Bone & Joint Open

# Supplementary Material

**Supplementary file 1.** Methods and results.

## Methods

All deep learning models were trained on a NVIDIA Telsa K80 GPU with 12 gigabytes of RAM. Given the memory size limitation, images were cropped into six separate segments with sizes of 512 pixels in width and 1024 pixels in height, and batch size was set to 2. A U-Net, a type of convolutional neural network, was trained using transfer learning to automatically segment relevant landmarks for femoral mechanical-anatomical axis angle calculations.[1] We used ResNet-34 as the base architecture for the U-Net.[2] The model was trained for 100 cycles and optimized on the dice coefficient, which assess the spatial overlap between the predicted segments and ground truth segments (0.0 indicating no overlapping and 1.0 indicating complete overlap).[3,4] Image training size was chosen based on studies employing segmentation for measurement automation related to orthopedic imaging.[5] Images were split in an 8:2 ratio for training and validation. Augmentation using image rotation, image flipping, image zoom, and image wrapping was utilized during each cycle of training to introduce variability in training data. After model creation, an additional image processing algorithm was created to combine segment predictions on new images and generate relevant measurements.

## Results

The optimized model had a multi-class dice segmentation coefficient of 0.84 after 100 cycles of training.

## References

1. **Ronneberger O, Fischer P, Brox T, editors.** *U-Net: Convolutional Networks for Biomedical Image Segmentation*. 2015; Cham: Springer International Publishing.

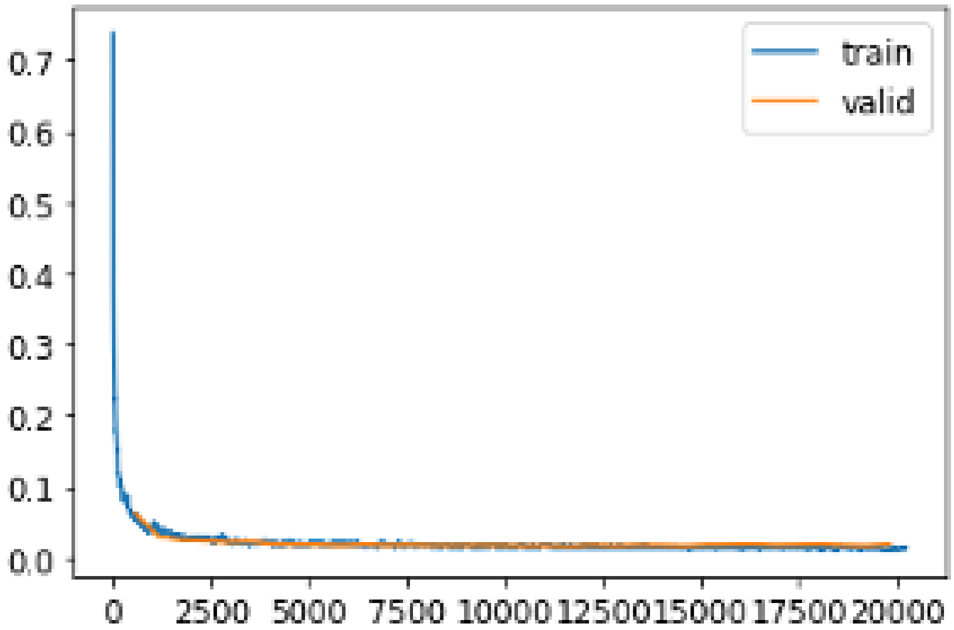
2. **Houserman DJ, Berend KR, Lombardi AV, Duhaime EP, Jain A, Crawford DA.** The viability of an artificial intelligence/machine learning prediction model to determine candidates for knee arthroplasty. *J Arthroplasty*. 2023;38(10):2075-2080.

3. **Rouzrokh P, Wyles CC, Philbrick KA, et al.** A deep learning tool for automated radiographic measurement of acetabular component inclination and version after total hip arthroplasty. *J Arthroplasty*. 2021;36(7):2510-7 e6.

4. **Zou KH, Warfield SK, Bharatha A, et al.** Statistical validation of image segmentation quality based on a spatial overlap index. *Acad Radiol.* 2004;11(2):178-189.

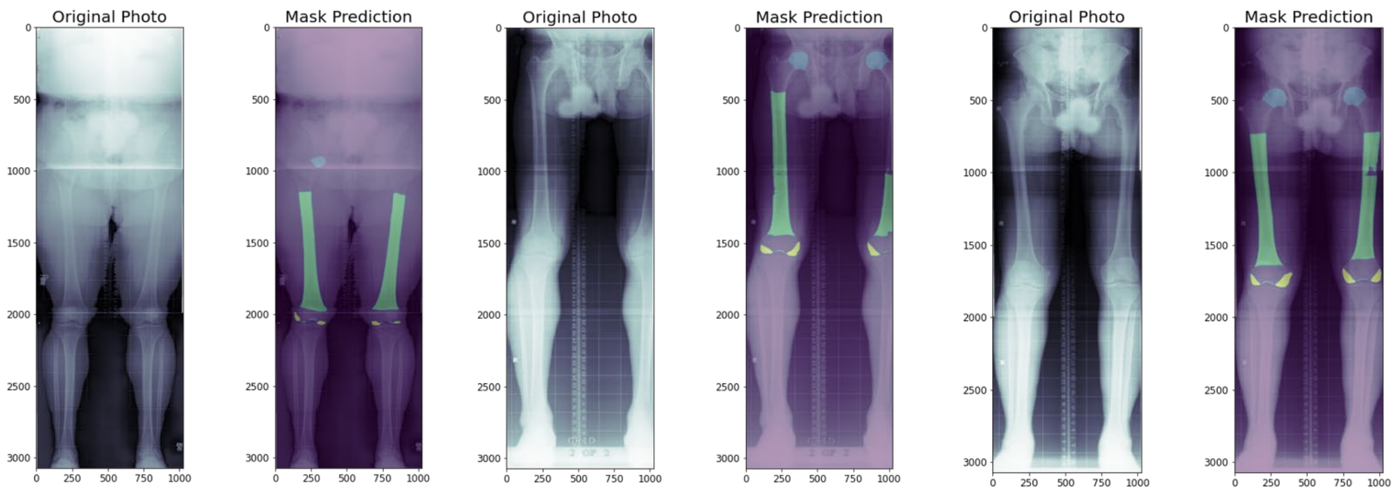
5. **Zheng Q, Shellikeri S, Huang H, Hwang M, Sze RW.** Deep learning measurement of leg length discrepancy in children based on radiographs. *Radiology*. 2020;296(1):152-158.

**Fig a.** Deep learning algorithm training.




*Y axis = loss, X axis = epochs.*

**Fig b.** Excluded images for final analysis.




*Left = wrong femoral head prediction; middle = cropped image; right = wrong femoral diaphysis prediction.*