

Functional Knowledge Transfer with Self-supervised Representation Learning

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Problem Statement

✓ No direct human supervision to learn representations

But

- Need massive amount of training data (ImageNet 1.2 millions images)
- Large batch size which requires heavy parallel computing
- SSL remains inaccessible to small-scale datasets with lack of computing resources

Self-supervised Representation Learning^{1,2,3} Approach

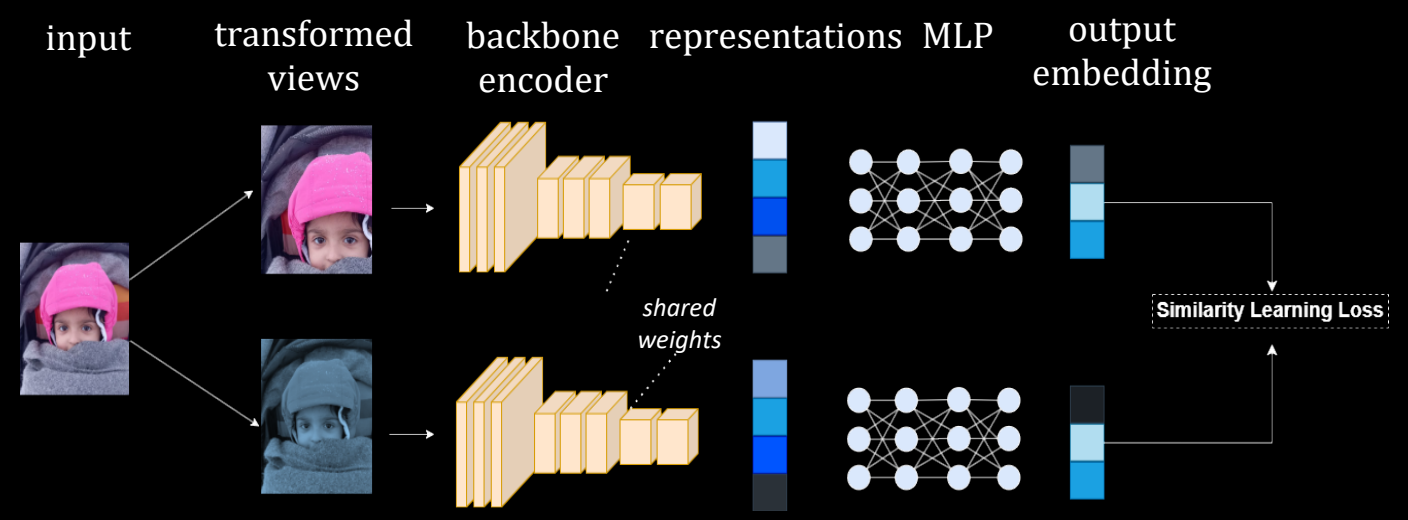


Figure Inspired : Chhipa, Prakash Chandra. "Self-supervised Representation Learning for Visual Domains Beyond Natural Scenes." Licentiate Thesis, Luleå tekniska universitet (2023).

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

²**Distillation**- Grill, Jean-Bastien, et al. "Bootstrap your own latent-a new approach to self-supervised learning." Advances in neural information processing systems 33 (2020).

³**Information Maximization**- Zbontar, Jure, et al. "Barlow twins: Self-supervised learning via redundancy reduction." International Conference on Machine Learning. PMLR, 2021.



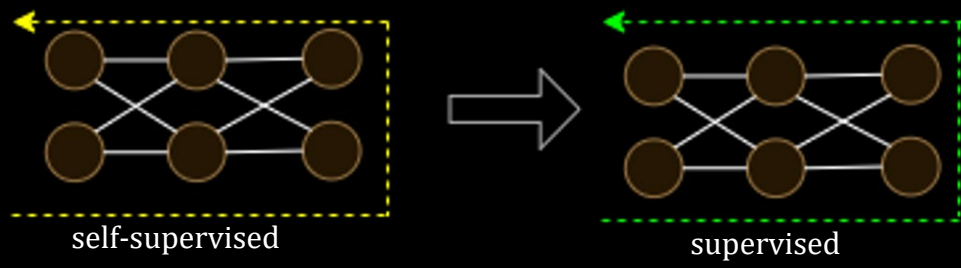
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Hypothesis

Shifting the **representational knowledge transfer paradigm to functional knowledge transfer⁴** can enable the learning of efficient self-supervised representations for small-scale data.

- Joint optimization in functional knowledge transfer is the key

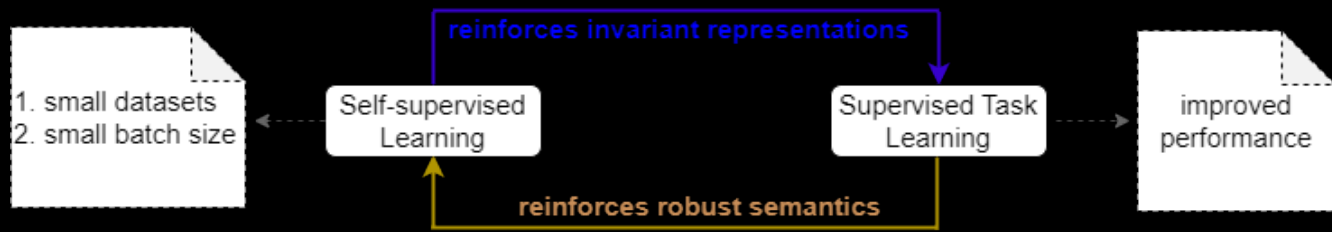
representational knowledge transfer



functional knowledge transfer



why it should work?

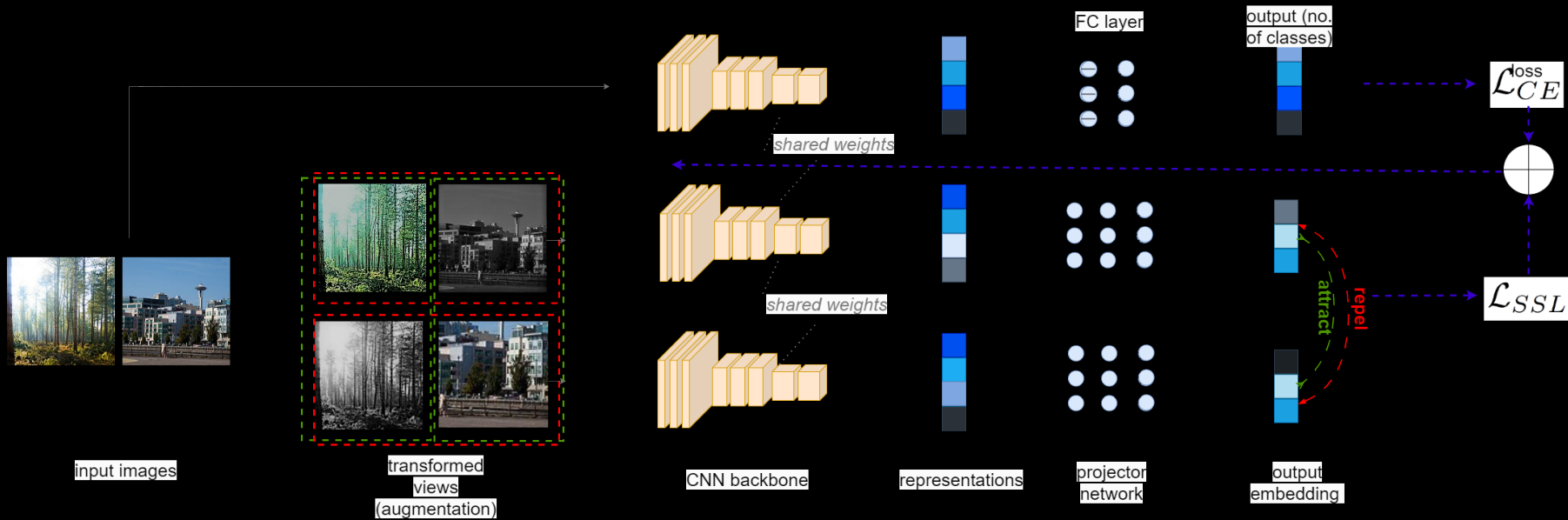


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⁴Functional Knowledge - R. Vilalta, C. Carrier, P. Brazdil, C. M. Soares et al., "Inductive transfer," 2017.

Method

Joint optimization of self-supervised representation learning and supervised learning task



$$\mathcal{L}_{SSL} = \sum_{(x', x'') \in \mathcal{T}(X)} -\log \frac{e^{\mathcal{A}}}{\sum_{k=1}^{2|X|} 1_{[k \neq x']} e^{\mathcal{B}}}$$

$$\mathcal{A} = (\text{sim}(g(\Theta_g; f(\Theta_f; x')), g(\Theta_g; f(\Theta_f; x'')))) / \tau$$

$$\mathcal{B} = (\text{sim}(g(\Theta_g; f(\Theta_f; x')), g(\Theta_g; f(\Theta_f; x^k)))) / \tau$$

$$\mathcal{L}_{CE} = -\frac{1}{|D|} \sum_{(x, y) \in D} \sum_{c \in \mathcal{C}} y_c \log(f(\Theta; x_c))$$

$$\mathcal{L}_{FKT} = \mathcal{L}_{CE} + \lambda \mathcal{L}_{SSL}$$



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Investigation Protocol

1. Identify small-scale datasets and task – *Aptos, CIFAR, Intel Images*
2. Chose self-supervised learning method – *Contrastive Learning*
3. Experimentation on Representational and Functional knowledge transfer – *Details on experimental configuration and parameters in paper*
4. Performance evaluation
 - ✓ *quantitative analysis*
 - ✓ *qualitative analysis*



Datasets - from diverse domains

CIFAR10¹ Dataset 

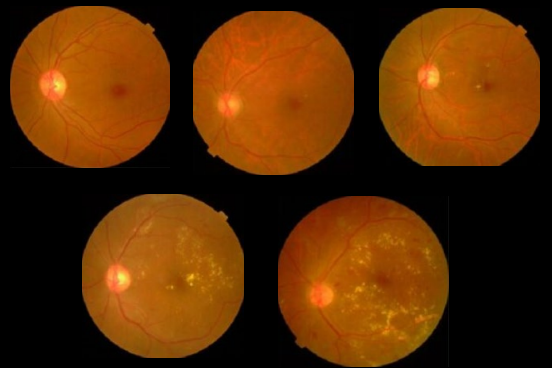
10 classes and 60,000 examples



Classes - airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks

Aptos² Dataset 

5 classes and 3660 examples



Classes - diabetic retinopathy severity level in eye fundus images

Intel Images³ Dataset 

6 classes and 25000 examples



Classes - buildings, forest, glacier, mountain, sea, street



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¹CIFAR10, <https://www.cs.toronto.edu/~kriz/cifar.html>

²Aptos, <https://www.kaggle.com/c/aptos2019-blindness-detection>

³Intel Images, <https://www.kaggle.com/datasets/puneet6060/intel-image-classification>

Results

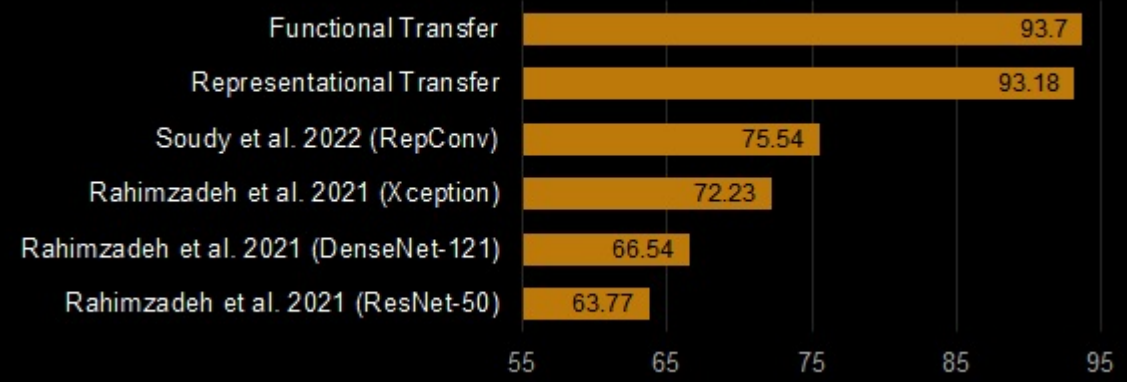
Dataset	Method	Accuracy	Precision	Recall
CIFAR10	Representational Transfer \$	92.20±0.11	92.18±0.10	92.21±0.10
	Functional Transfer	93.60±0.10	93.62±0.13	93.59±0.11
Intel Image	Representational Transfer	93.18±0.15	93.15±0.18	93.17±0.20
	Functional Transfer	93.70±0.13	93.33±0.11	93.31±0.11
Aptos 2019	Representational Transfer	83.10±0.10	83.05±0.09	83.05±0.12
	Functional Transfer	83.32±0.11	83.14±0.10	83.04±0.10



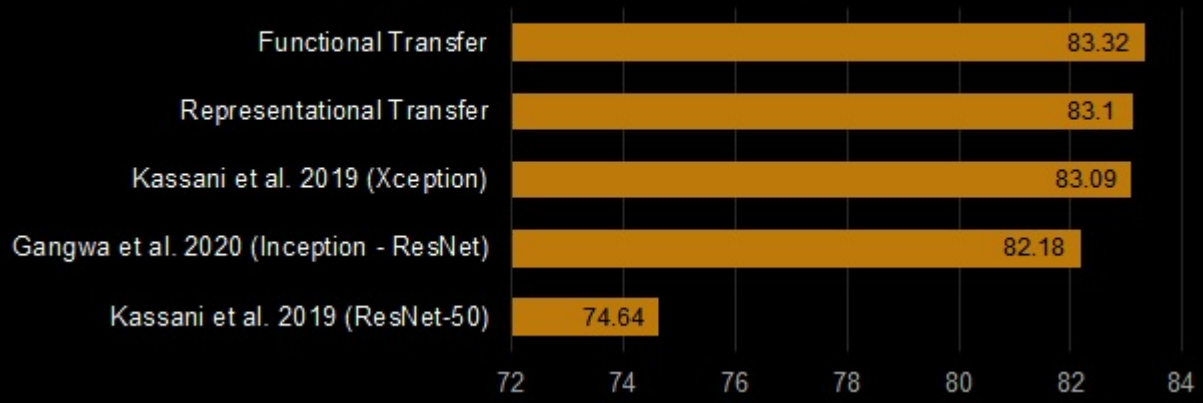
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Results - Comparing SoTA

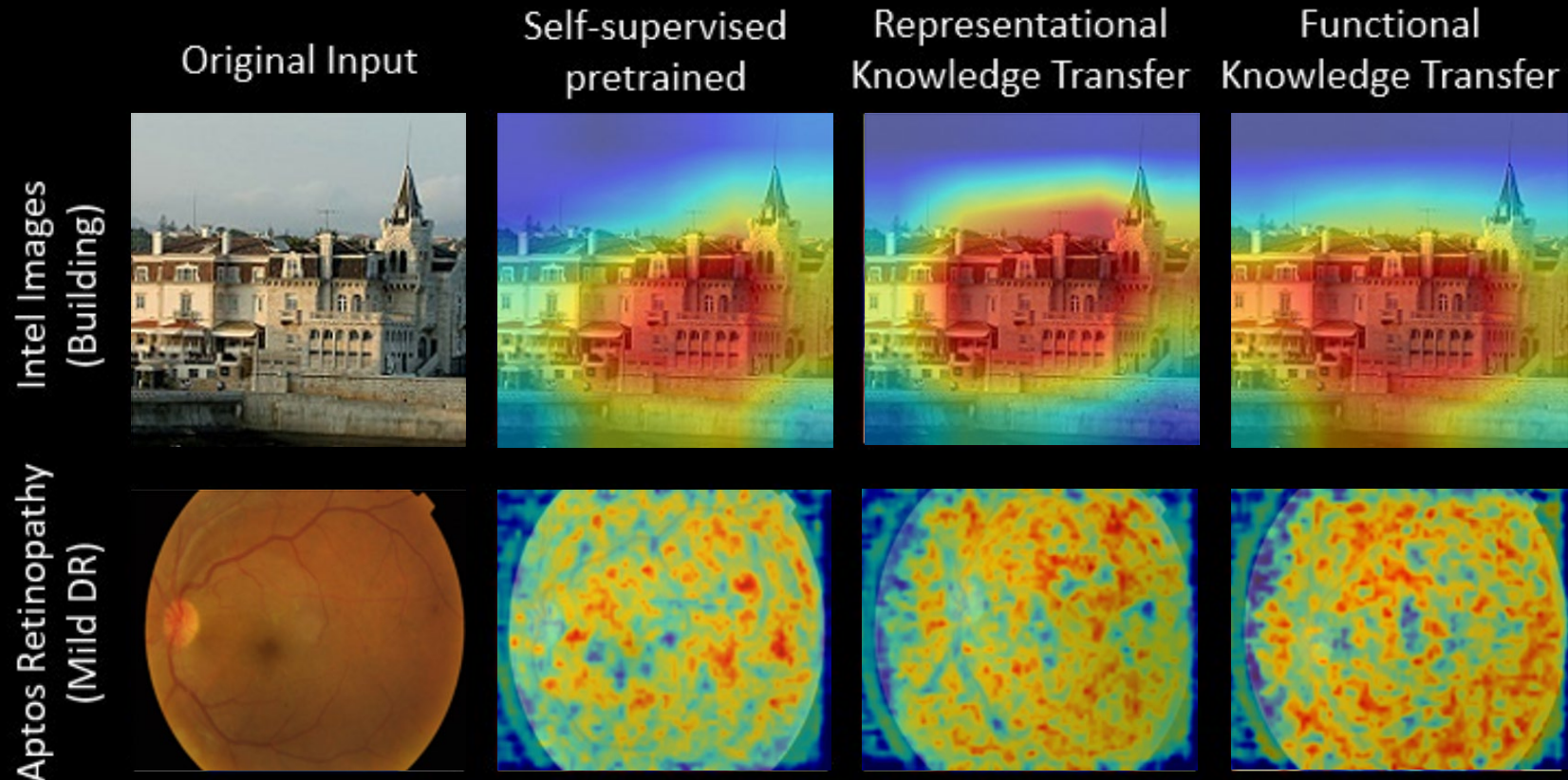
Intel Image Dataset - Accuracy



Aptos Dataset - Accuracy

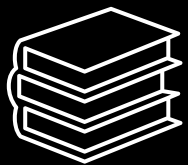


Qualitative Analysis





Conclusions



Contribution

Introduces functional knowledge transfer to overcome the inaccessibility of SSL due to small-scale and small batch **by formulating and examining joint optimization hypothesis**



Achievements

Achieved improved downstream task results across diverse datasets **supported by qualitative analysis**



Future Work

Further investigation on adapting other SSL approaches and evaluating **representational knowledge transfer capability of jointly optimized models**



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Thank you
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GitHub

<https://github.com/prakashchhipa>

Scholar

https://scholar.google.com/citations?hl=en&user=AF-zbRoAAAAJ&view_op=list_works&sortby=pubdate

LinkedIn

<https://www.linkedin.com/in/prakash-chandra-chhipa/recent-activity/all/>

LTU profile

<https://www.ltu.se/staff/p/prachh-1.201078?l=en>



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