Anatomical region calling via semantic segmentation

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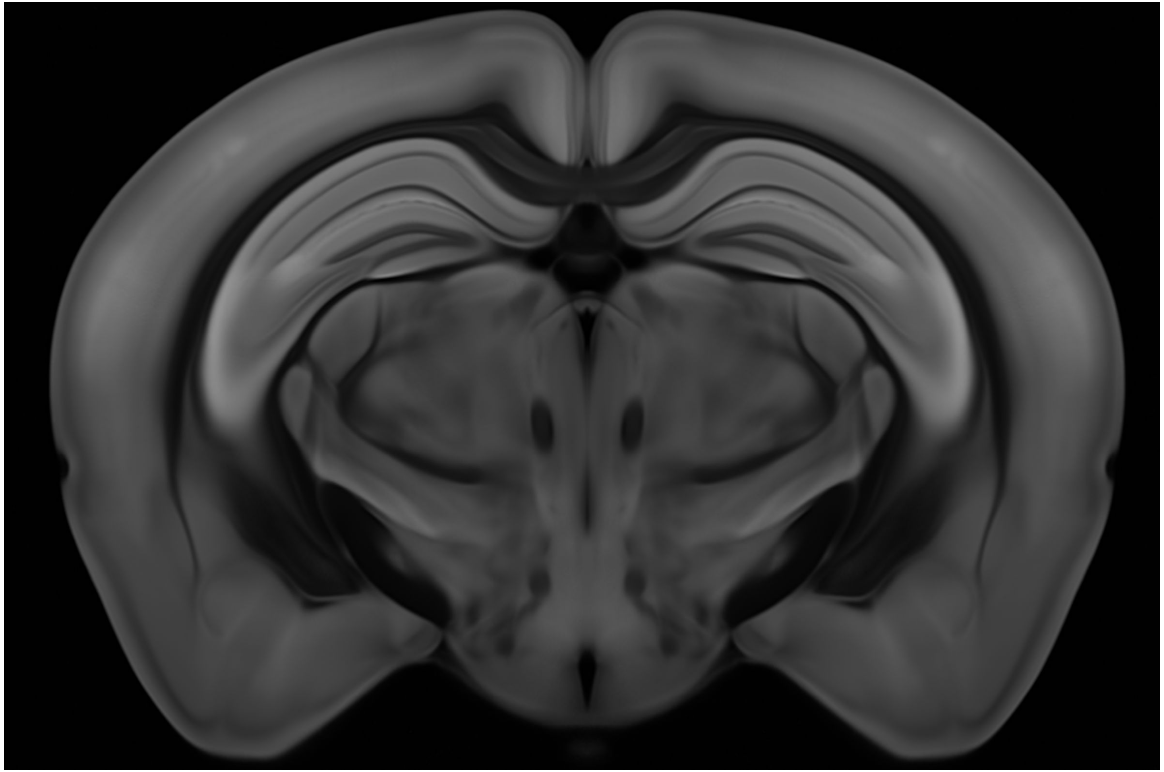
Introduction to project

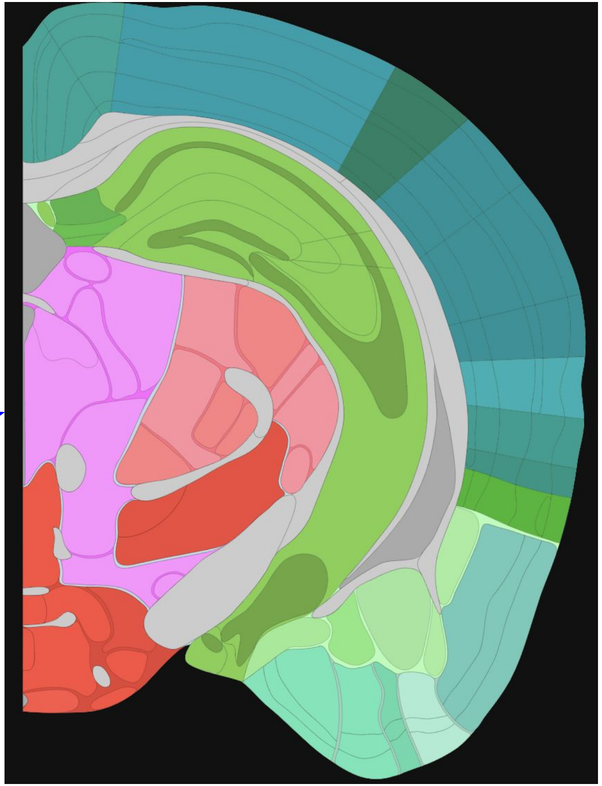
This is an image from Allen CCFv3 representing a coronal slice of a mouse brain.



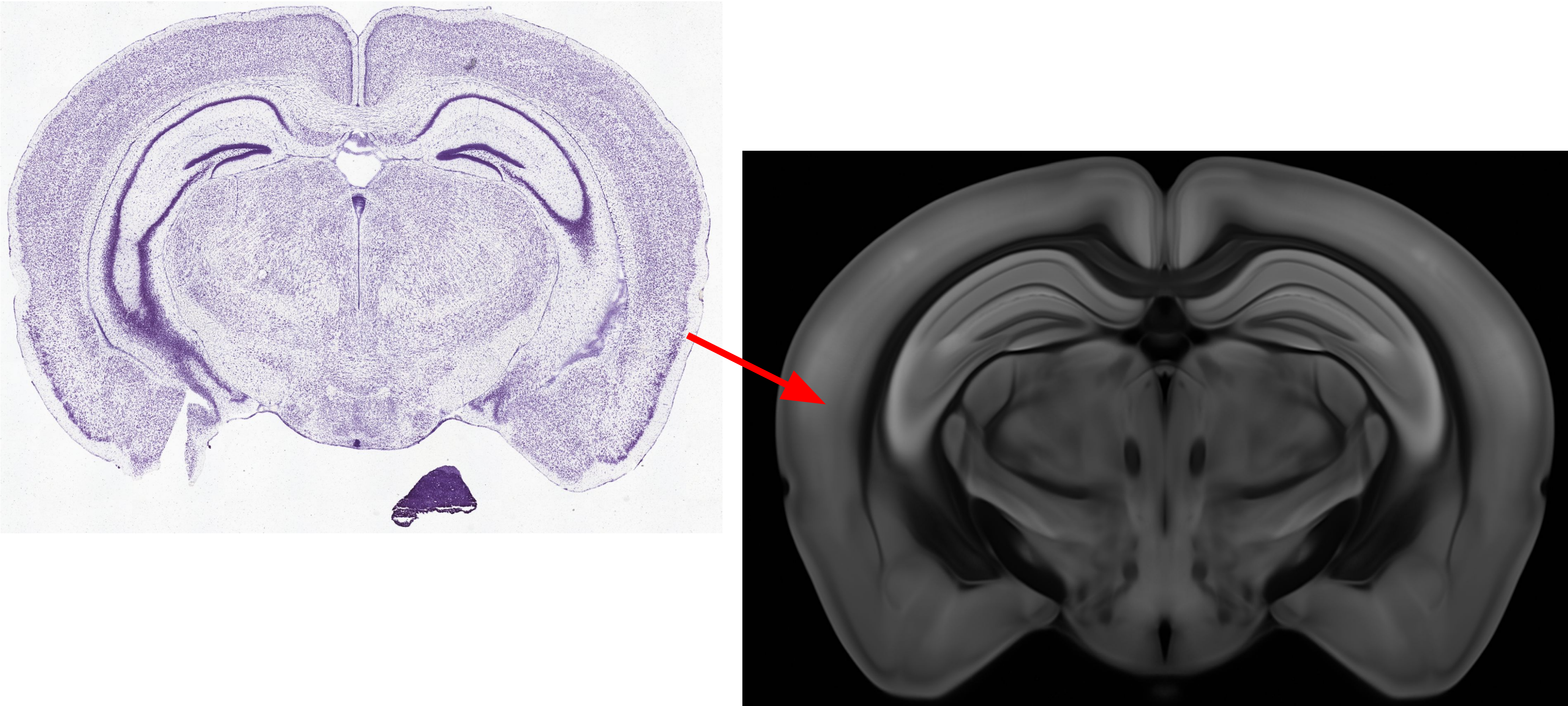
The reason why people like Allen CCF is that is annotated

This segmentation mask overlaps with the CCF image

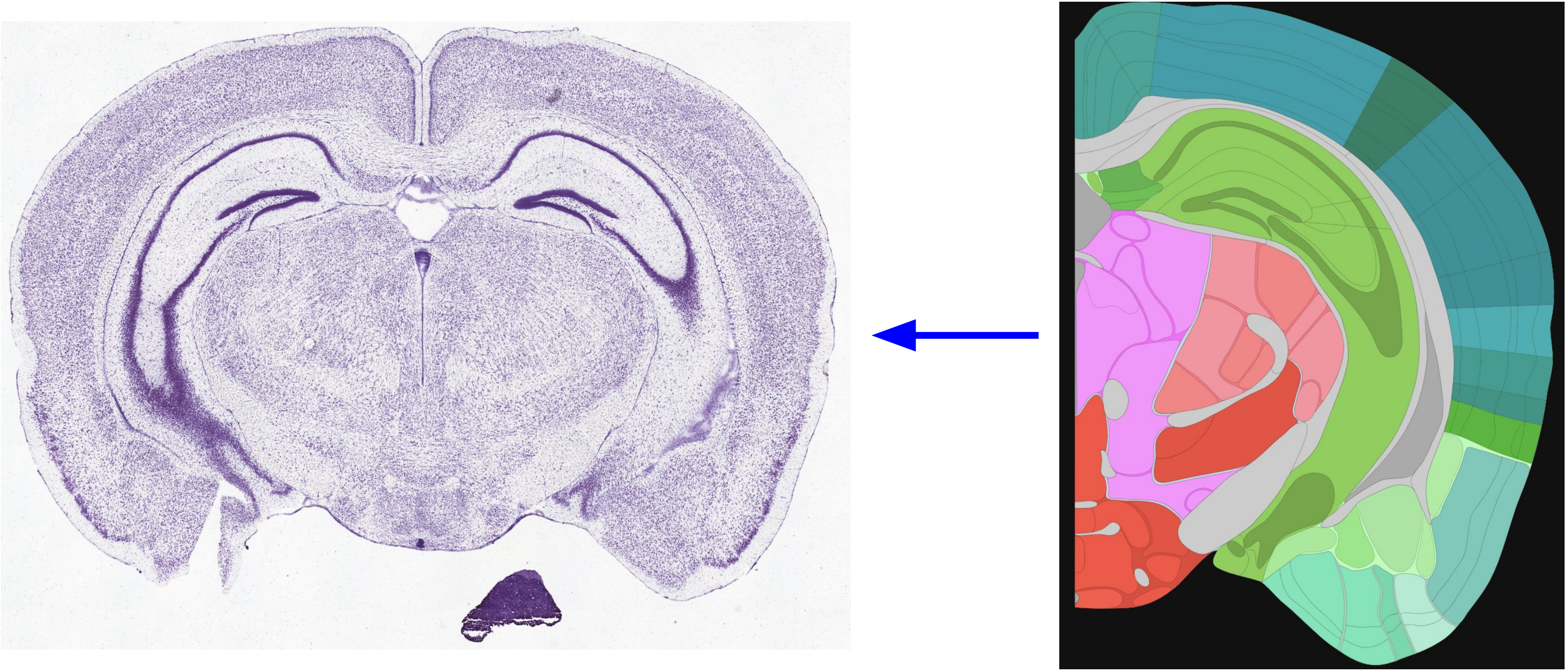
Each color corresponds to an anatomical structure



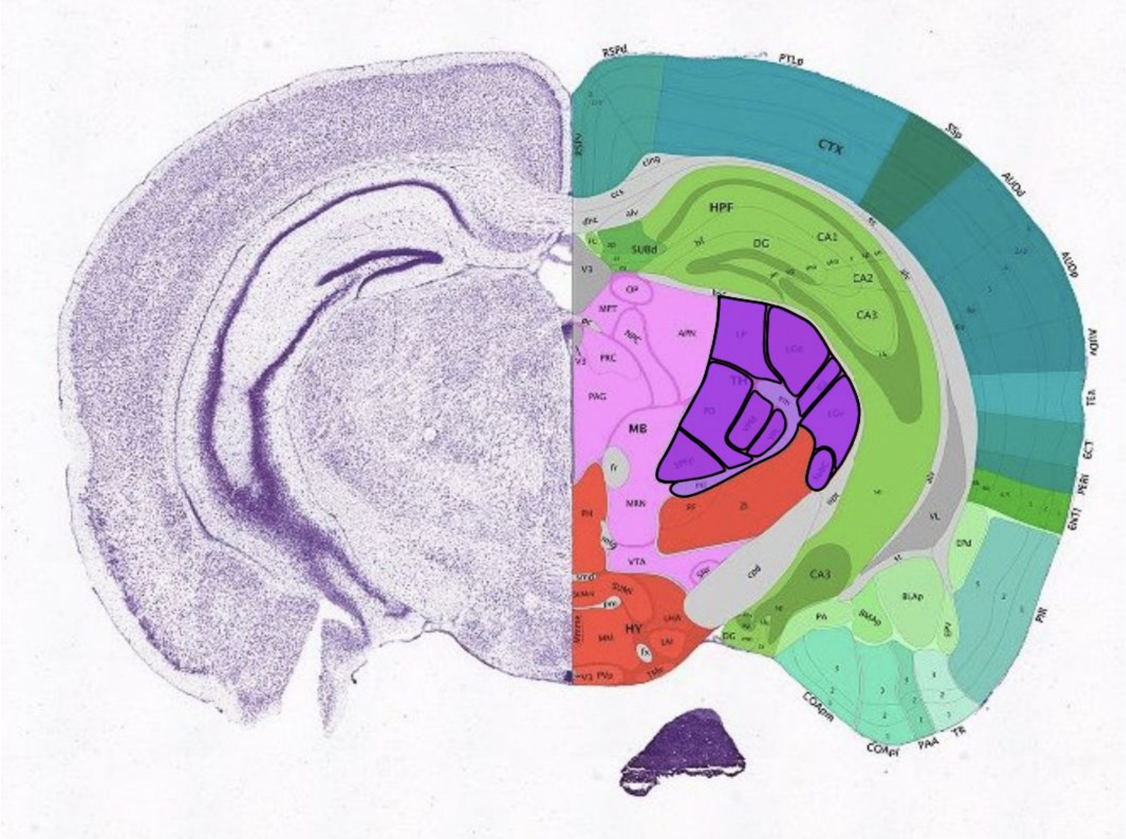
Morphological images need to be registered to Allen CCF (which is what BICCN is doing)...



...because by doing so, annotations can be transferred from the CCF to the actual image.



The final result is a fully annotated morphological image



From Allen P56 Coronal Atlas

Problem

We do not have a fully automated way to register images to consensus atlases.

My proposed solution

We produce anatomical maks using semantic segmentation and we register the masks rather than images.

Background

Semantic segmentation is a branch of ML which combines:

- the fact that similar pixels belong to same region
  (*ie* classic segmentation concepts).

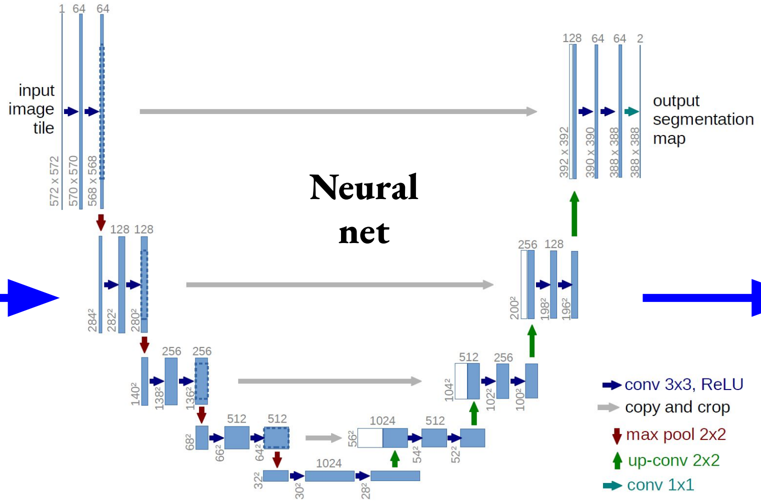
- with the fact that AI can distinguish (say) a cat from a dog
- (*ie* semantic understanding).

Semantic segmentation is a solved problem in AI and has been successfully applied to different fields

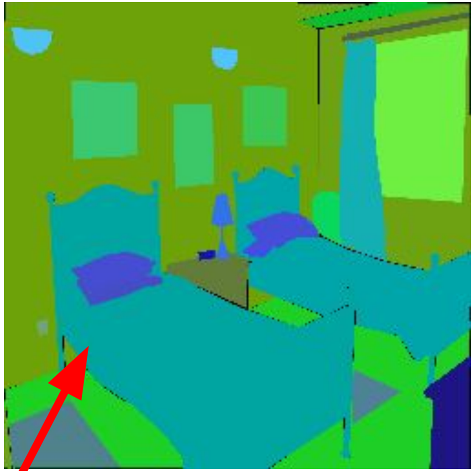
The way it works: we supervise a proper neural net with images and labels...

Image

Neural net



Labels



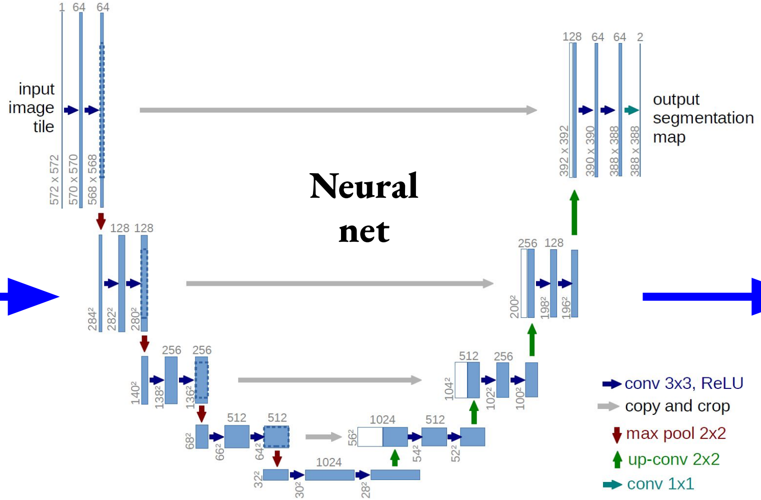
Training.....

(the model learns this is a bed)

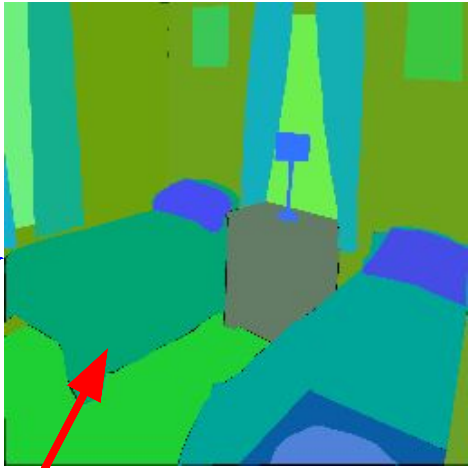
The way it works: ....then *abracadabra* it works.

Image

Neural net



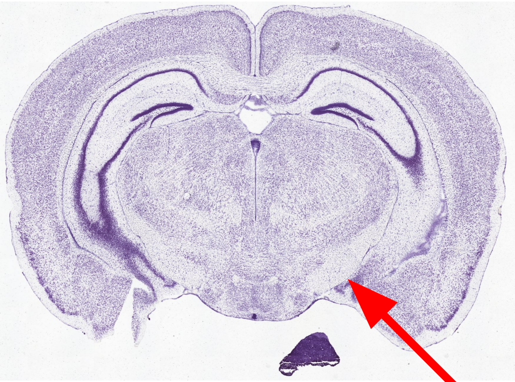
Labels

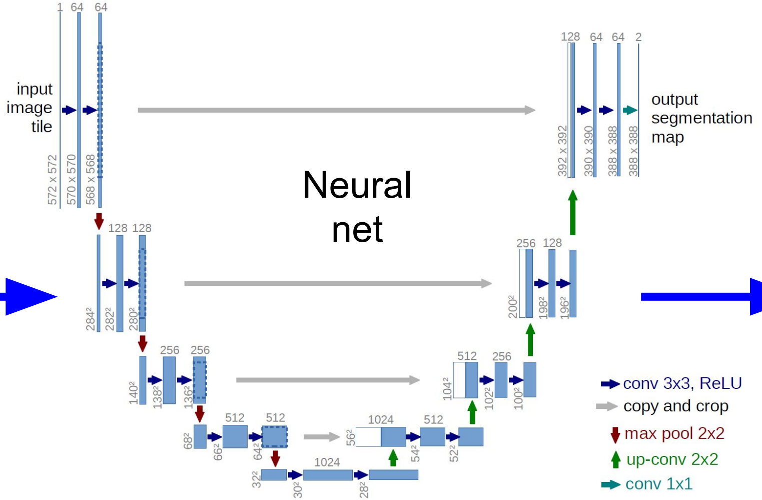


The model **recognizes** a (different) bed in an unseen image

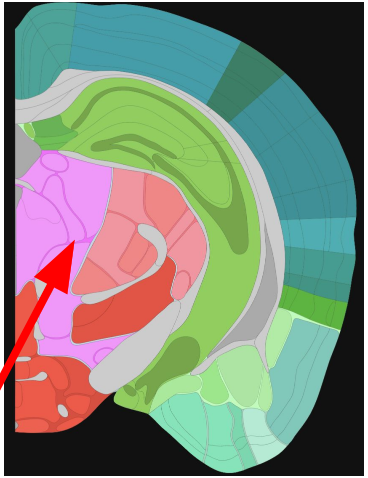
What I propose: to supervise a neural net with morphological images and annotations from (eg) Allen

Image





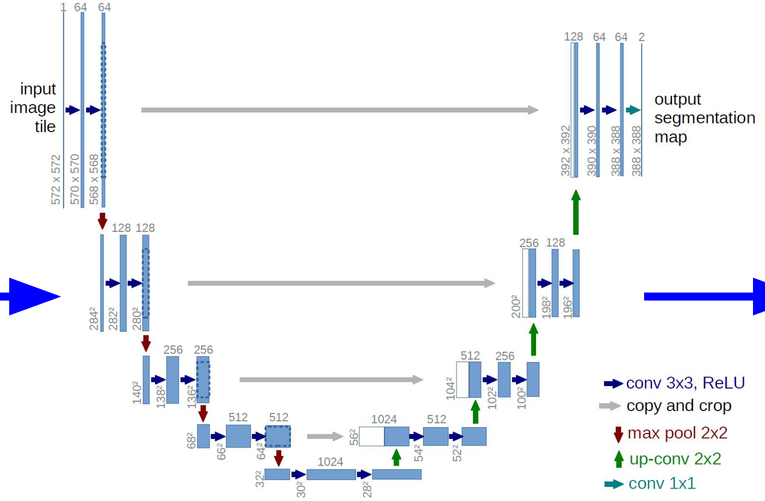
Labels



during training it learns (eg) to distinguish thalamus from hypothalamus.

What should happen: the model outputs a segmentation mask for an unseen image

Image

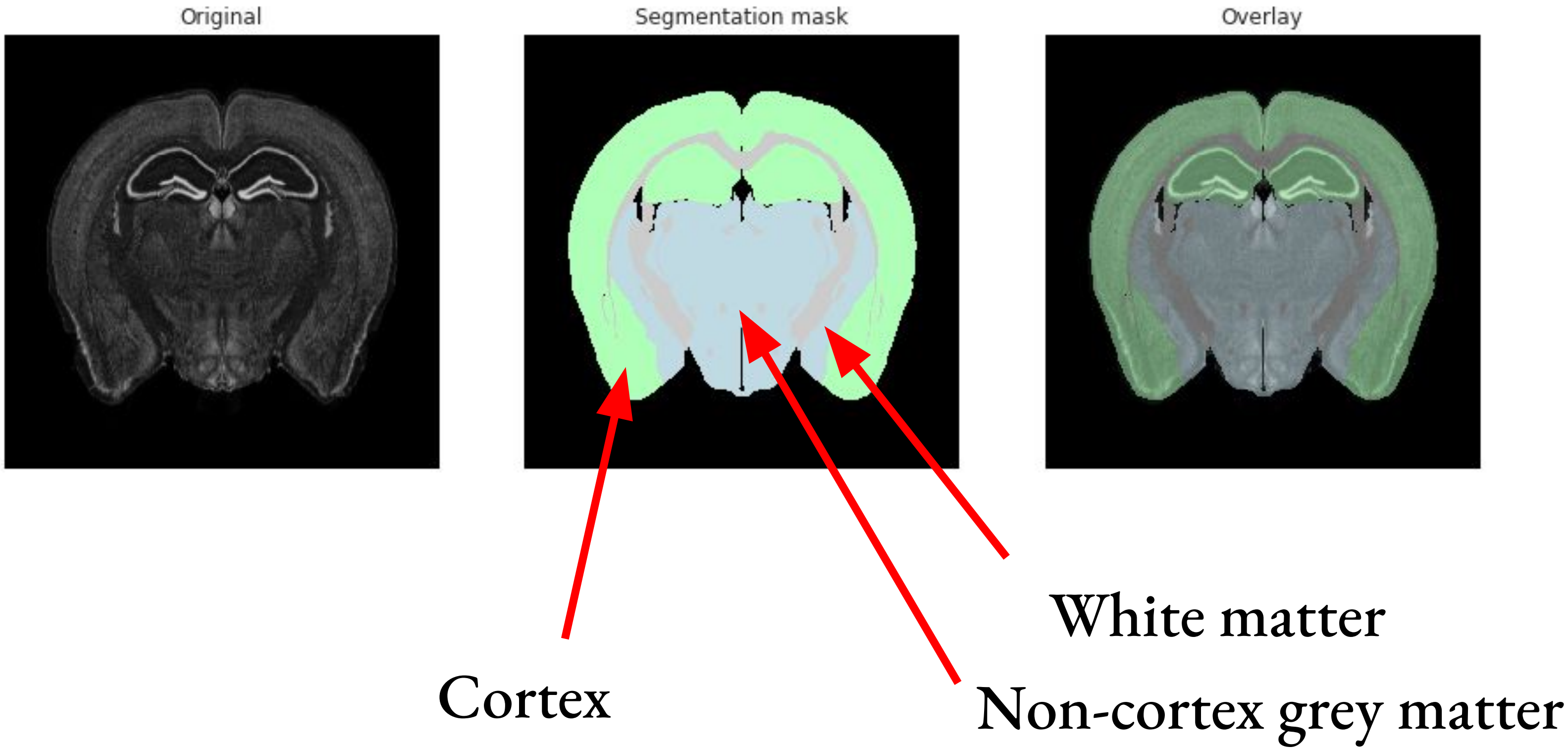


?

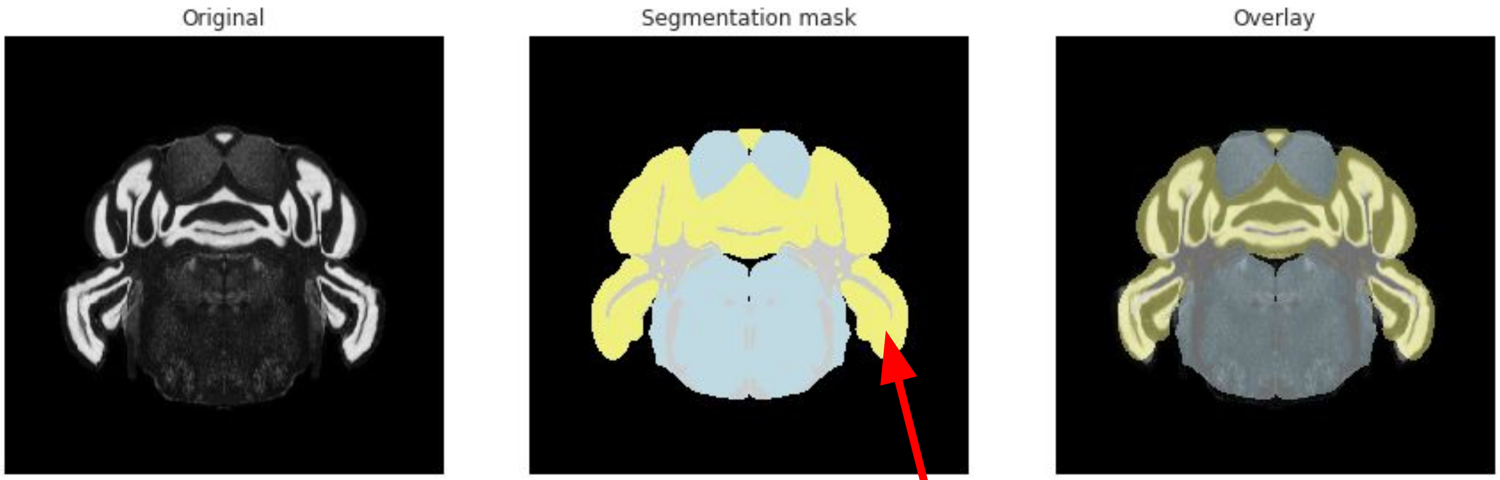
Image from BrainMaps (UC Davis). Same staining, mouse age but unseen.

Preliminary results

We build training set using Allen CCFv2 and v3. This is an example training sample (image + mask):



Another example image:



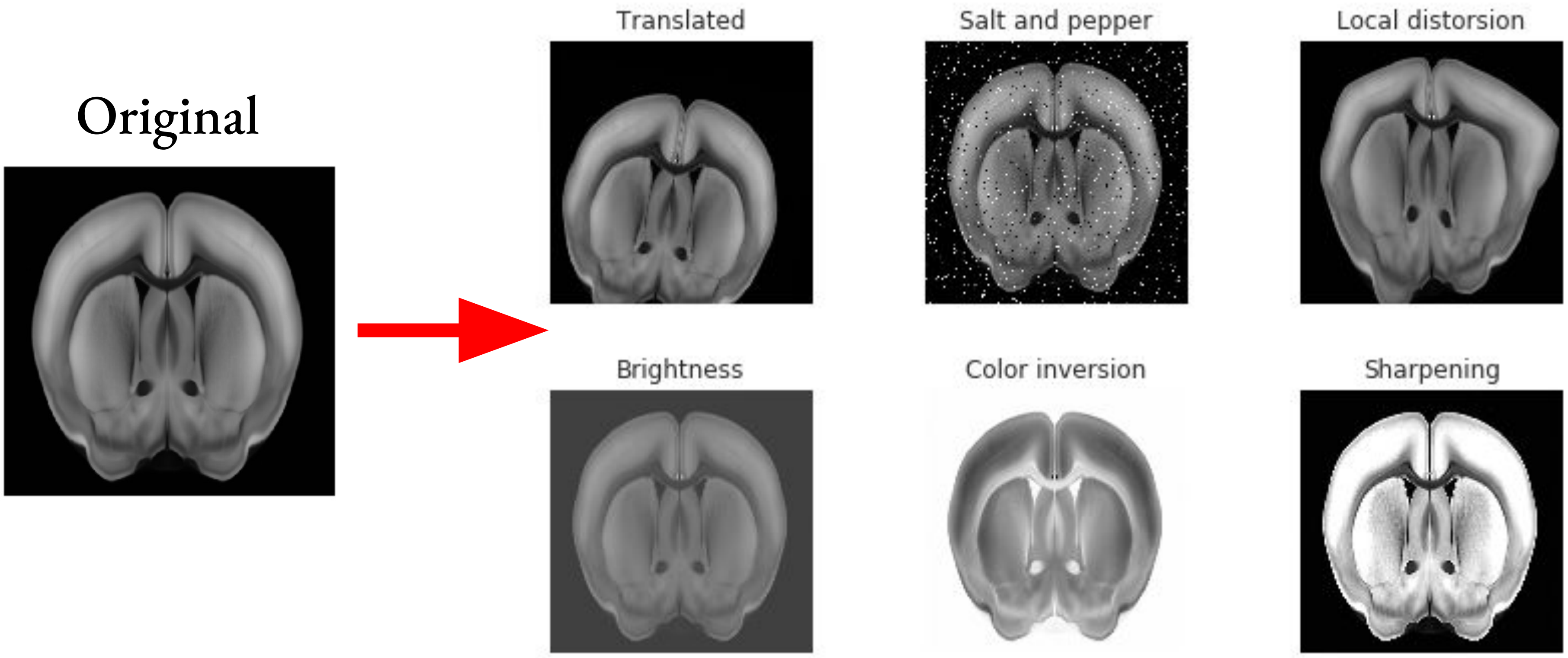
Cerebellum

This ML problem is difficult because of the scarce dataset

- 512 x 512 pixels ~ **268k features**.
- **5 classes**: *background, cortex, cerebellum, white matter, other grey matter.*
- just **234 annotated images** in training set.

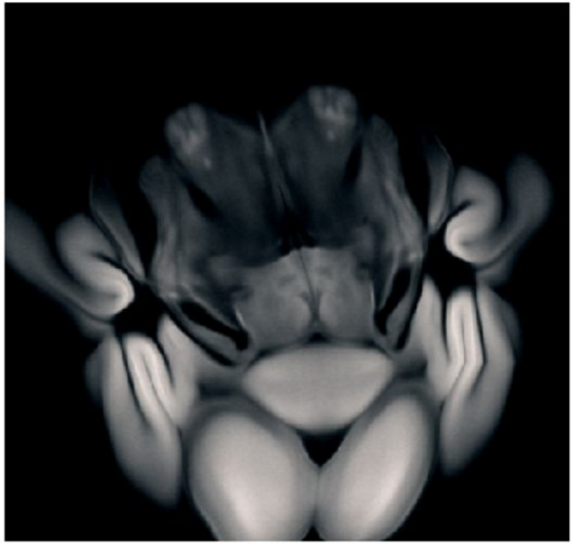
no. features >> no. training samples

We augment each image by applying several transforms



Transforms are stochastically combined so that one image becomes zilions

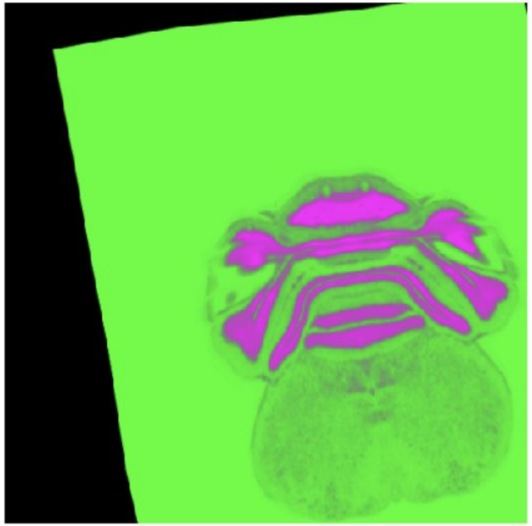
Training image



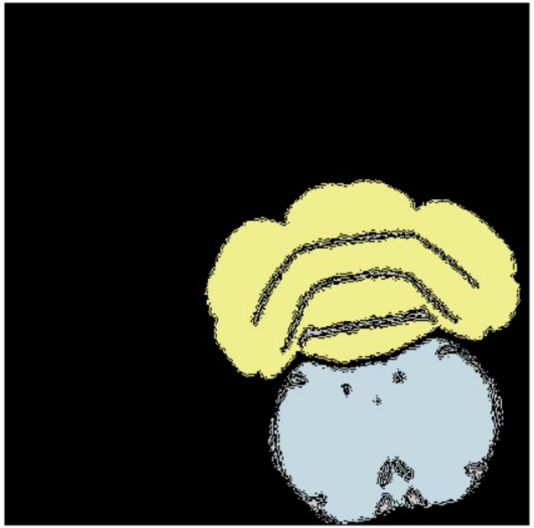
Training mask

Transforms are stochastically combined so that one image becomes zilions

Training image



Training mask

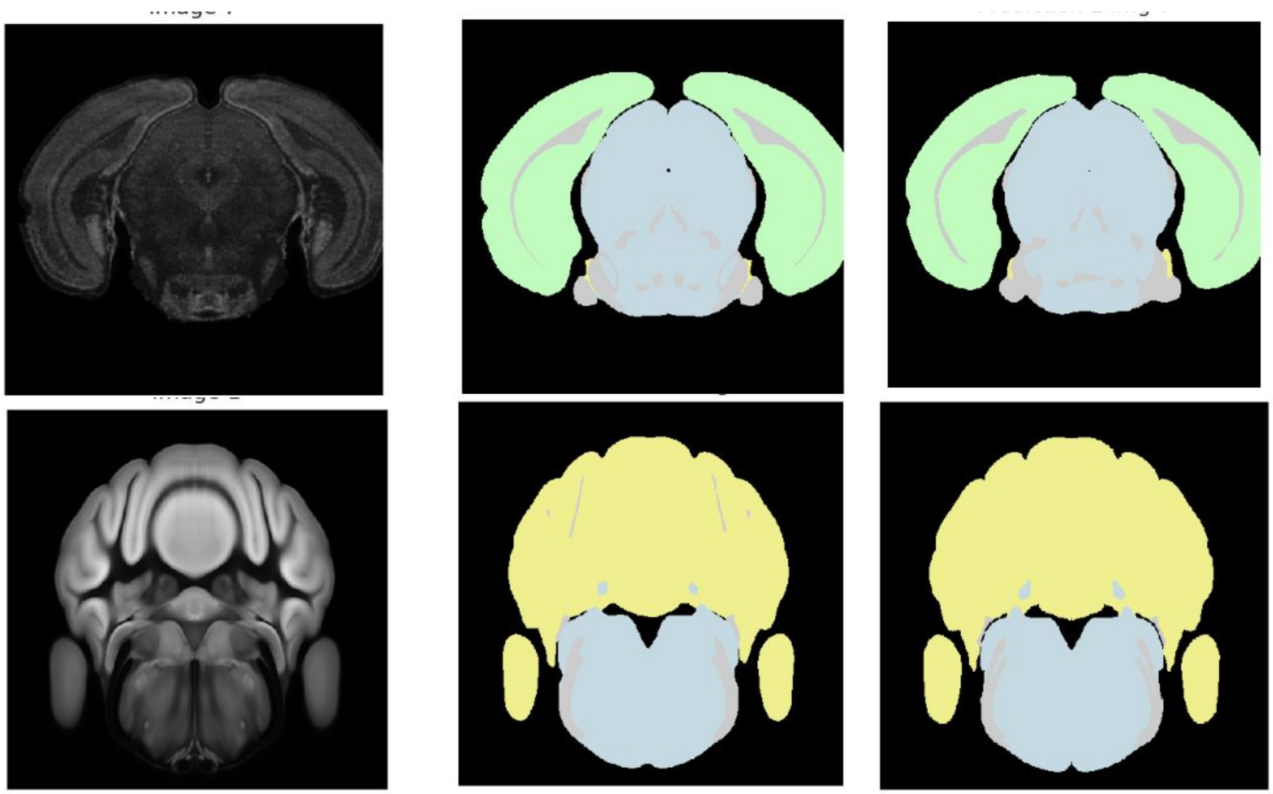


Result:model predicts well the unaugmented training set

Image | Ground truth | Prediction

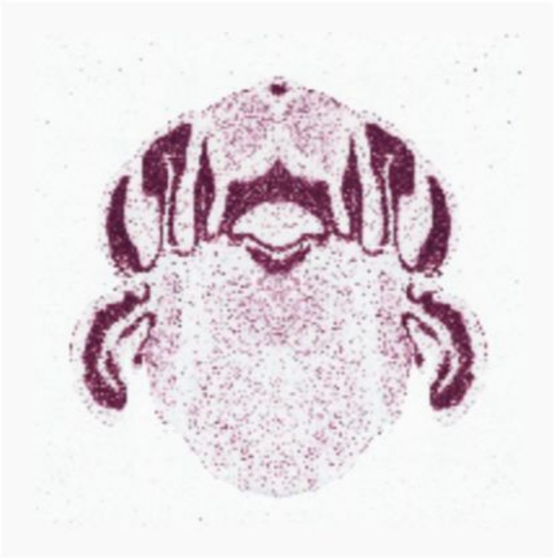
Image from CCFv2

Image from CCFv3



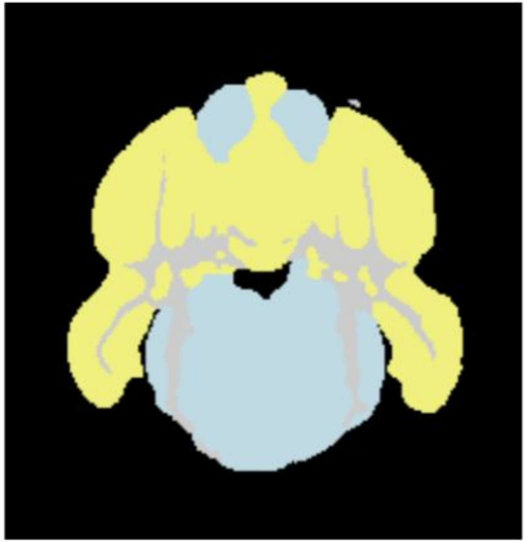
Result: model predicts the unseen P56 Coronal Atlas - 1

Image



Ground truth

Prediction



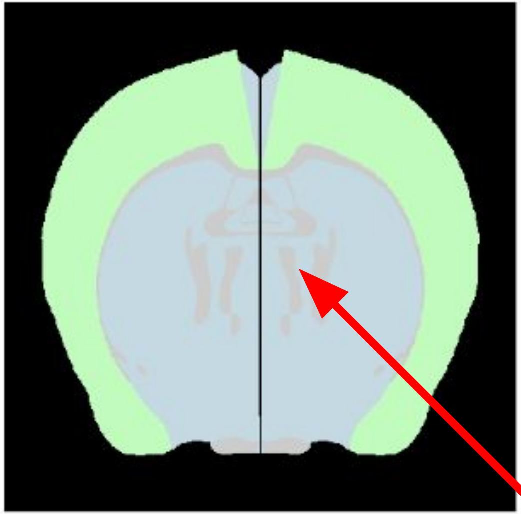
Result: model predicts the unseen P56 Coronal Atlas - 1

Note: this cranial nerve is actually there. It is not annotated in P56c but our model correctly finds it (because we train on CCF which is better).

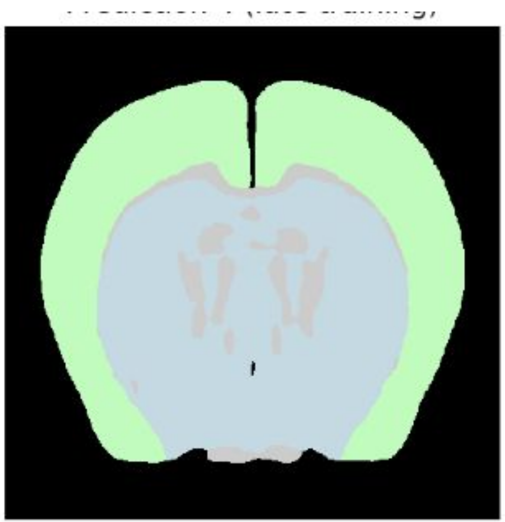
Result: model predicts the unseen P56 Coronal Atlas - 2

Image

Ground truth

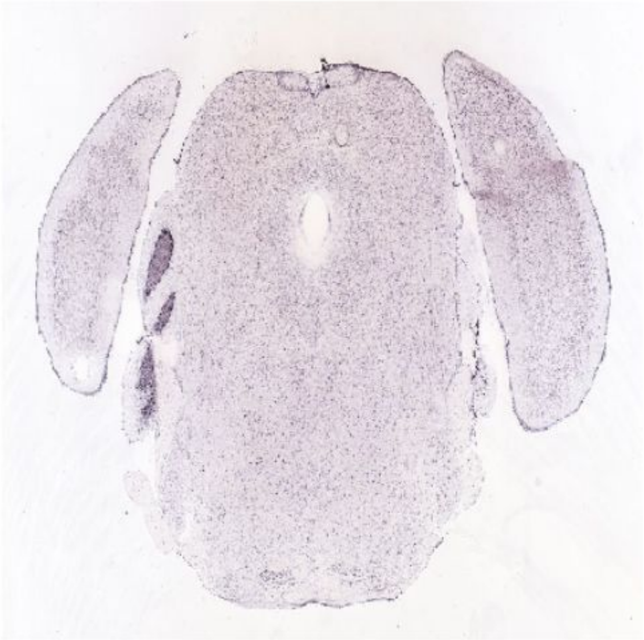


Prediction

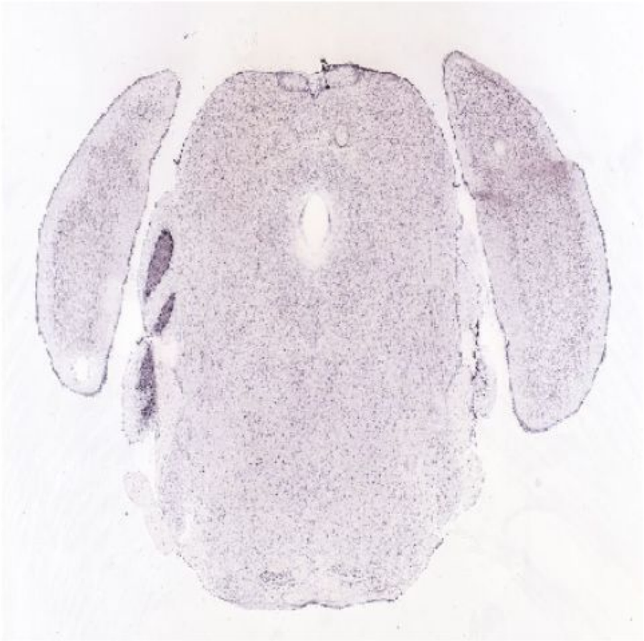


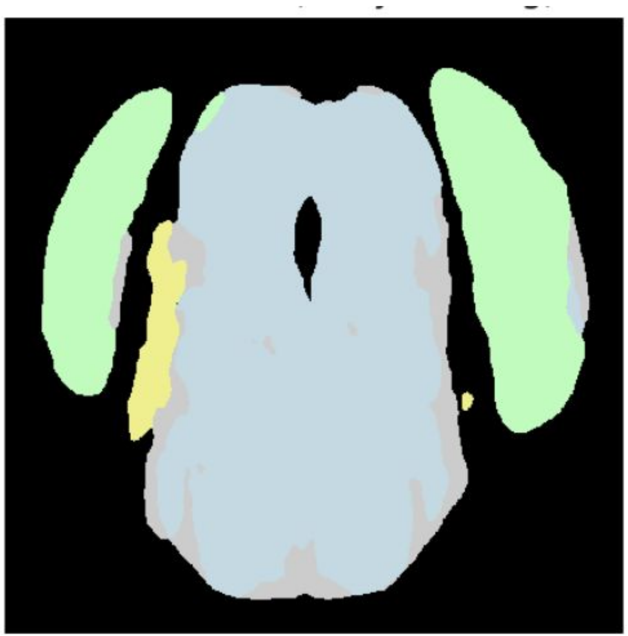
Indeed, ground masks of P56c aren't very good, *eg* this vertical line should not be here. Our predicted masks are better.

I now try to predict an ISH image from Allen. These images are very low quality wrt atlas images.



(Result) Yet, our model does a nice job





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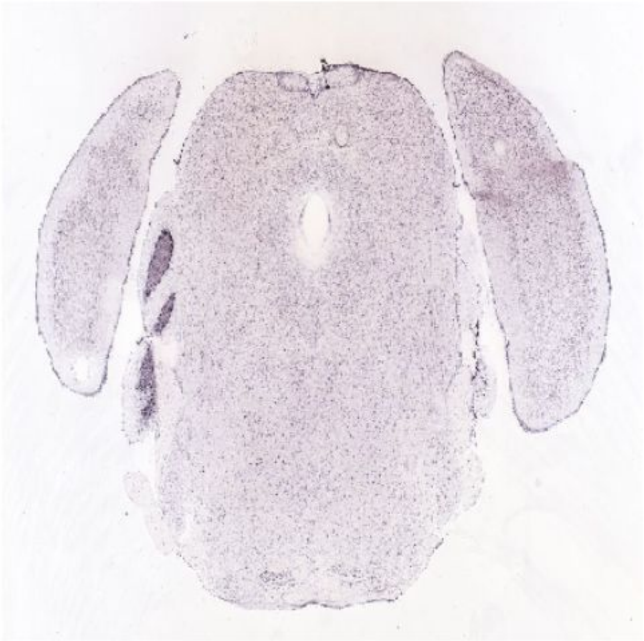
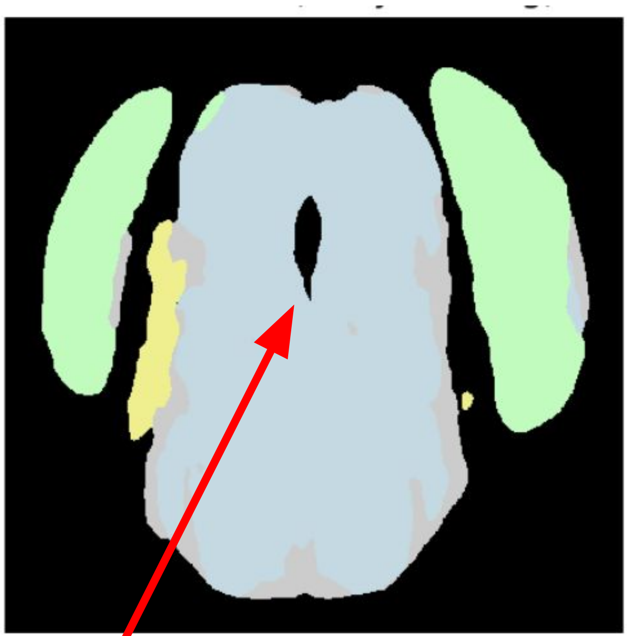
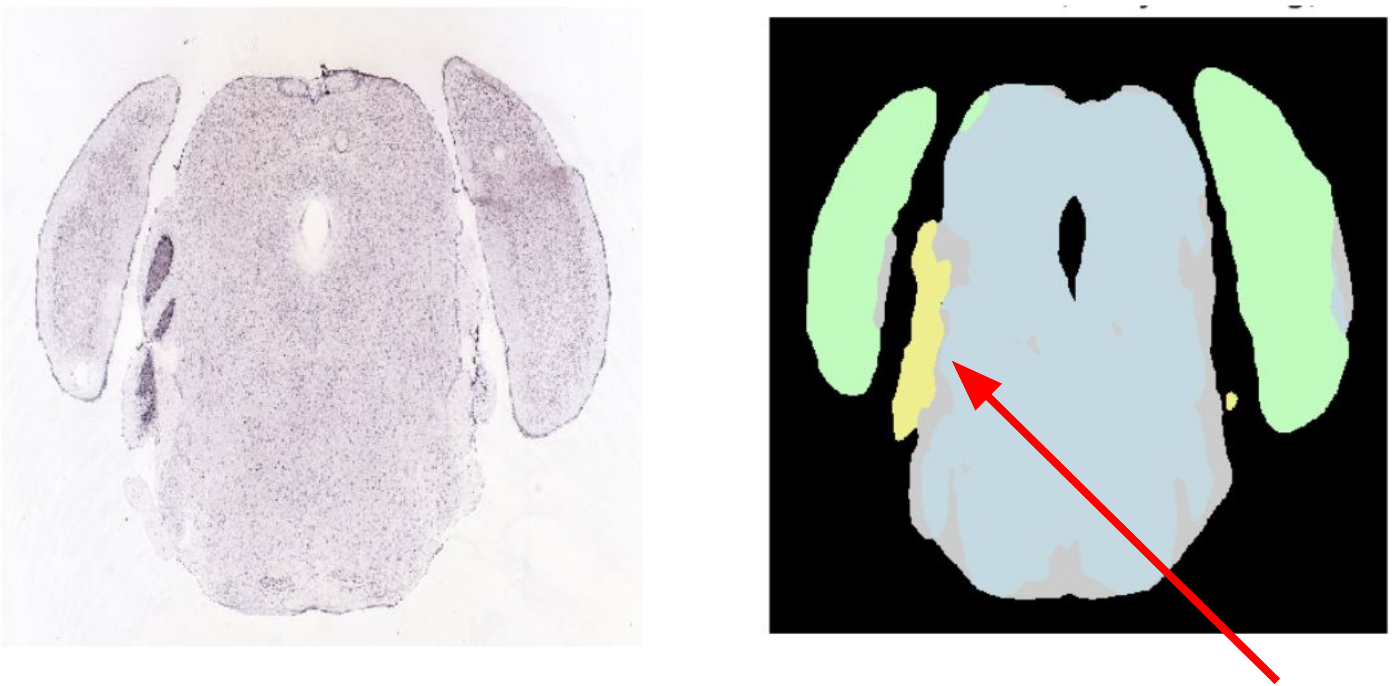




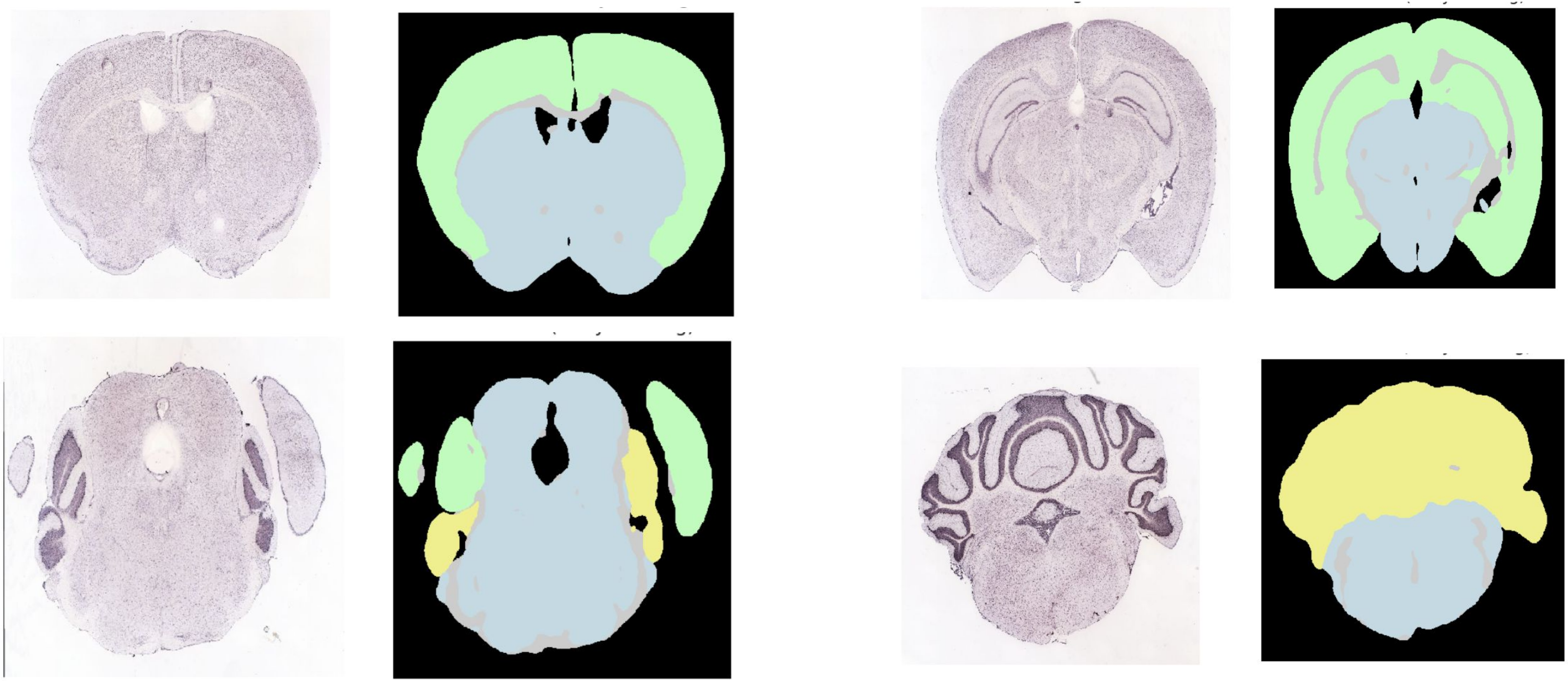
Distortions are classified as background

(Result) Yet, our model does a nice job

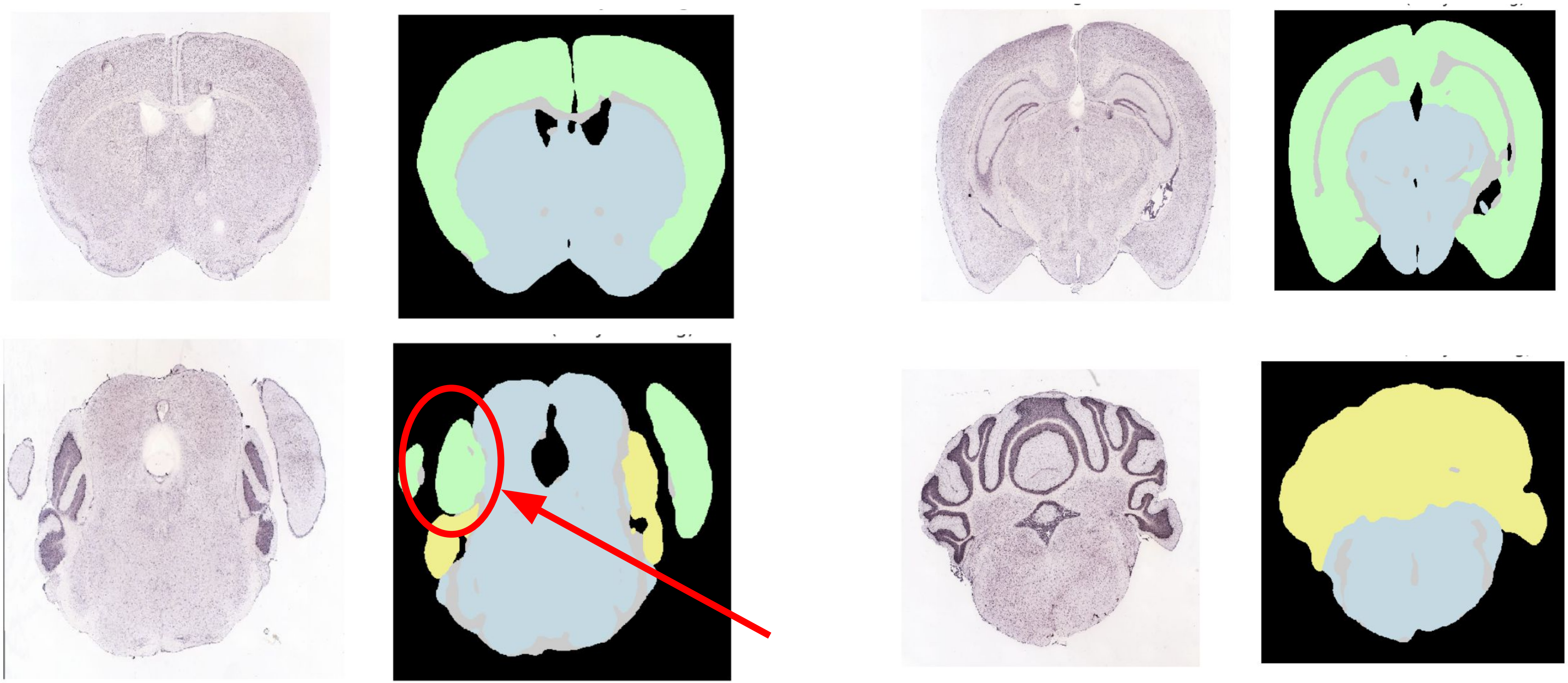


This slice is not precisely coronal (because asymmetrical), but the model recognize that cerebellum is only on one side.

Some other pair image/prediction:



Overall seems OK even though there are some errors here and there



Not every prediction is nice though.
4-5% of them can be improved.