Cell Counting using CNNs in Retrograde Neuroanatomical Tracer Data

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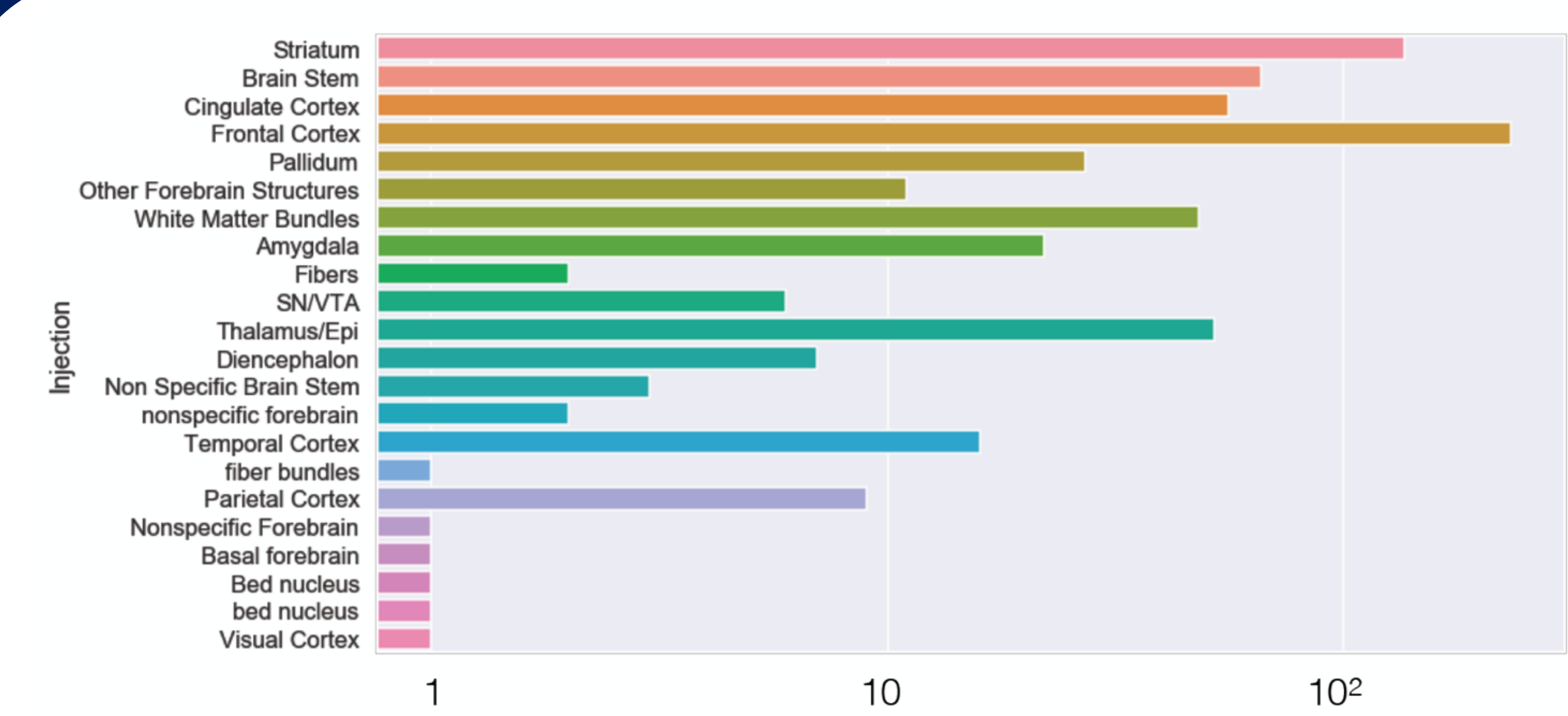
Summary

PROBLEM. Building next-generation connectivity models of the macaque brain is based on a robust and quantitative analysis of histological tracer data. However, manual labelling of these datasets is not feasible.

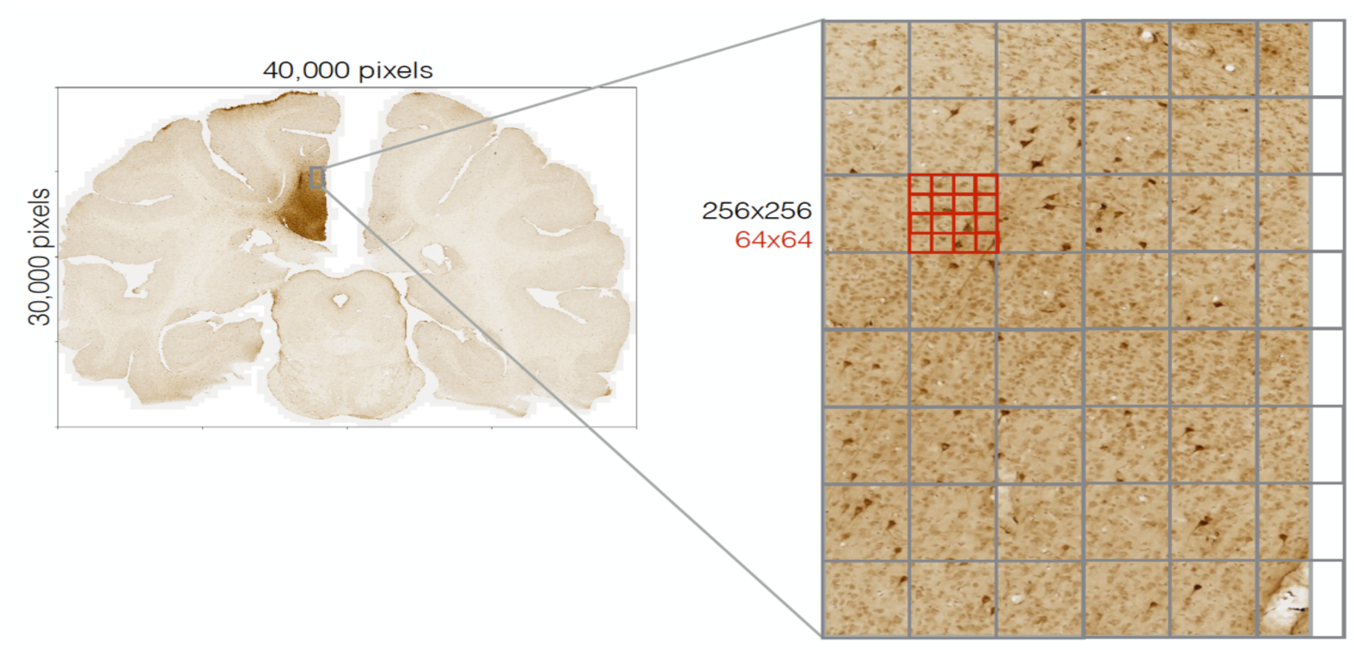
PROPOSAL. Exploring the performance of various convolutional neural networks (CNN) architectures in automatically counting retrogradely-labelled cell bodies. CNNs have not yet been used in the analysis of tracer data.

DATASET. The world's largest collection of macaque tracers, collected over 40 years.

TRAINING AND TESTING: Training: 10,000 manually-annotated patches, taken from 9 macaques, 10% held back for validation. **Testing: 1000** patches seen during training, and **1000 unseen** during training.



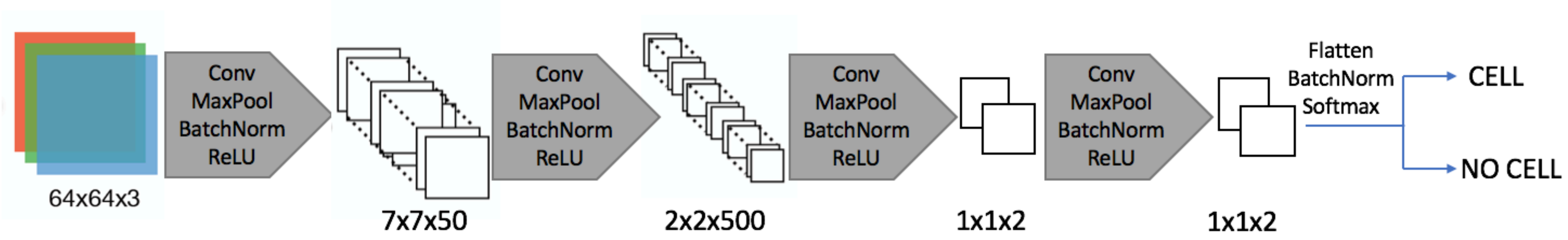
Injection sites for the Haber dataset.



An example histological slide, blown up to show individual cells.

Method 1

Evaluation of the performance of 7 different CNN architectures: an Alex-Net inspired CNN[1], VGG15[2], ResNet[3], Xception[4], DenseNet121[5] and MobileNet versions 1[6] and 2[7].



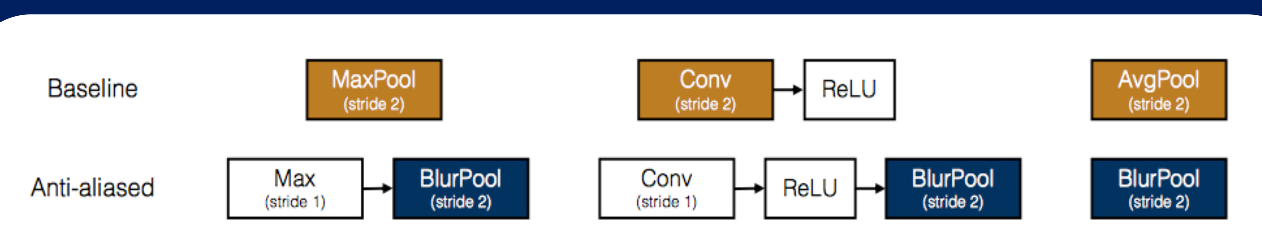
Architecture of the Alex-Net-inspired CNN.

Results

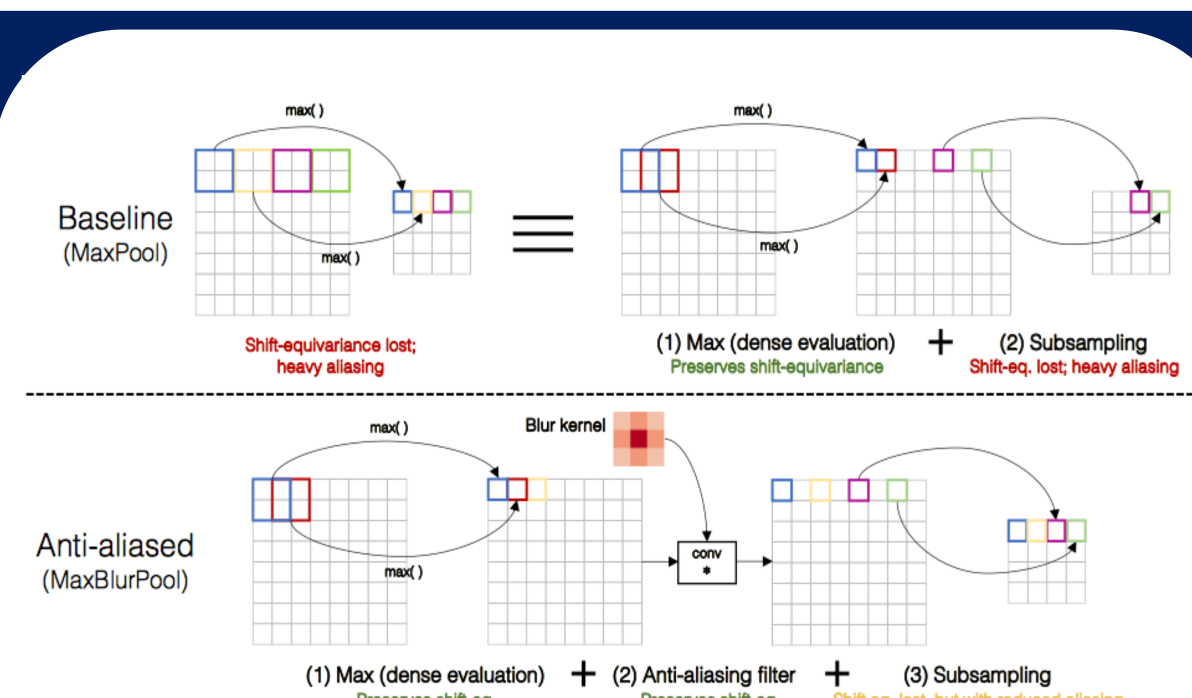
Architecture	Dataset seen during training								Dataset unseen during training							
	With data augmentation				Without data augmentation				With data augmentation				Without data augmentation			
	Randomly initialised weights		ImageNet (frozen) weights		Randomly initialised weights		ImageNet (frozen) weights		Randomly initialised weights		ImageNet (frozen)		Randomly initialised weights		ImageNet (frozen)	
	P	R	P	R	P	R	P	R	P	R	P	R	P	R	P	R
Classic CNN	85	98.8	N/A	N/A	80	99.8	N/A	N/A	91.5	40.8	N/A	N/A	90.5	85.8	N/A	N/A
VGG16	76.5	100	82.7	94	84.1	99.8	81.3	100	95.5	63.6	83.1	68.2	93.3	70.2	82.6	92.2
ResNet	83.6	99	85.7	1.2	80	100	0	0	91.1	76	100	3.4	90.8	57.2	0	0
XCeption	76.2	98.6	67	46.8	81	99.2	56.9	80.2	90	50.2	63	48.8	93	66.4	56.9	93.4
DenseNet	85.6	99	59.7	90.2	83.2	99	76.3	68.2	81.4	11.4	83.7	73.8	94.3	82	90.3	54.0
MobileNet V1	86.3	99.6	90	14.4	81.5	99.8	72	15.4	84.4	27.2	86.6	22	93.4	85.4	74.2	20.2
MobileNet V2	83.6	99.8	65	45.6	83.2	100	48.5	34.8	93.2	68.6	69.5	43.8	86.9	75.8	55.5	37.4

Method 2

Introduction of an anti-aliasing layer to increase shift-invariance. This takes the form of a convolution with a blurring filter, which effectively acts as a low-pass filter. This approach was explored on the Alex-Net-inspired CNN.



Anti-aliasing configurations for max pooling, strided convolution and average pooling[8].



Implementation of the anti-aliasing filter[8].

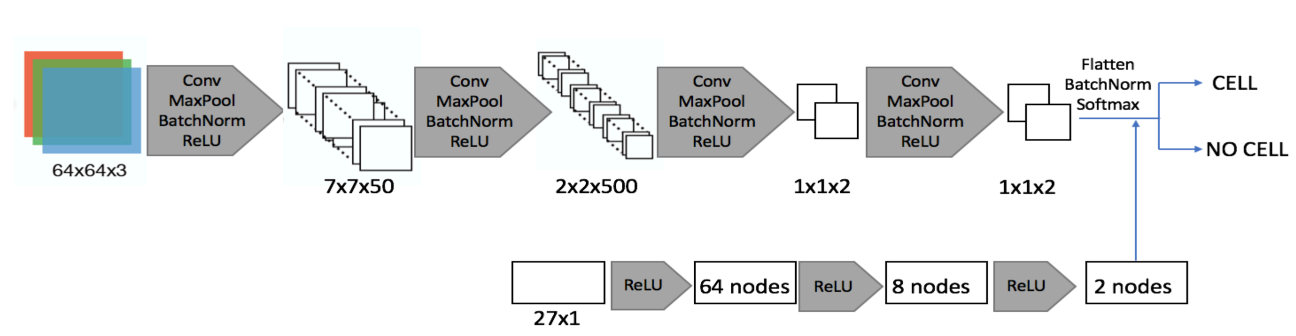
Results

	Filter number	With data augmentation		Without data augmentation	
		P	R	P	R
Dataset seen during training	1	86.83	97.6	80.1	99.8
	2	86.25	95.4	84.1	98.4
	3	83.84	95.4	80.8	98.4
Dataset unseen during training	1	93.4	39.6	91.6	58.8
	2	94.8	48	90.9	44
	3	94.9	48	85.7	44

Method 3

Extracted 9 statistical features related to pixel intensity for each 64x64 patch, for each individual channel.

Features: minimum, maximum, mean, standard deviation, median, 5th, 25th, 75th and 95th percentile values.



Architecture used to inject hand-crafted features

Results

	Architecture	With data augmentation		Without data augmentation	
		P	R	P	R
Dataset seen during training	Convnet	77.1	98.8	77.9	99.9
Dataset unseen during training		92.44	85.6	89.39	91.0

Conclusions

- Need to annotate more data and provide more comprehensive training and testing datasets.
- Need pre-trained weights on microscopy, not naturalistic, images.

References

Project Report

EPSRC

MRC Medical Research Council