# Morphological Characterization of Median Nerve and Transverse Carpal Ligament from Ultrasound Images using a Convolutional Neural Network

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INTRODUCTION: Ultrasound is a safe and inexpensive imaging modality that has previously been used as a diagnostic tool for carpal tunnel syndrome. Median nerve cross-sectional area is the primary measurement used for diagnosing carpal tunnel syndrome (CTS), but CTS has also been associated with parameters relevant to the transverse carpal ligament (TCL), such as TCL thickness and carpal arch height. Because image analysis can be time-consuming and subjective, convolutional neural networks (CNNs) have become increasingly popular for image detection and segmentation tasks. Successful implementation of a CNN for segmentation of the median nerve and TCL from ultrasound images could provide an objective and time-efficient method for ultrasound assessment of the carpal tunnel. Use of this method for comparison of carpal tunnel morphology between healthy subjects and CTS patients could provide more insight into the morphological effects of carpal tunnel syndrome. The purposes of this study were to 1) automatically segment the transverse carpal ligament and median nerve from B-mode ultrasound images using a CNN, 2) calculate median nerve cross-sectional area (CSA), median nerve circularity, carpal arch width, carpal arch height, carpal arch area, TCL thickness, and distance between the TCL and median nerve centroid using the CNN predictions, and 3) compare carpal tunnel morphological parameters between carpal tunnel syndrome patients and healthy adults.

METHODS: Ninety five healthy young adults were recruited for this study. Each subject's right hand was splinted with their wrist in a neutral position and their thumb radially abducted, and one ultrasound image of the distal carpal tunnel was collected. Ten additional ultrasound images of the distal carpal tunnel collected on patients diagnosed with CTS by a licensed physician were obtained from a previous study. Binary segmentation maps of the median nerve and transverse carpal ligament were manually drawn using GIMP. The 10 images of CTS patients and 10 images of healthy subjects that age- and gender-matched the CTS patients were reserved for testing, 10 other images were randomly selected for validation, and the remaining images were used for training. Augmented versions of the training images were generated by applying random cropping, scaling, and adjustments of brightness and contrast, doubling the size of the training dataset. All images were resized to 256x512 pixels using bilinear interpolation and pixel grayscale values were normalized to values between -1 and +1. A CNN consisting of convolution, maxpooling, dropout, upsampling, and concatenation layers was implemented using LabVIEW NI-Vision (National Instruments, Austin, TX) and Toolkit DeepLTK (Yerevan, Armenia). For training, an initial learning rate of 0.008 with a decay of 0.5 every 10 epochs was applied, and binary cross-entropy loss was used for loss evaluation. Training was performed separately for TCL and median nerve segmentation, resulting in two separate models with unique weights. Each model was trained for 100 epochs, and the weights resulting in the minimum validation loss were saved to the model. Predictions for TCL and median nerve segmentation were generated by feeding the test dataset through the network, and performance was evaluated using Dice Score Coefficient (DSC), Intersection-Over-Union, Recall, and Precision. Median nerve cross-sectional area, median nerve circularity, carpal arch width, carpal arch height, carpal arch area, TCL thickness, and distance between the median nerve centroid and TCL were measured using both manual and predicted segmentation maps. Mean absolute error of the predicted measurements was calculated, and agreement between the predicted and manual measurements was assessed using the intra-class correlation coefficient. Morphological parameter measurements and performance evaluation parameters were compared between the CTS patients and healthy subjects using Wilcoxon signed-rank test.

RESULTS: The manual segmentation and predicted segmentation of one test image is shown in Figure 1. The model trained for median nerve segmentation achieved a higher DSC ($p = 0.01$) when performing on healthy subjects than on CTS subjects. The model trained for TCL segmentation achieved a higher DSC ($p < 0.01$), recall ($p = 0.02$), and precision ($p = 0.01$) when performing on healthy subjects than on CTS subjects. For median nerve segmentation, the DSC, Recall, and Precision for healthy subjects were $0.89 \pm 0.81$, $0.94 \pm 0.04$, and $0.86 \pm 0.08$, respectively, and for CTS subjects were $0.81 \pm 0.08$, $0.86 \pm 0.10$, and $0.77 \pm 0.11$, respectively. For TCL segmentation, the DSC, Recall, and Precision for healthy subjects were $0.87 \pm 0.03$, $0.88 \pm 0.04$, and $0.87 \pm 0.05$, respectively, and for CTS subjects were $0.77 \pm 0.10$, $0.77 \pm 0.12$, and $0.77 \pm 0.09$, respectively. Median nerve CSA was significantly larger in the CTS group than the healthy group ($p = 0.01$). No difference was found between the two groups in median nerve circularity, CAW, CAH, CAA, thickness, or distance between the median nerve centroid and TCL. Agreement between the predicted and manual masks was excellent for calculations of median nerve CSA (ICC = 0.91), CAW (ICC = 0.95), and CAA (ICC = 0.90), good for calculations of median nerve circularity (ICC = 0.87), CAH (ICC = 0.88), and distance between the TCL and median nerve centroid (ICC = 0.84), and moderate for calculations of thickness (ICC = 0.70).

DISCUSSION: This study implemented a CNN for automatic segmentation of the median nerve and TCL at the distal end of the carpal tunnel. Our model trained for median nerve segmentation performed with excellent accuracy in healthy and CTS subjects, and our model trained for TCL segmentation performed with excellent accuracy in healthy subjects and acceptable accuracy in CTS subjects. More error occurred when segmenting the CTS images, most likely due to the models being trained using healthy images, and the CTS images containing more anatomical variants, such as increased median nerve echogenicity. To assess the clinical potential of our models, we used the network predictions to measure morphological parameters relevant to carpal tunnel syndrome. We found that median nerve CSA was significantly larger in CTS subjects than healthy subjects, and no significant difference was found in median nerve circularity, CAW, CAH, CAA, TCL thickness, or distance between the median nerve centroid and TCL. The morphological parameters measured from the predictions agreed with those manually measured, demonstrating the models' potential for reliable quantification of carpal tunnel anatomy. Future studies should further develop these models by increasing the size and variation of the dataset to include more pathological images, and include a larger sample size of CTS subjects for more robust comparison of healthy and CTS subjects.

SIGNIFICANCE/CLINICAL RELEVANCE: CNNs provide accurate and automatic assessment of carpal tunnel anatomy from ultrasound images, which could aid in the diagnosis of carpal tunnel syndrome.

**Figure 1.** Manual (upper) and predicted (lower) segmentation of one test image