

An application of neural networks to identifying cellular bone growth processes

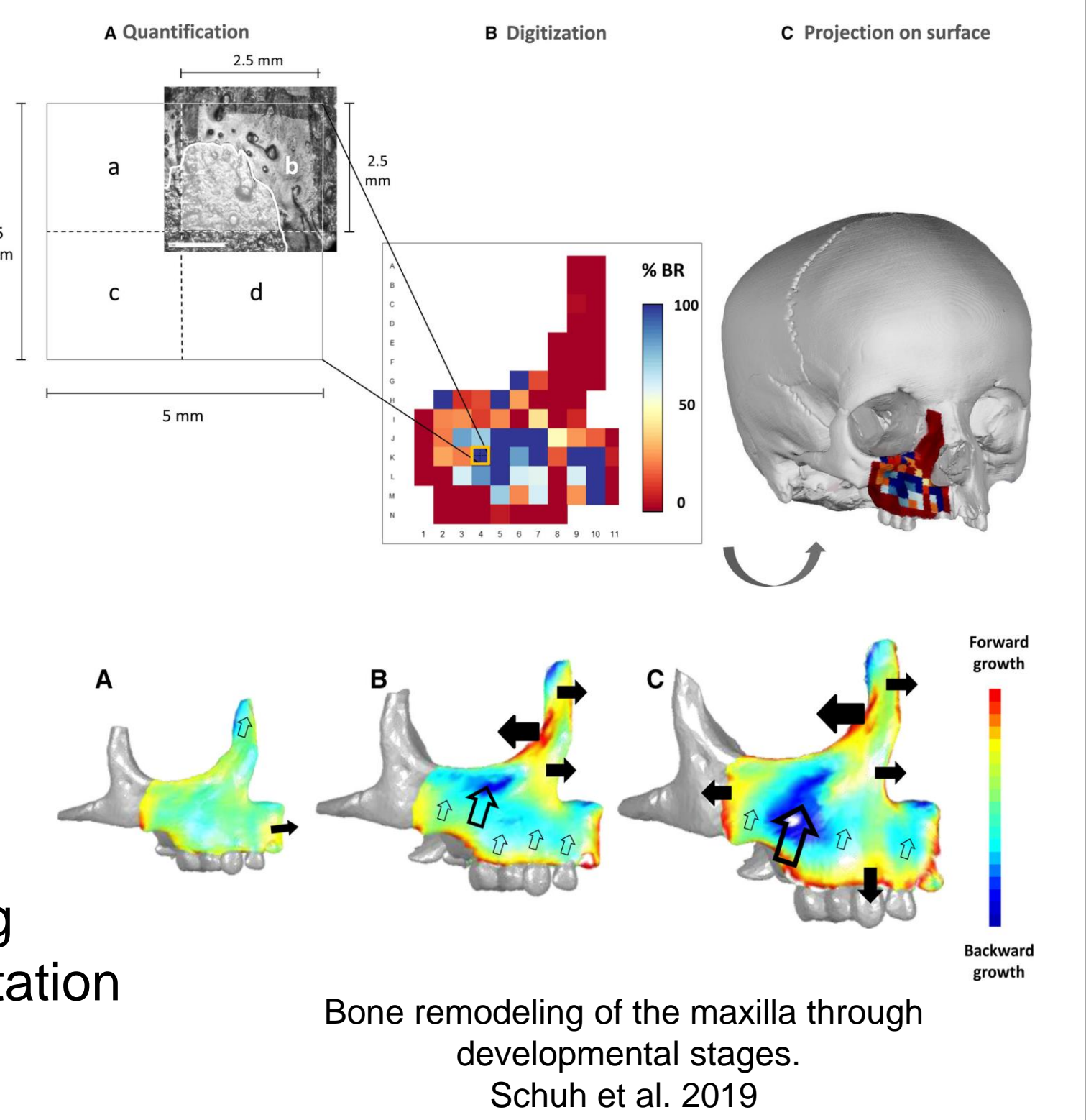
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The Problem

Quantifying bone remodeling manually is a time consuming and tedious process: 1) photo micrographs of a gridded area are recorded (normally with a confocal microscope), 2) these images are segmented into zones of bone formation and resorption, 3) the proportion of bone resorption is calculated, and 4) this proportion is mapped across the area of study.

We wondered if machine learning could fully automate the segmentation step of this process.



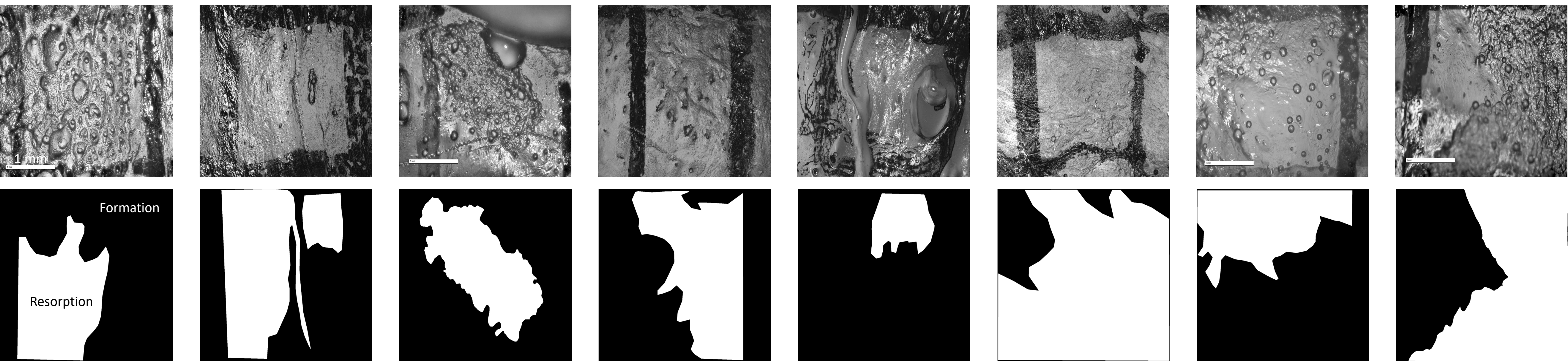
Conclusions

We tried three neural network models. Two were U-Net architectures. One was trained on the grey-scaled images and the other on three derived textures. Both models learned the training data well, but failed to generalize well to the test data. In the third try, we trained a YOLOv8 model on our images. This model performed overall better than the U-Net models on the test data, but also completely failed more often.

What's next?

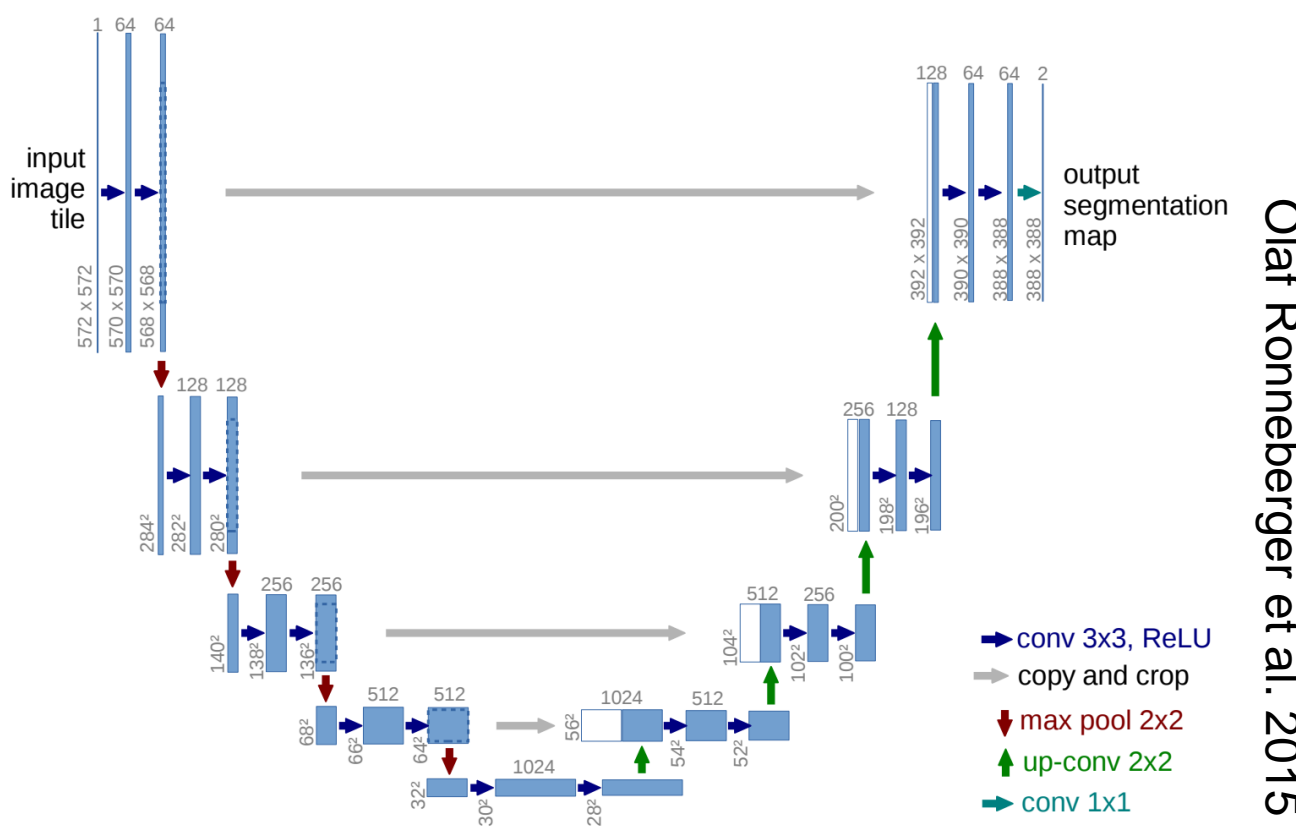
Machine learning may require modifying the initial work flow. One critical decision in our study was to use the images and manual segmentations from Schuh et al. (2019) without modification. However, this may not be ideal for machine learning. Thus, we are currently working with segmentation software based on the Segmenting Anything Model to re-segment our training images and in doing so to better understand which cases these otherwise highly performant models struggle to properly segment.

Example Images and Segmentation Data



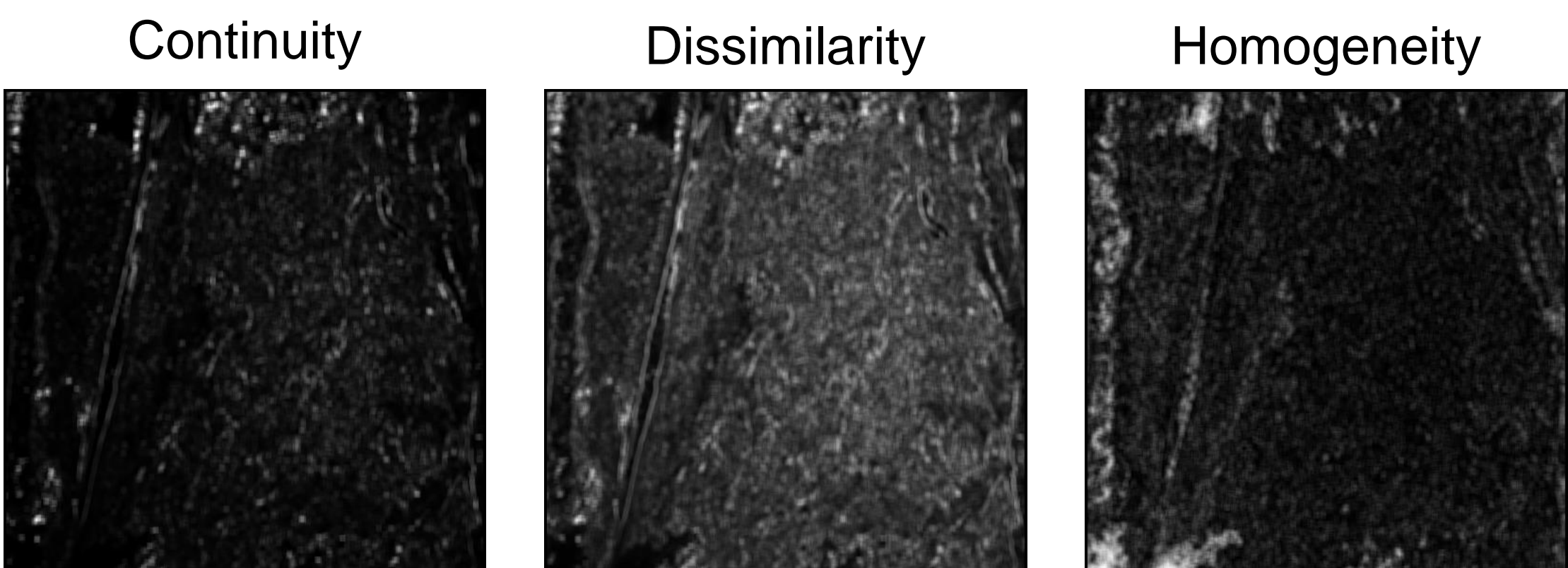
Model 1

- U-Net neural network architecture
- 256 x 256 input image resolution
- Adam, Binary-Crossentropy, MCC
- Trained on 142 gray-scale images
- Validated on 48 images
- Tested on 48 images



Model 2

Because texture differences are key to distinguishing bone formation from resorption, we trained a U-Net model using three texture layers. Textures are computed by quantifying differences in grey-scale pixel intensities within a sampling window. Haralick et al. (1973) initially described 13 such measures. We used three of these that showed some sensitivity to our texture differences.



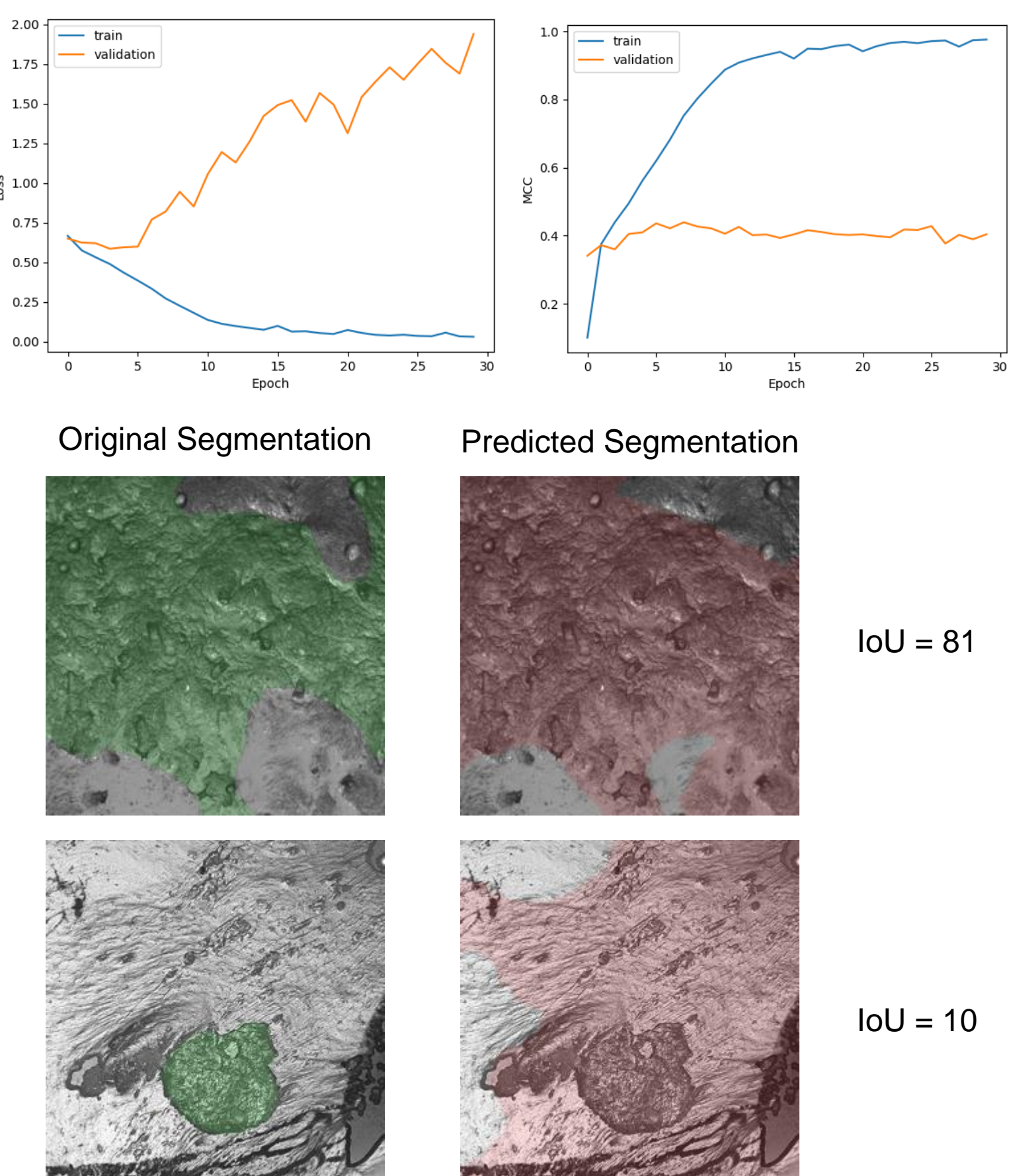
Model 3

An alternative approach is to use an existing, highly trained, highly performant model which is then additionally trained on a specialized data set. We used YOLOv8 (You Only Look Once version 8). This model is tuned to real-time image labeling but also does segmentation.

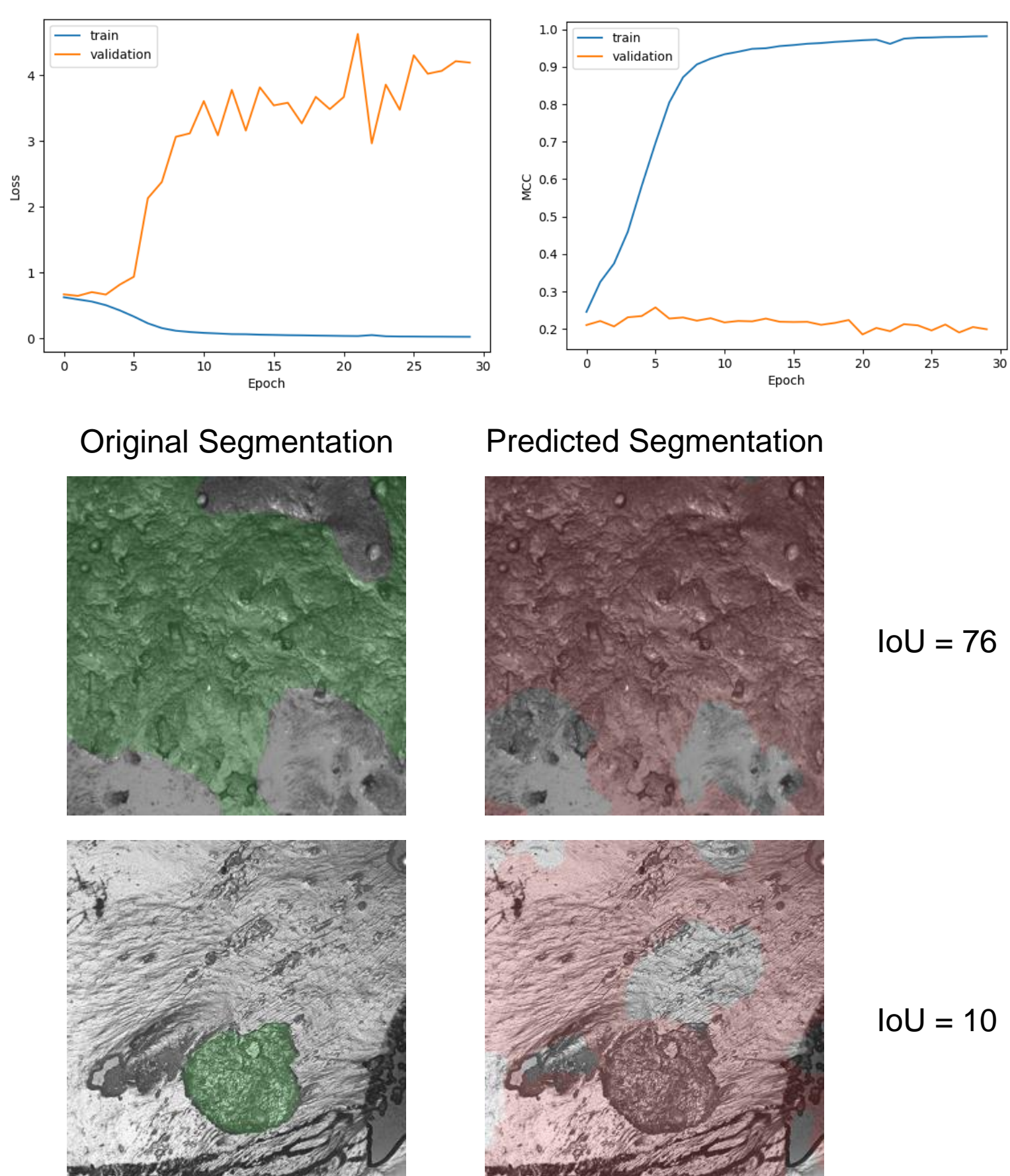
- YOLOv8
- 640 x 640 input image resolution
- Same training, validation, and test data set



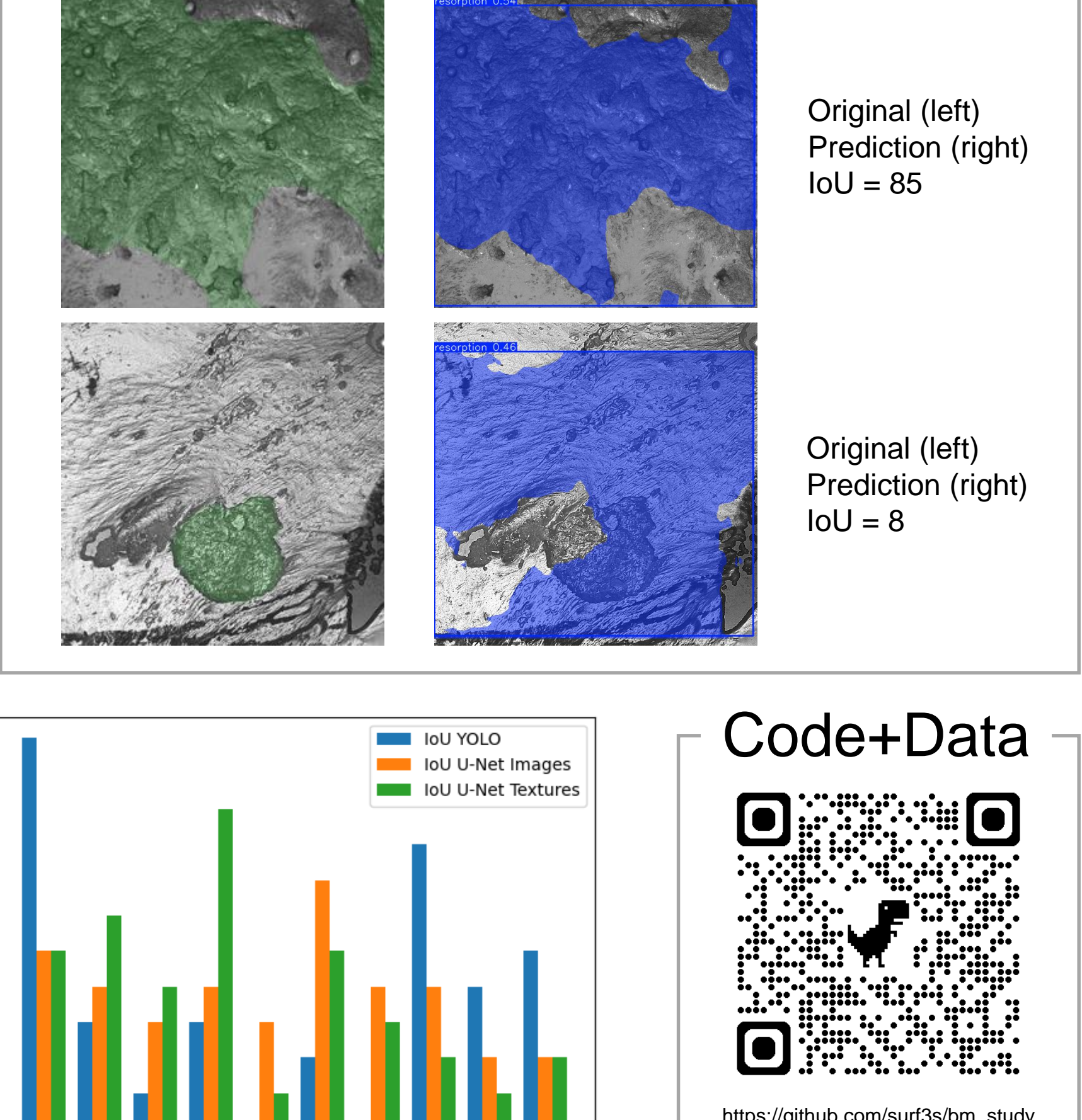
Results – Model 1



Results – Model 2



Results – Model 3



We would like to thank the Max Planck Society and Tracy Kivell for supporting our work. We would also like to thank the European Society for the study of Human Evolution and the local organizers for hosting this meeting.

Robert M. Haralick, K. Shanmugam, and Its'hak Dinstein, "Textural Features for Image Classification", IEEE Transactions on Systems, Man, and Cybernetics, 1973, SMC-3 (6): 610–621.
Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5–9, 2015, proceedings, part III 18. Springer International Publishing, 2015.
Schuh, Alexandra, et al. "Ontogeny of the human maxilla: A study of intra-population variability combining surface bone histology and geometric morphometrics." *Journal of Anatomy* 235.2 (2019): 233–245.
<https://docs.ultralytics.com/>