# Contrastive Learning of Cytoarchitecture using Spatial Information


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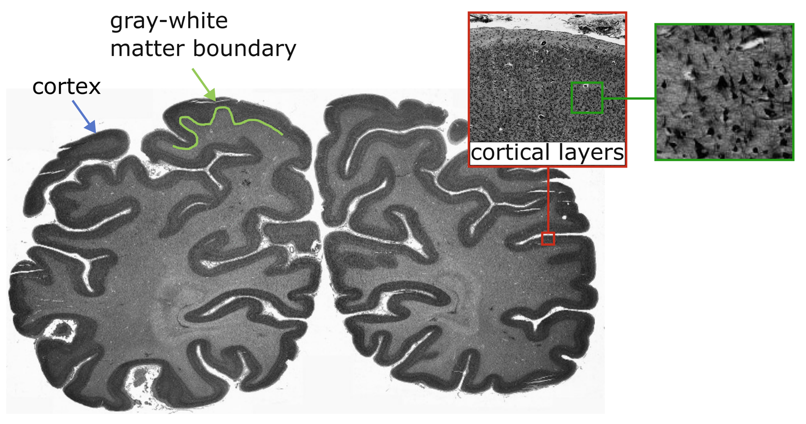
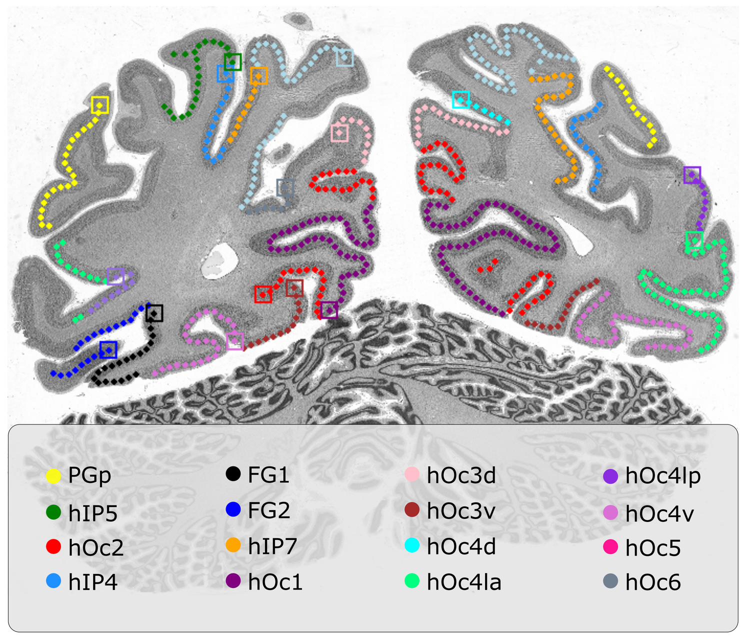
## Mapping of Cytoarchitectonic Areas in Histological Sections




**Cytoarchitecture** can be analyzed in high-resolution microscopic scans of cell-body stained histological sections. It encompasses the distribution and size of neuronal cell bodies, their shape, orientation, type, as well as their columnar and laminar organization.




Postmortem human brains were obtained from the body donor programs of the anatomical institutes of the universities of Düsseldorf, Rostock and Aachen.

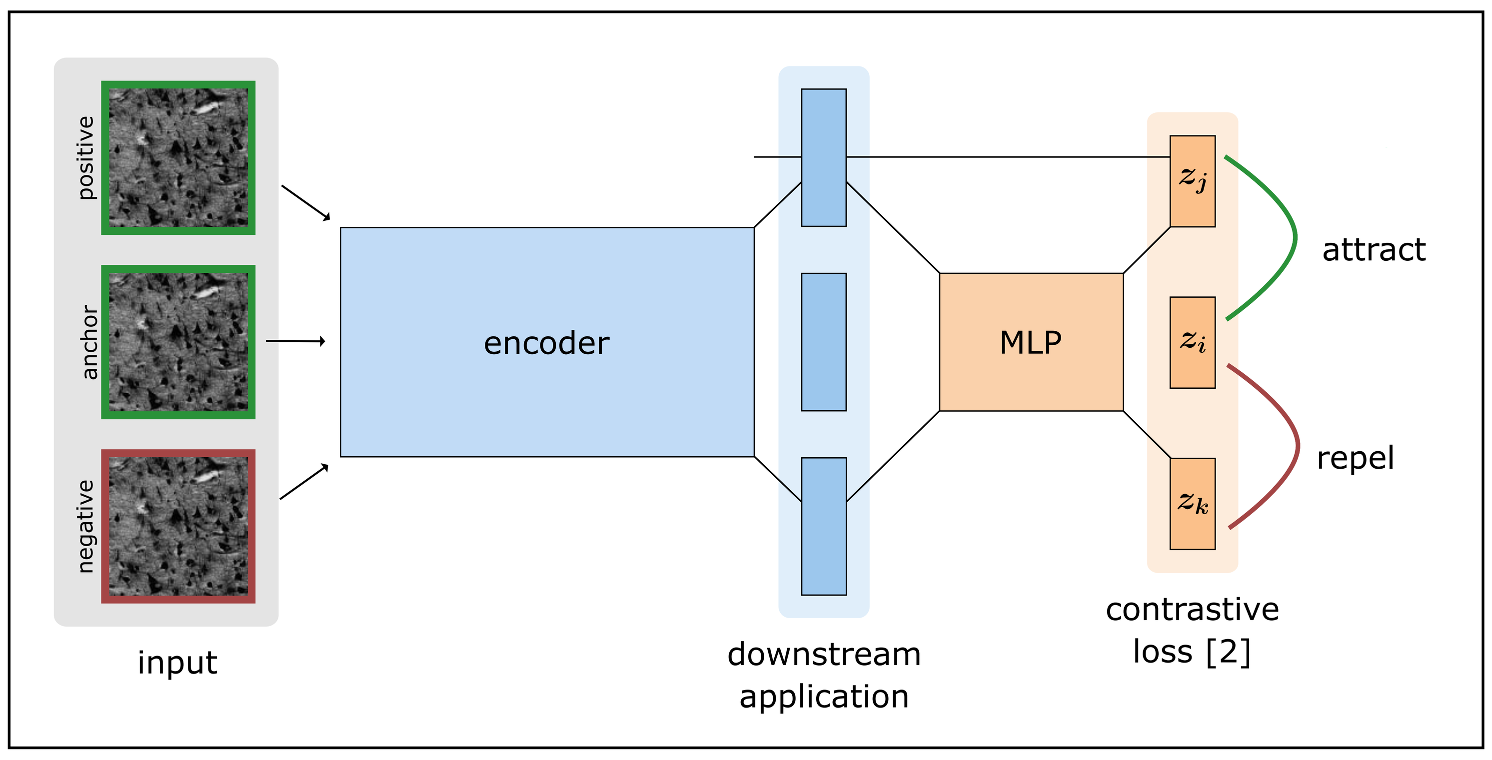
Histological processing of a postmortem brain [1]

- Cutting brain into 6000-7500 thin histological slices
- Staining for cell bodies
- Scanning with high-throughput light microscopic scanners at a resolution of 1μm/px

**Aim: Cytoarchitectonic Brain Mapping**
We train deep neural networks to predict brain areas from high-resolution image patches sampled along the midline of the cerebral cortex.

## Method: Distance-Based Representation Learning for Brain Mapping

### Representation Learning: Distance-Based Contrastive Learning




Number of samples in a batch

Cosine similarity

$$\ell_{dist}(i) = \frac{1}{\sum_{j=1}^{b} w_{ij}} \sum_{j=1}^{b} \mathbb{I}_{i\neq j}\, w_{ij} \log \frac{\mathbb{I} \quad \exp(\mathrm{sim}(\boldsymbol{z_i},\boldsymbol{z_j})/\tau)}{\sum_{k=1}^{b} \ {}_{k\neq i} \exp(\mathrm{sim}(\boldsymbol{z_i},\boldsymbol{z_k})/\tau)}$$

Sample in the batch at index i

Weighting of pairs based on geodesic distance along the MNI-Colin27 brain

Feature vector computed by the neural network

**Assumption**: Image patches sampled from *spatially close* locations are more similar than those extracted from distant locations.

**Prerequisite**: Registration of each brain in an anatomical reference space to obtain canonical spatial coordinates.

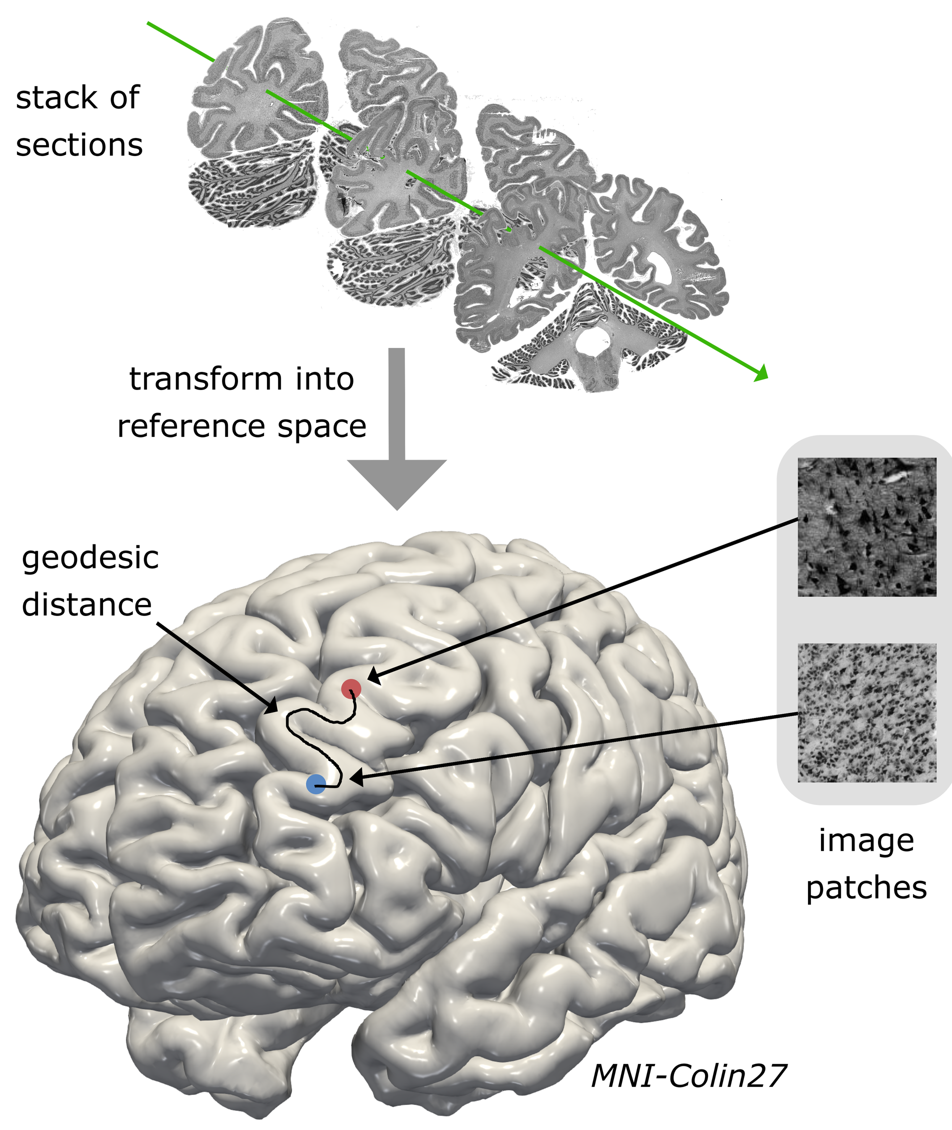
**Idea**: Learn latent space so that representations of similar inputs are closer than those of negative pairs

**Geodesic distance**:
Length of the shortest path along the surface of an object.
➜ similarity measure used to weight pairs of patches

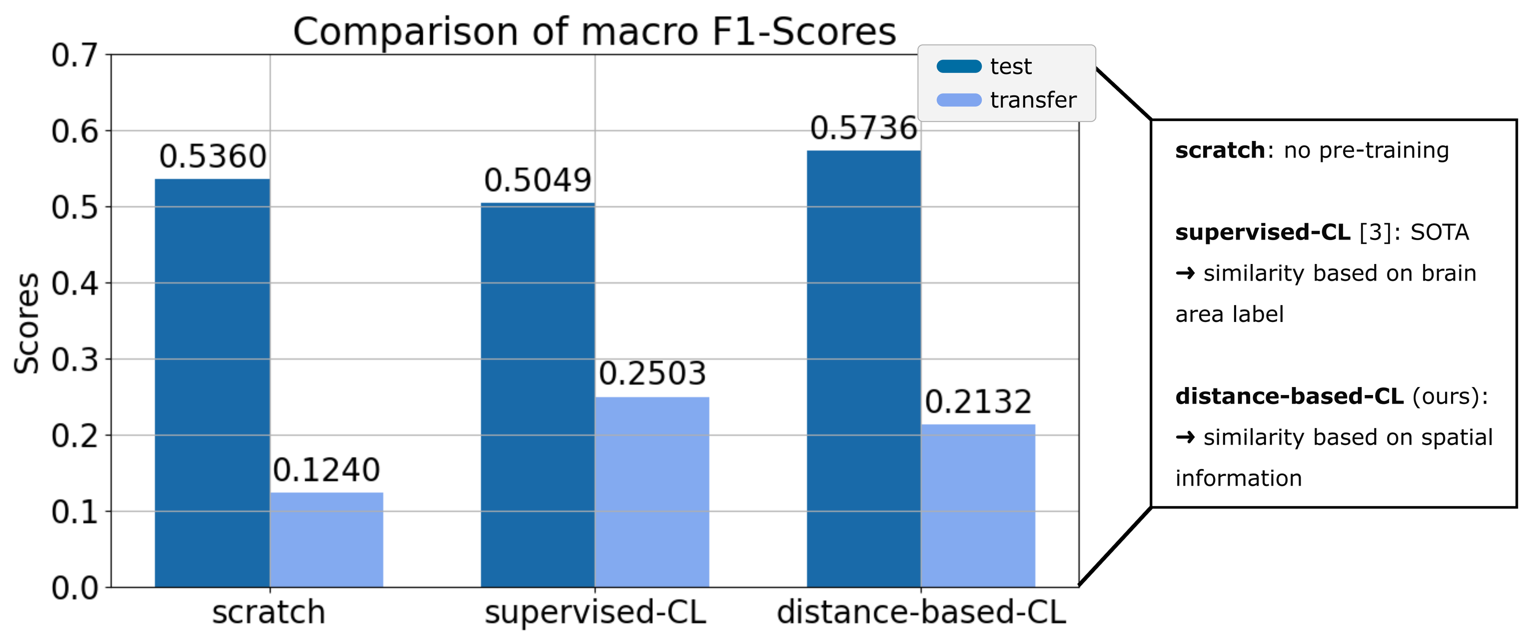
**Data sampling**:

- Uniform sampling of coordinates within cerebral cortex
- Patches are centered around these coordinates
- Image patches of size 2048 x 2048 px at 2μm resolution

### Registration of Sections to MNI-Colin27




## Results

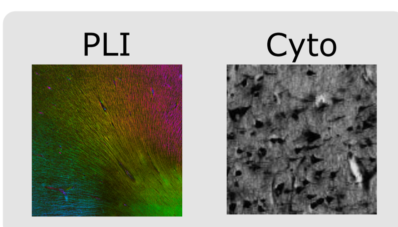



The proposed method enables learning of cytoarchitectonic features and outperforms the supervised contrastive learning method on the test dataset. However, generalization to unseen brains is a challenging task that remains unsolved.

Compared to the sota method [3], the proposed method does not use annotations for pre-training, has **lower inductive bias with respect to predefined areas**, and is thus applicable to a wider range of applications.

## Next Steps: Multi-Modal Learning

Training deep neural networks on image patches derived from various imaging techniques [1,6], with the goal of learning representations to **identify and extract both shared and distinct features**.




Sections derived from various imaging modalities contain shared and **complementary information**:

- Cell-body staining: cellular architecture
- Polarized light imaging [6]: connectivity and fiber tracts

**Motivation**:

- Spatial anchoring: attaching patches to specific locations in a 3D brain volume
- Cross-modality image generation: predict one image modality from the other
- Identifying common and shared information in both modalities

**Idea**: Our goal is to develop a CLIP-inspired [4] neural network architecture that integrates image patches from different modalities and learns meaningful representations from them. As our work has shown promising results, future work will further investigate the capabilities of learning from spatial information.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