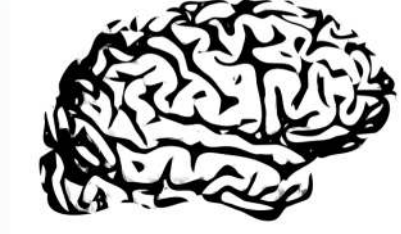


AxonDeepSeg: Automatic Myelin and Axon Segmentation Using Deep Learning

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Introduction

Background

Quantitative MRI techniques that can probe tissue microstructure, such as diffusion MRI (NODDI, AxCaliber)¹, magnetization transfer², and myelin water fraction imaging³ are under constant scrutiny when it comes to biological specificity (e.g., axon diameter, myelin density, g-ratio). Validation of these techniques can be done with histology statistics (e.g., axon diameter distribution).

Problem

Manually segmenting histology images is time consuming and prone to inconsistent labelling due to human error. Several axon/myelin segmentation tools have been proposed using conventional image processing techniques⁴, however they lack flexibility and are not fully automatic.

Solution

We propose a deep learning approach in order to overcome these limitations, and to offer the neuroscience community a free and open source alternative for segmenting myelin and axons in their histology slides: **AxonDeepSeg**. We also offer a graphical user interface (GUI) allowing for manual corrections if needed.

Material & Methods

Deep Learning Model

A U-net deep learning architecture⁵ was developed in Python with Keras. Data pre-processing steps involve resampling the images to a standard pixel size, and generating 512x512 patches. Data augmentations (e.g., rotations, shifting, scaling, etc.) were implemented using Albumentations⁶. Two models were trained using scanning and transmission electron microscopy (SEM and TEM) datasets, which consisted of rat spinal cords (SEM) and mouse brains (TEM), acquisition parameters are detailed in⁷. Ground truth data was manually segmented to identify three classes: myelin, axon, and background. Model training was performed on high performance NVIDIA P100 GPUs. Models were evaluated on testing data using the Dice coefficient.

Software & Data

The code and demo Jupyter Notebooks are available on GitHub (github.com/neuropoly/axondeepseg), whereas the datasets are hosted on OSF.io (osf.io/bj9eu/). Usage is described in our documentation website (axondeepseg.readthedocs.io).

User Interface

Both a command line interface (CLI) and graphical user interface (GUI) were developed. The CLI is useful for processing large datasets, whereas the GUI is useful for careful processing and manual correction of small datasets. The GUI was developed as a plugin for FSLeves⁸. Lastly, a post-processing step to generate axon-wise morphometric statistics is available through the GUI.



Results

Figure 1

- Rat spinal cord SEM histology slice (1541x1096 pixels).
- Ground truth mask (manual segmentation).
- Mask automatically segmented using **AxonDeepSeg**. Segmentation was completed in 28 seconds on a 2016 MacBook Pro. The pixelwise accuracy and dice coefficients were :
 - for axons : 0.942 and 0.904
 - for myelin : 0.858 and 0.810

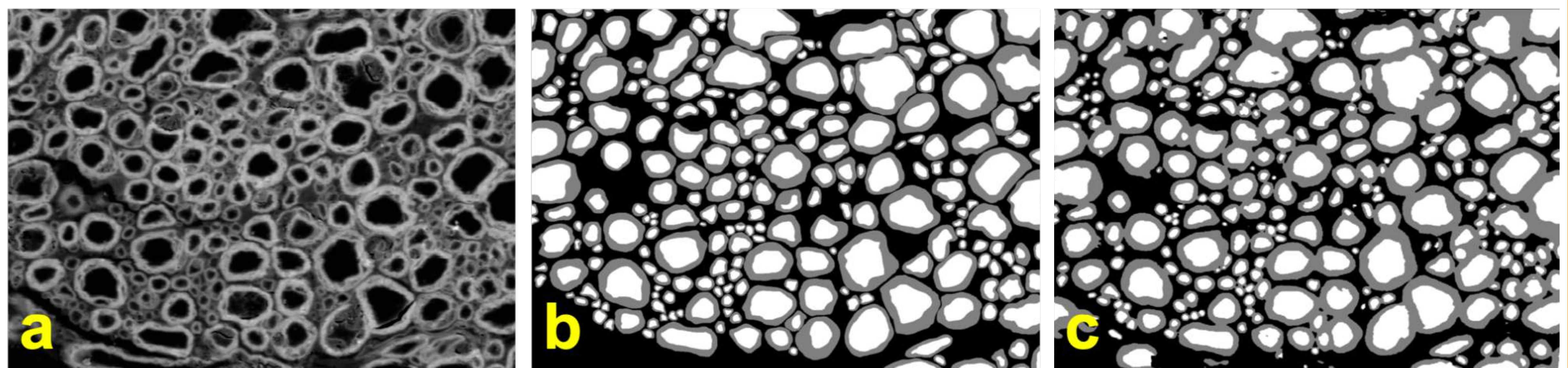
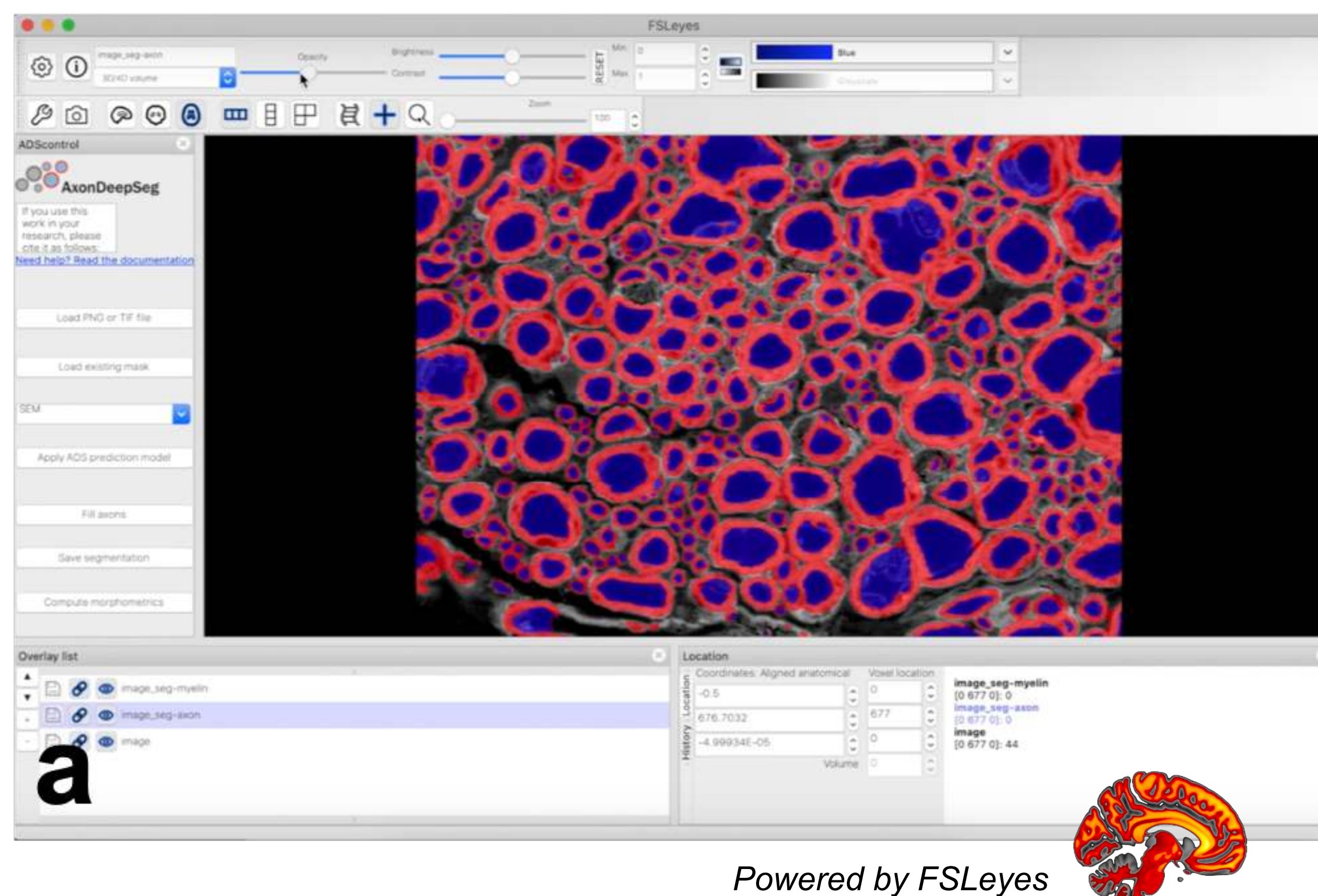


Figure 2

- The graphical user interface (GUI) of the **AxonDeepSeg** FSLeves plugin. The plugin lets you import an image, run and save an automatic segmentation, manually correct the mask, and generate a spreadsheet of morphometric data (b).
- Sample spreadsheet of morphometric statistics generated by **AxonDeepSeg**. The morphometrics data exported includes :
 - axon-wise position
 - g-ratio
 - axon and myelin area
 - axon diameter
 - myelin thickness
 - solidity
 - eccentricity
 - orientation



	x0	y0	ratio	axon_area	myelin_area	axon_diam	myelin_thickness	axomyelin_area	solidity	eccentricity	orientation
0	117.6772	5.045147	0.545633	2.170700779	5.120500088	1.462742484	0.692206065	7.291200161	0.9526889	0.975879	-0.02225
1	233.8	1.96	0.485443	0.122500002	0.396899999	0.394532717	0.209141761	0.515040001	0.89287	0.922948	-0.04024
2	375.3706	37.57217	0.696033	25.66620064	27.31259918	5.716574192	1.248253465	52.97880173	0.959516	0.611674	-0.9306
3	500.8148	2.648148	0.370681	0.264600009	1.66110003	0.58043015	0.492708504	1.925699949	0.981818	0.929507	0.033267
4	542.5499	16.23359	0.67834	3.733799934	4.380599976	2.180372	0.516952395	8.11439991	0.959698	0.553871	1.416795
5	692.3124	45.03473	0.786208	60.66660063	37.46009872	8.78887296	1.154965243	98.1470017	0.877762	0.847389	0.113108
6	886.1608	5.374449	0.463421	2.224600077	8.133999825	1.682988048	0.974337697	10.35859966	0.926531	0.975405	0.081434
7	1132.405	4.839694	0.52488	1.283800006	3.376100063	1.278508002	0.578650415	4.659900188	0.939068	0.938059	-0.02637
8	1195.224	32.09241	0.643695	0.172800064	12.96539974	3.41748023	0.945842266	22.13820076	0.899135	0.814282	1.187289
9	1241.232	18.27784	0.649097	4.356100082	5.982900143	2.355070829	0.636577547	10.33899975	0.888112	0.660514	1.113851
10	1492.607	38.64118	0.735971	33.19748832	28.0914996	6.50121868	1.16618824	61.28919981	0.9744	0.507607	0.292074
11	2587209	25.10465	0.387073	0.842800021	4.782400131	1.035898805	0.820167482	5.625197995	0.868887	0.994182	1.568881
12	171.2511	12.90411	0.486314	1.073099971	1.464299917	1.168894053	0.617343009	4.573799769	0.924051	0.584456	0.363959
13	578.4298	17.09649	0.473021	1.117200017	3.87590003	1.192670584	0.664360166	4.993100166	0.938272	0.395446	1.255569
14	1089.044	15.04412	0.449868	0.333200008	1.311399997	0.65133971	0.394253769	1.846399975	0.860759	0.639733	0.158418
15	442	14.5	0.460302	0.0098	2.485199976	0.111703835	0.870347381	2.654999933	1	1	-1.5708
16	53.4108	43.66354	0.571274	6.262199879	12.92619991	2.823699713	1.059558034	19.18840027	0.959459	0.739558	1.535839
17	1336.19	78.41296	0.677564	45.14860153	53.19440079	7.581885338	1.804014921	98.34300232	0.926682	0.33263	0.013915
18	508.9403	50.95378	0.611826	5.830999851	9.746100426	2.724740565	0.864359379	15.5770998	0.933333	0.706639	-0.9286
19	254.8316	70.58132	0.627301	14.40500003	22.4110031	4.284403559	1.273552385	36.67100034	0.96875	0.675581	1.195767
20	117.7533	74.78953	0.611581	13.94540024	23.53869934	4.213767052	1.338097811	37.28409958	0.951486	0.829887	1.118882
21	577.5735	49.67647	0.44141	0.999599993	4.130700111	1.128153443	0.713822007	5.130300045	0.914798	0.729914	1.063546
22	1011.908	95.57	0.732755	48.51490021	41.84109879	7.859458447	1.43321836	90.35600281	0.937683	0.898142	0.22049
23	1143.838	73.71772	0.549375	4.895100117	11.32390022	2.496524572	1.02388823	16.21899986	0.948718	0.754918	-0.65423
24	1232.409	45.96227	0.456196	0.779100001	2.96449995	0.995982409	0.593624532	3.743599892	0.932825	0.330458	1.30258
25	883.8148	70.55556	0.434091	0.526100016	3.888600015	1.058585406	0.707816124	4.914700031	0.908554	0.783582	-1.31522
26	330.0449	77.93932	0.501824	1.85710001	5.517399788	1.537703872	0.763263047	7.374499798	0.900238	0.631367	0.432354
27	832.6842	72.7807	0.692092	0.558600008	0.607599974	0.843345463	0.187599763	1.166200042	0.942149	0.723364	1.158321
28	426.028	145.8179	0.665276	35.13299942	44.24700165	6.688252926	1.682546377	79.37999725	0.90166	0.923901	0.825
29	49.87719	84.36842	0.348248	0.279300004	2.023699999	0.536335292	0.558026075	2.302999973	0.904762	0.792665	0.075929
30	335.747	96.98795	0.234839	0.406699985	6.967800014	0.719601631	0.172314167	7.374499798	0.922222	0.816779	-0.03174
31	763.3617	118.6522	0.647643	14.44029999	19.9871006	4.287885189	1.166432142	34.42739888	0.962129	0.804625	0.328171
32	842.562	104.994	0.629986	1.621899962	2.464699984	1.43703413	0.422011375	4.086599827	0.919444	0.819703	-0.52782
33	542.7125	132.2175	0.570721	3.425100088	7.093300083	2.088294268	0.78576251	10.51539993	0.94844	0.365485	-0.48878
34	180.6564	127.814	0.476217	0.875100136	20.03120041	2.735037551	1.50410831	25.90629959	0.851563	0.952738	0.789251
35	915.5625	103.5625	0.160644	0.078400001	0.959599972	0.315946162	0.825401425	3.038000107	0.761905	0.888143	1.110937
36	872.1622	108.6622	0.477907	0.362599999	1.225000024	0.679467916	0.371144921	1.587599993	0.891566	0.576324	-1.37873
37	296.5764	117.8056	0.368057	0.705600023	4.503999918	0.947838485	0.813706756	5.208700018	0.947368	0.64036	1.443176
38	1234.928	123.9284	0.589901	3.763200045	7.051099777	2.188939333	0.760873616	10.81429958	0.917563	0.872621	-0.05408

Powered by FSLeves

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Conclusion

- AxonDeepSeg**⁷ is a fast, accurate, and open-source tool to automatically segment axon and myelin in histology images.
- The **AxonDeepSeg** FSLeves plugin provides a GUI that makes it easy to use and lets you do manual corrections when necessary.
- Future work will focus on implementing active learning⁹ to improve the efficiency and performance of deep learning models using scarce data, an important limitation when considering biomedical images.

