Disentangled representations of microscopy images

Jacopo Dapueto, Vito Paolo Pastore, Nicoletta Noceti, Francesca Odone
University of Genoa, Italy
Contacts: jacopo.dapueto@edu.unige.it

UniGe | MaLGa

INTERNATIONAL JOINT CONFERENCE ON NEURAL NETWORKS IJCNN2025

Introduction and motivations

The analysis of microscopy images is crucial for biomedical research. Interpretable human-reliable insights are highly desirable in this specific domain of application, but **DNNs lack** of such **interpretability**.

We propose a Disentangled Representation Learning (DRL) framework as a way to enhance DNN's interpretability in this context. DRL aims to learn models that can identify and disentangle underlying Factors of Variations (FoVs) hidden in the observable data.

In [1] we show that a disentangled representation learnt from a synthetic dataset **can be transferred** to a real one. Although promising, the analysis is limited to real datasets whose FoVs are controlled and known a priori.

Contributions of the paper

- ***Assess a weakly-supervised DRL [2] on microscopy datasets with partially known FoVs.***
- ***Adopt pretrained deep features in the DRL framework to obtain a better balance between accuracy and intepretability.***

Datasets

We select **Target** datasets coming from three different biological domains: plankton microorganisms, budding yeast vacuoles, and human cancer cells.

We design a synthetic **Source** Dataset suitable for DRL to capture morphological FoV of the targets.

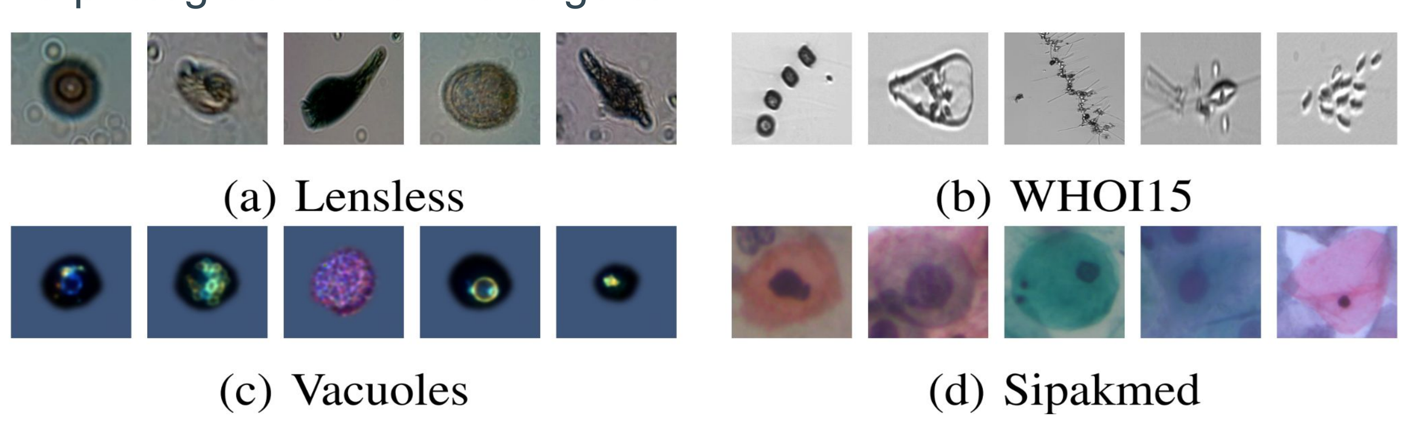


Fig. 1: 5 random samples for each Target dataset

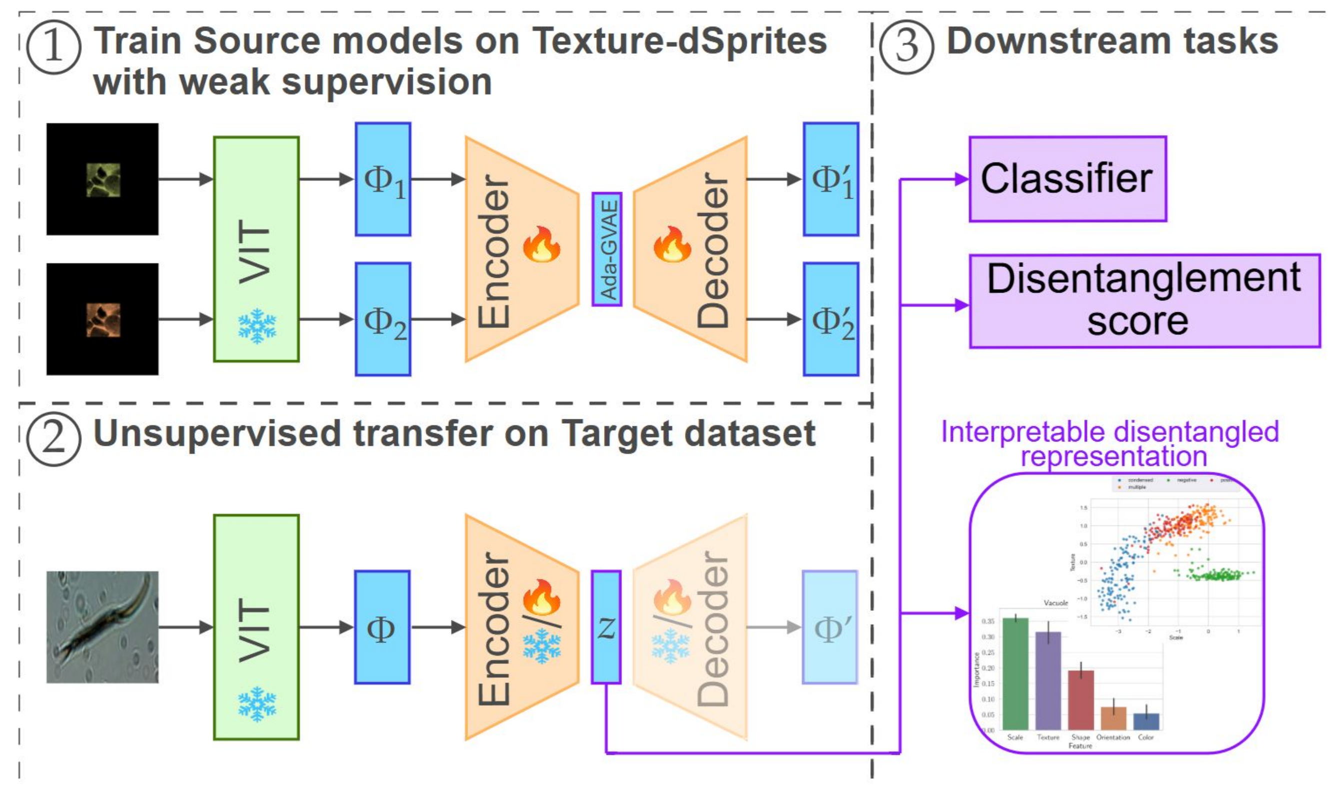
Dataset FoVs

Texture-dSprites	
FoV	**# values**
Texture	5
Color	7
Shape	3
Scale	6
Orientation	40
PosX	32
PosY	32

Random Samples

Tab.1: Texture-dSprites: the FoV generating the dataset (Left), examples randomly generated from the FoVs (Right)

Proposed methodology



Results

Method	✗ Finetuning GBT	✗ Finetuning MLP	✓ Finetuning GBT	✓ Finetuning MLP
Lensless				
[1]	70.32 ± 0.029	71.93 ± 0.030	73.04 ± 0.024	75.48 ± 0.027
Our	77.06 ± 0.020	77.46 ± 0.022	93.55 ± 0.019	94.62 ± 0.017
WHOI15-2007				
[1]	49.90 ± 0.014	48.20 ± 0.018	50.98 ± 0.016	49.29 ± 0.020
Our	47.92 ± 0.015	51.96 ± 0.023	60.74 ± 0.026	63.17 ± 0.033
Vacuoles				
[1]	64.03 ± 0.041	59.89 ± 0.053	65.45 ± 0.054	62.77 ± 0.057
Our	84.95 ± 0.02	85.10 ± 0.018	90.45 ± 0.019	89.97 ± 0.019
Sipakmed				
[1]	52.63 ± 0.043	51.25 ± 0.050	55.10 ± 0.041	55.69 ± 0.038
Our	61.75 ± 0.019	63.33 ± 0.014	71.17 ± 0.025	72.98 ± 0.022

Tab.2: Accuracy (%) and SD of the classifiers trained on the disentangled representation extracted from the VAE.

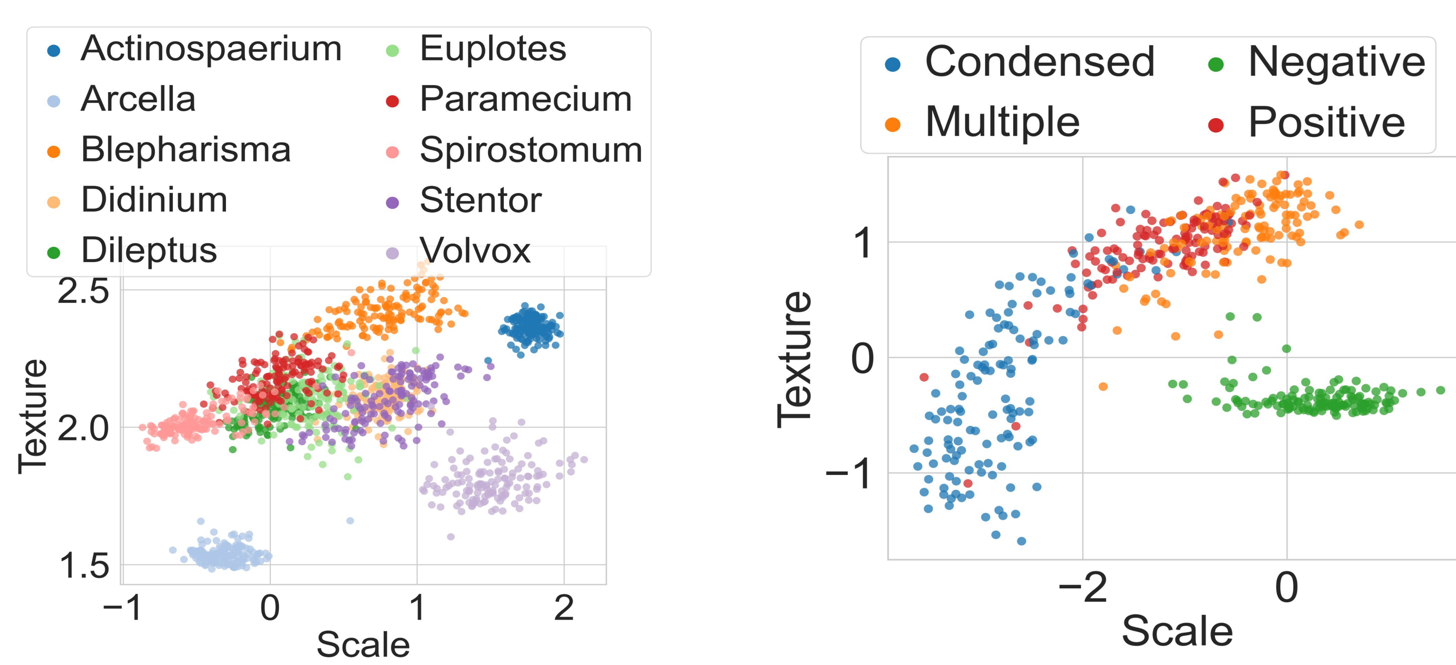


Fig.3: Representation of Lensless (Left) and Vacuoles (Right) using the two most important features

Disentanglement scores

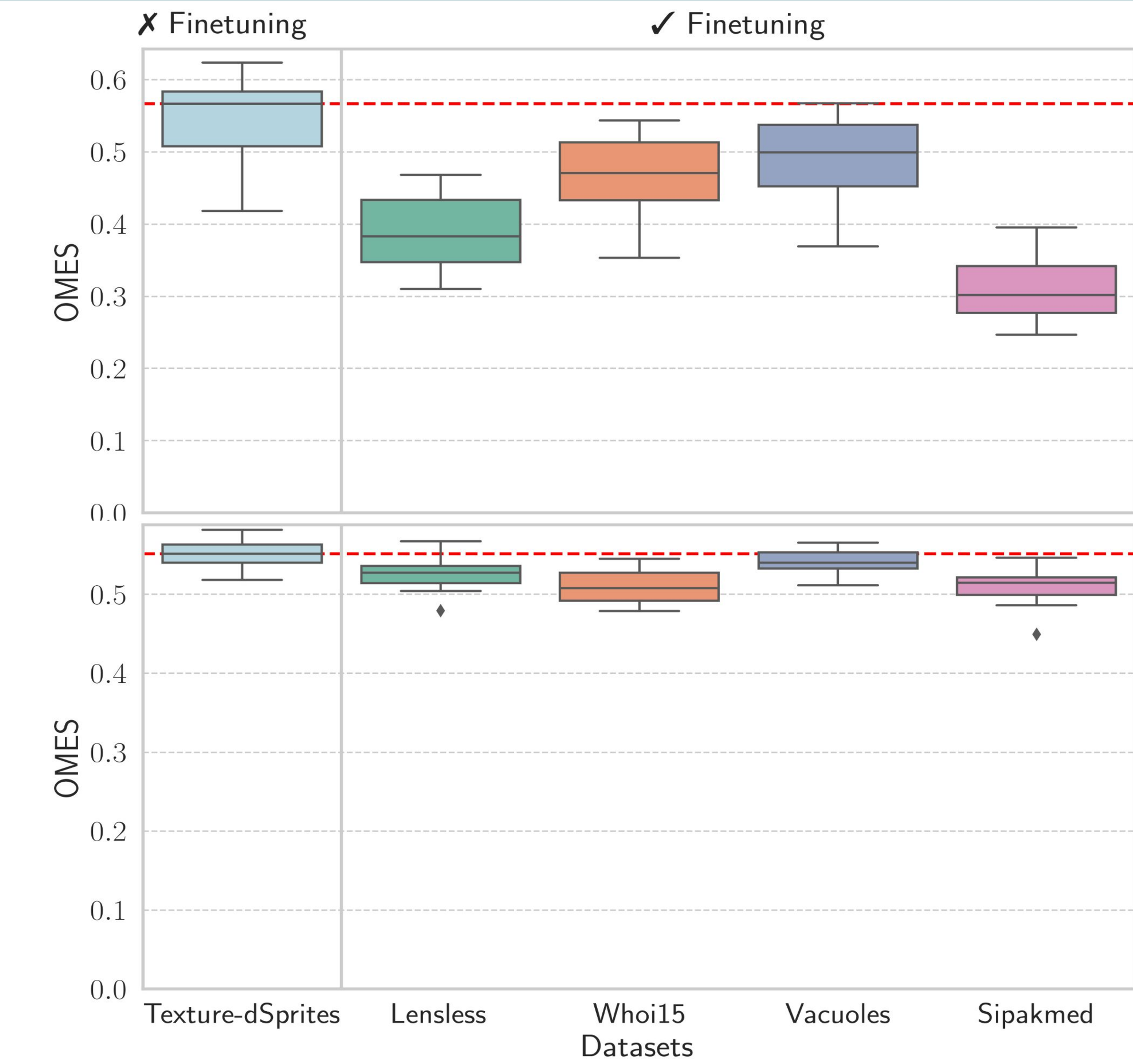
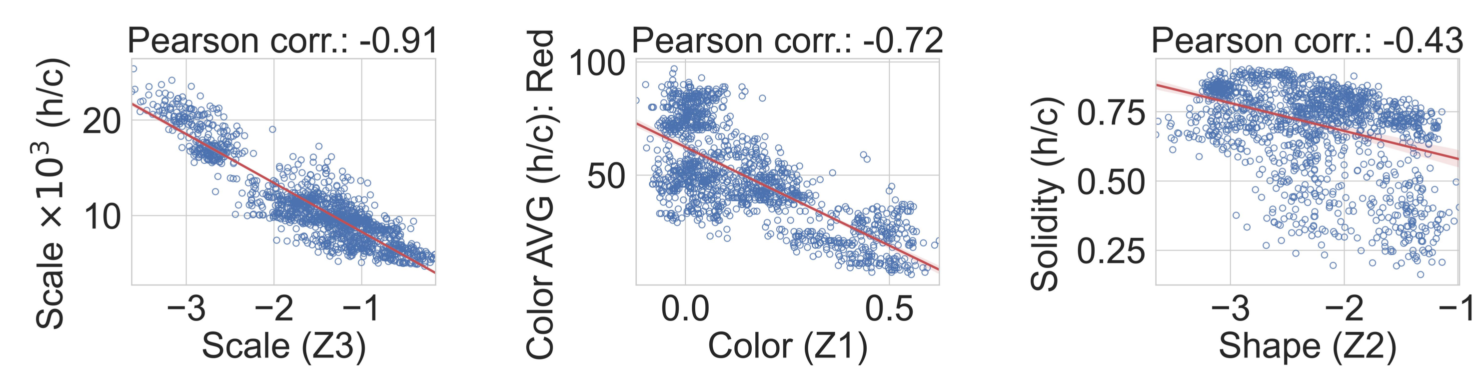


Fig. 4: Disentanglement score of Source and Finetuned models trained with [1] (above) and our (below) methods



Conclusions

Deep features allows for robust transfer with finetuning:

- ***improve downstream tasks on human-interpretable representation.***
- ***preserve disentanglement across the domains very different from the Source dataset.***

Future directions

- We will study the methodology with more complex and powerful methods than VAE.
- We will study the generation a synthetic FoV annotated dataset more specific to a Target.

References

[1] Dapueto, J., et al.(2024). "Transferring disentangled representations: bridging the gap between synthetic and real images.". In: Advances in neural information processing systems.

[2] Locatello, F., et al (2020). "Weakly-supervised disentanglement without compromises". In: International Conference on Machine Learning. pp. 6348–6359.

Github