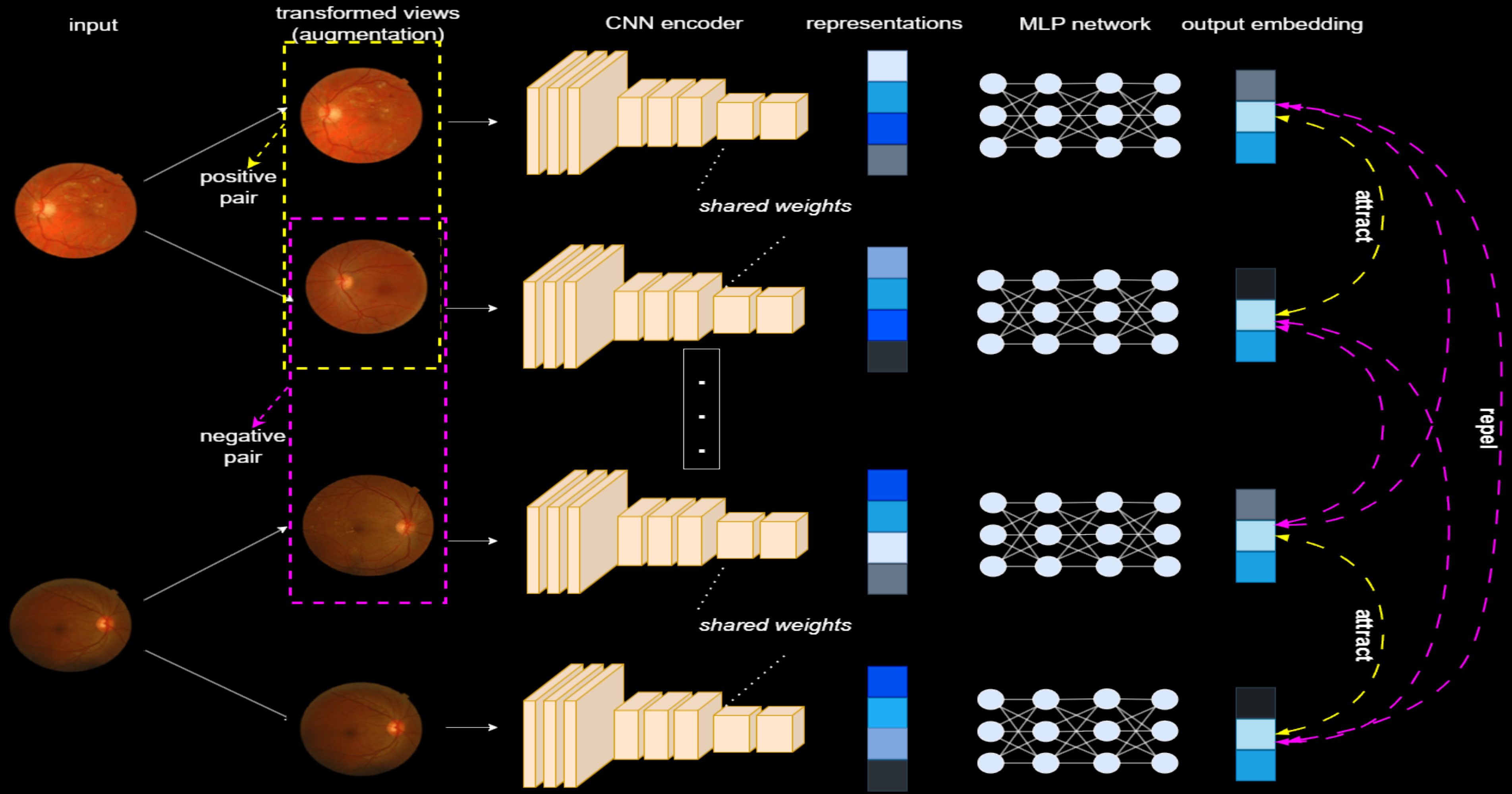


Figure Inspired : Chhipa, Prakash Chandra. "Self-supervised Representation Learning for Visual Domains Beyond Natural Scenes." Licentiate Thesis, Luleå tekniska universitet (2023).

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Cross–Domain Knowledge Transfer

Source Dataset

- EyePACS[2]

proliferative DR

severe DR

moderate DR

no DR

Target Datasets

- Aptos 2019[3]

3660 examples

no DR

mild DR

moderate DR

severe DR

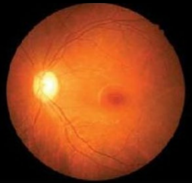
prolific DR

- Messidor I[4]

1200 examples

grade 0

grade 1



grade 2

grade 3

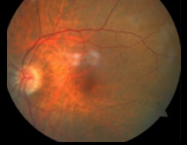
- Fundus[5]

747 examples

no DR

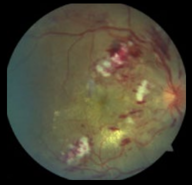
mild NPDR

Moderate NPDR

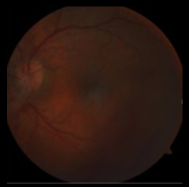


severe NPDR

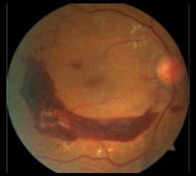
very severe NPDR



PDR



advanced PDR



[2]*Diabetic Retinopathy Detection Dataset, https://www.kaggle.com/c/diabetic-retinopathy-detection/data*

[3]*Aptos 2019, https://www.kaggle.com/competitions/aptos2019-blindness-detection/data*

[4]*Messidor I dataset, https://www.adcis.net/en/third-party/messidor/*

[5]*Fundus Dataset, Benítez, Veronica Elisa Castillo, et al. "Dataset from fundus images for the study of diabetic retinopathy." Data in brief 36 (2021): 107068.*

Experimental Evaluations on SSL Knowledge Transfer

1. Downstream Tasks

- Binary classification
- Multi-class classification

2. Label Efficiency Analysis

- 10%,
- 20%
- 50%
- 100%

3. Qualitative Analysis

- Class Activations

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Binary classification Task

- Finetuned on respective target datasets

Method	Accuracy	Precision	Recall
Dataset - Messidor			
Abramoff et al [281]	96.7	96.8	87
Chakraborty et al [26]	97.13	97.2	97
Dhanasekaran et al. [29] (SVM)	97.89	**98.68**	100
Dhanasekaran et al. [29] (PNN)	94.76	96.64	98.46
Proposed work - SSL Cross domain*	**98.49**	98	**100**
Dataset - Aptos 2019			
Islam et al [27]	98.36	98.37	98.36
Proposed work - SSL Cross domain*	**99.59**	**100**	**99**

**SSL pretrained on EyePACS dataset*

Multiclass classification Task

- Finetuned on respective target datasets

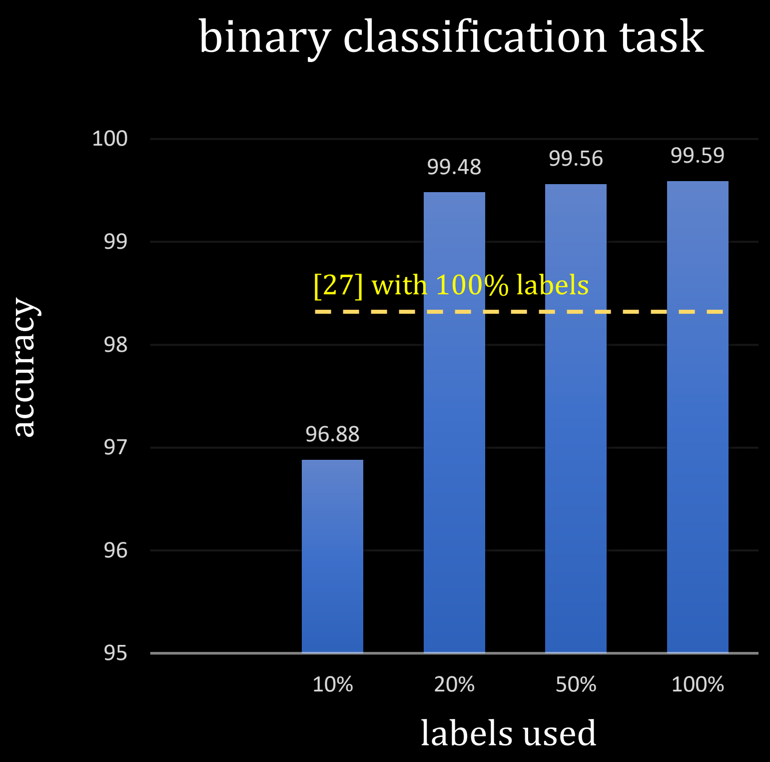
Dataset - Aptos 2019

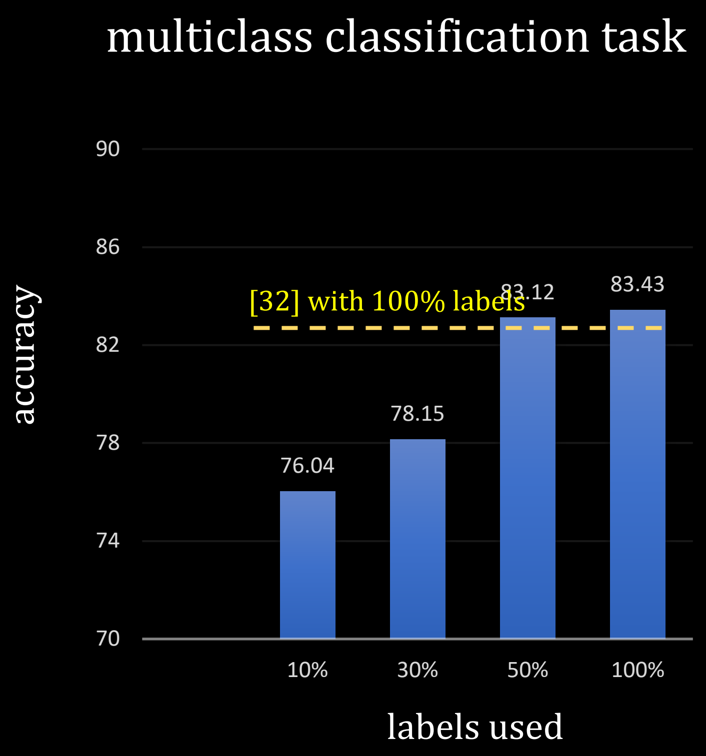
Authors	Accuracy	Precision	Recall
Kassani et al [32]	83.09	**88.24**	82.35
Gangwar & Ravi [33]	72.33	/	/
Proposed Work - SSL Cross domain*	**83.43**	81.00	**85.00**

**SSL pretrained on EyePACS dataset*

Label Efficiency of SSL Knowledge Transfer

- SSL Pretrained on EyePACS data and finetuned on Aptos 2019 data

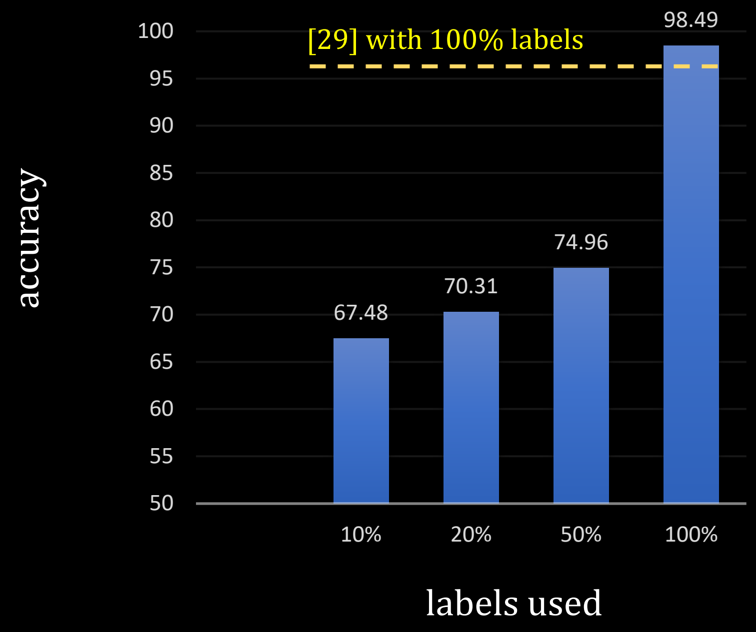




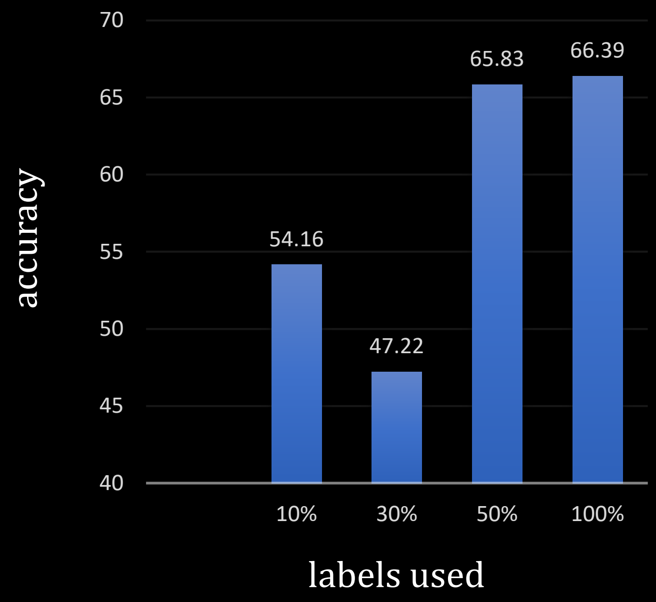
Label Efficiency of SSL Knowledge Transfer

- SSL Pretrained on EyePACS data and finetuned on Messidor I data

binary classification task

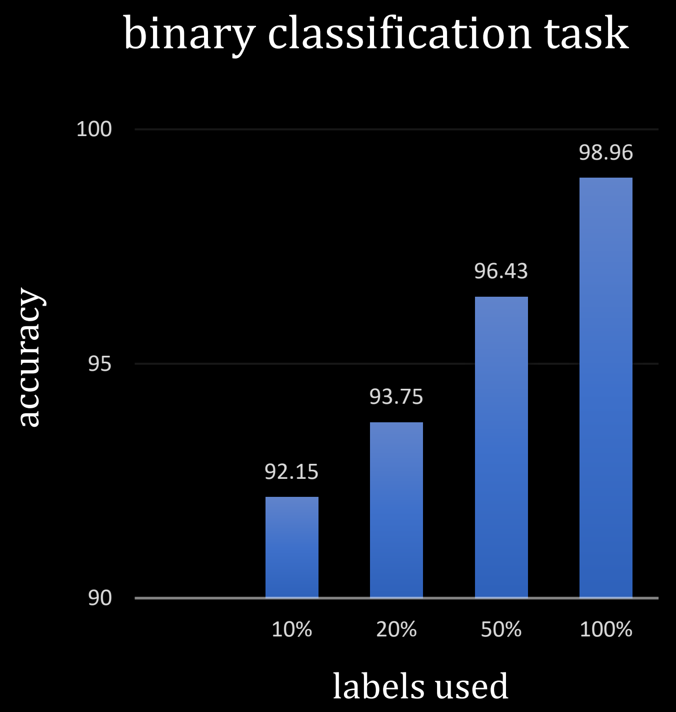


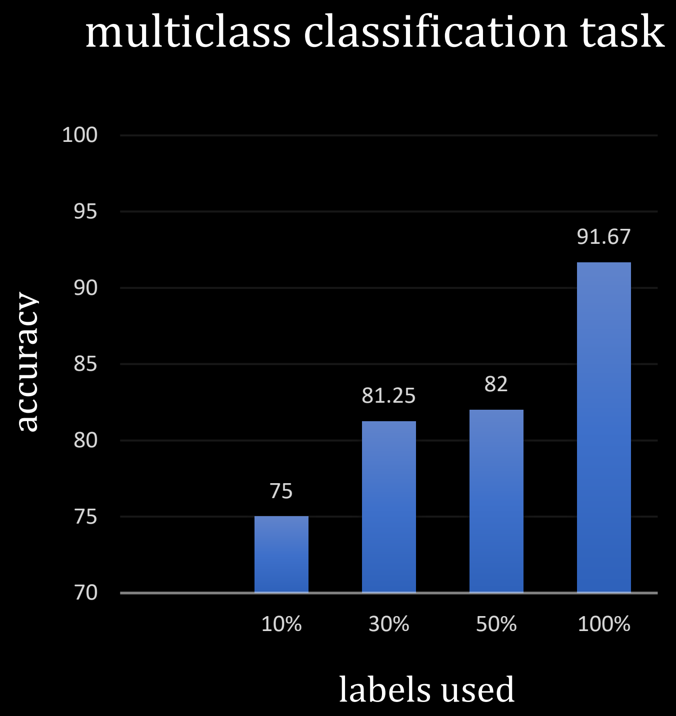
multiclass classification task



Label Efficiency of SSL Knowledge Transfer

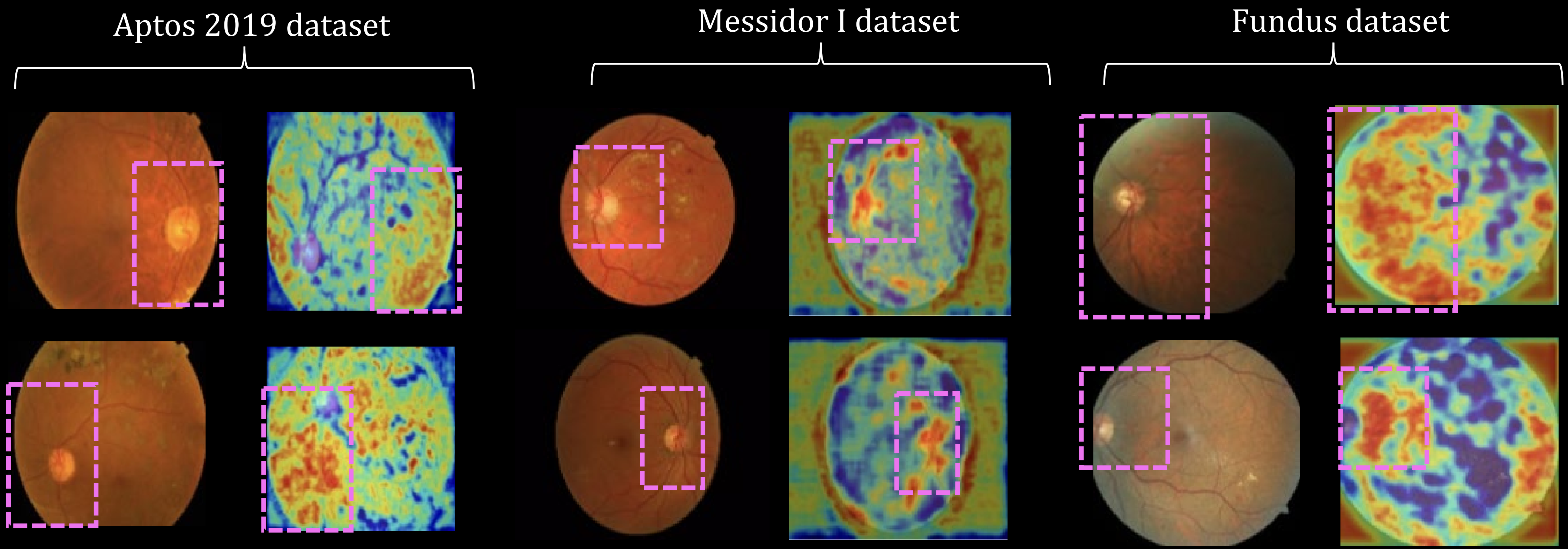
- SSL Pretrained on EyePACS data and finetuned on Fundus data





Qualitative Analysis

- Attention maps for samples from target datasets



Conclusions

Contribution

Adapting contrastive self-supervised representation learning to medical image domain concerning diabetic retinopathy towards label free approaches

Achievements

Achieved cross-domain knowledge transfer to multiple target small-scale datasets and shown performance improvement in multiple downstream tasks

Future Work

Further investigating other SSL approaches and the knowledge transfer for challenging downstream tasks including segmentations and detections

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Thank you

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GitHub