Sciatic Nerve Segmentation in MR Images of the Upper Leg via Convolutional Neural Networks

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INTRODUCTION

- Charcot-Marie-Tooth (CMT) diseases [1,2] are a heterogeneous group of inherited neuropathies (1:2,500) characterized by muscle atrophy and length-dependent motor/sensory impairment
  - Autosomal-dominant CMT1A (duplication of PMP22 gene, 50% of CMT cases) affects peripheral nerves with highly variable degree of observed disability amongst affected population
- CMT Neuropathy Score (CMTNS) is current outcome measure
  - Nerve conduction studies + scored clinical assessment
  - PROS: reproducible, relates to impairment
  - CONS: floor/ceiling effects, requires expertly trained rater
  - Slow annual progression rate in CMT1A clinical trial [3,4]
- Sciatic nerve (SN) hypertrophy may serve as a novel CMT1A biomarker[1]
  - Longest and widest nerve in human body extending through the pelvis to the lower leg
  - PROS: Can be readily measured from standard MRI sequences, sciatic nerve diameter relates to impairment (Fig. 1) [5]
  - CONS: Expert raters required to properly segment nerve, and inconsistencies occur between various raters effects
  - **Convolutional Neural Networks (CNN) such as the "U-Net"[6] have recently shown promise in a number of biomedical image segmentation applications**

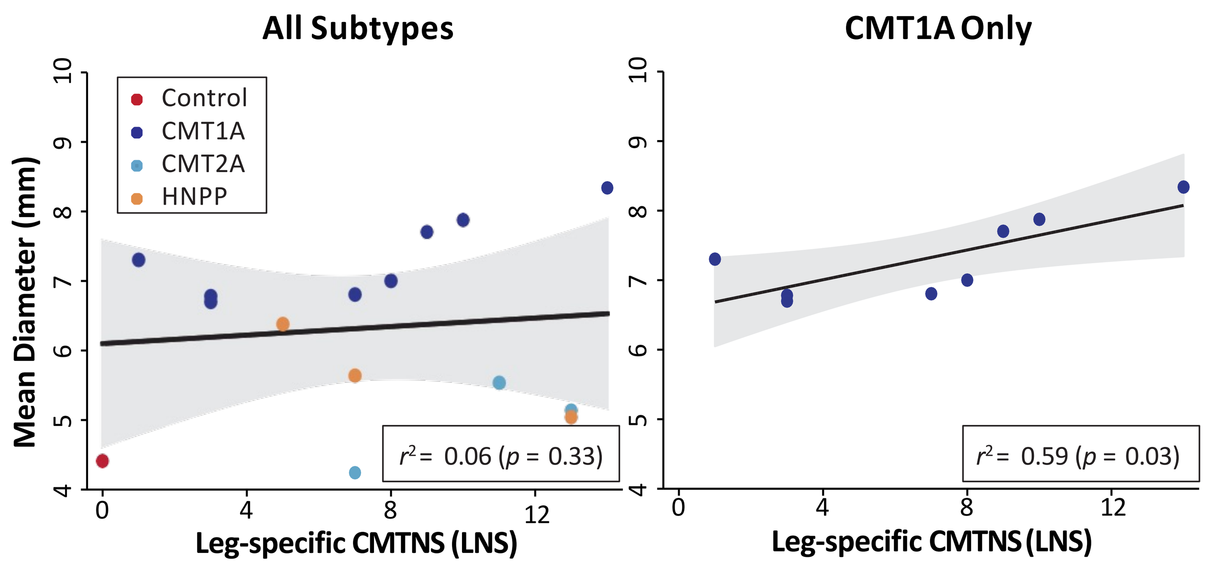

Fig. 1. Sciatic nerve diameters versus impairment for all subtypes (left) and CMT1A only (right). The relationship between nerve diameter and impairment is unique to CMT1A.

Goal: Develop a algorithm that automatically and accuaracty performs peripheral nerve segmentation in computationally challenging 3D MR volumes

MRI ACQUISITION

- Ø 3.0-T PhilipsAchieva
- Ø MRI performed in one thigh (see Figs. 2 and 3).
- 3D, T_1-weigthed multishot-EPI
  - PROSET fat suppression
  - F-H coverage = 144 mm
  - TR/TE = 60/11 ms
  - Scan Time = 3 min
- Sciatic nerve manually labelled by several expert raters in 3D MRI acquisitions (256x256x40 matrices) from 72 subjects: 34 cases (CMT), 38 controls

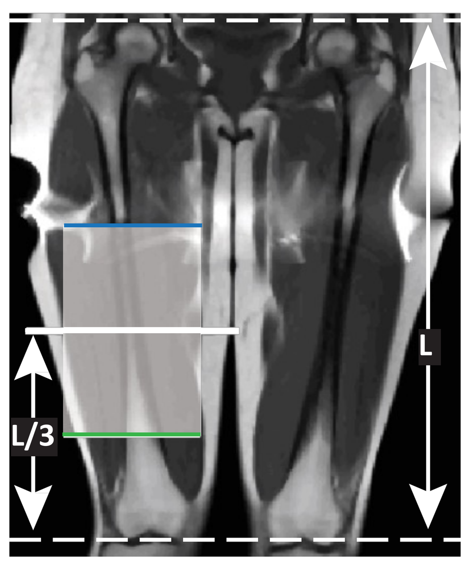

Fig. 2. MRI volumes centered 1/3 femur length (L) from lower extremity.

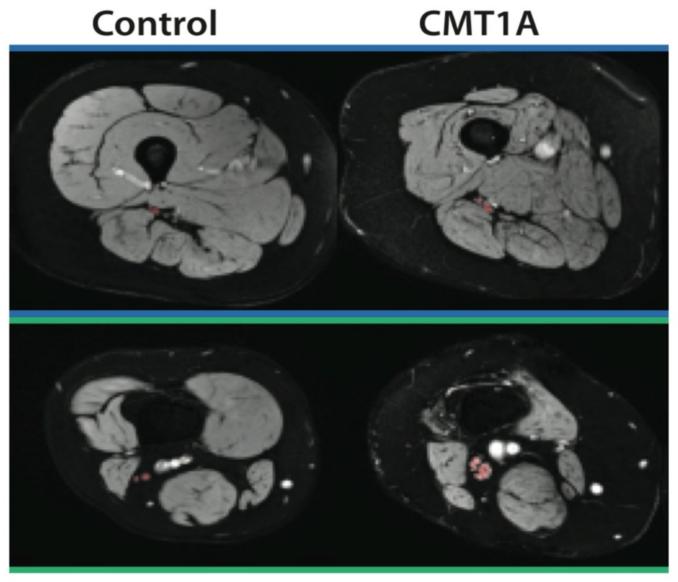

Fig. 3. MRI in proximal/distal (top/bottom) slices in both control and CMT1A patients. Expert rated SN region of interest (ROI) is highlighted (red).

SEGMENTATION ALGORITHM

- Convolutional Neural Networks (CNNs)[7] are a class of multi-layer feedforward deep learning artificial neural networks heavily utilized in image processing characterized by trainable shared-weight convolutional filters allowing for learned feature identification

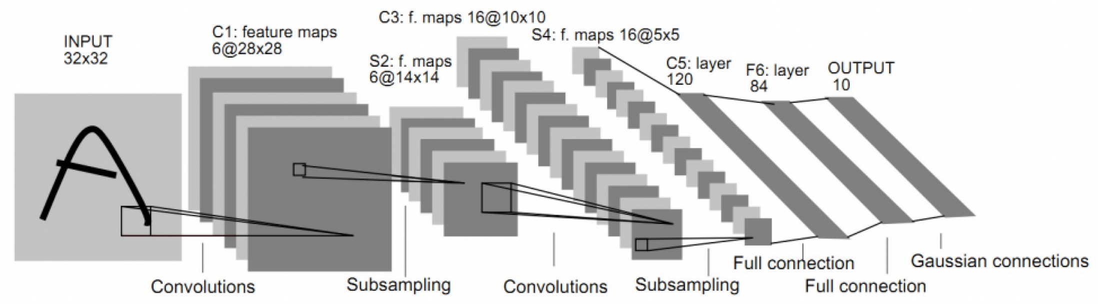

Fig. 4: Convolutional Neural Network Architecture (LeNet-5) consisting of convolutional, pooling, and fully connected hidden layers proposed in Lecun et al.

- 3D convolutional filters[6] allow for 3D volume traversal generating spatial feature activation maps important for capture of peripheral nerve spatial variance
- Images were fed into custom implemented U-Net[6] 3DCNN architecture implemented in Python 2.7 using Keras 2.0 API (Google TensorFlow 1.0 backend) utilizing 3x3x3 convolutions and 2x2x2 pooling operations
  - Stochastic Gradient Descent (SGD) loss function used to fit shared 3D convolutional filter and network weights with learning rate/Momentum of 0.0001/0.99
  - Training set partitioned as 80% of cohort (58 patients)
  - Training occurred over 5000 training epochs with batch size set to 5
  - Slight on-the-fly elastic deformations applied to training volumes to generate new training data unseen by the network
  - 48x48x40 windows were cropped around the SN to reduce model convergence time

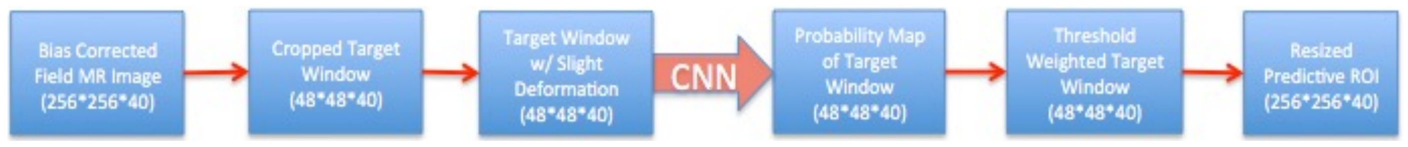

Fig. 5: Representation of data pipeline. Prior to the CNN, bias corrected MRI is cropped to 48x48 window around the SN, then augmented with nonlinear elastic transformation. User defined batches are fed into the CNN producing a matrix containing voxel probabilities, then tresholded to produce the ROI and resized to the original input.

- 4 CNN networks[6] were tested for SN segmentation capabilities :
  - 2D U-Net with data augmentation (via nonlinear elastic transforms to minimize network overfitting),
  - 3D U-Net with data augmentation
  - 3D U-Net with data augmentation and batch normalization[8] (minimizes internal covariance shift)
  - 3D U-Net without data augmentation or batch normalization

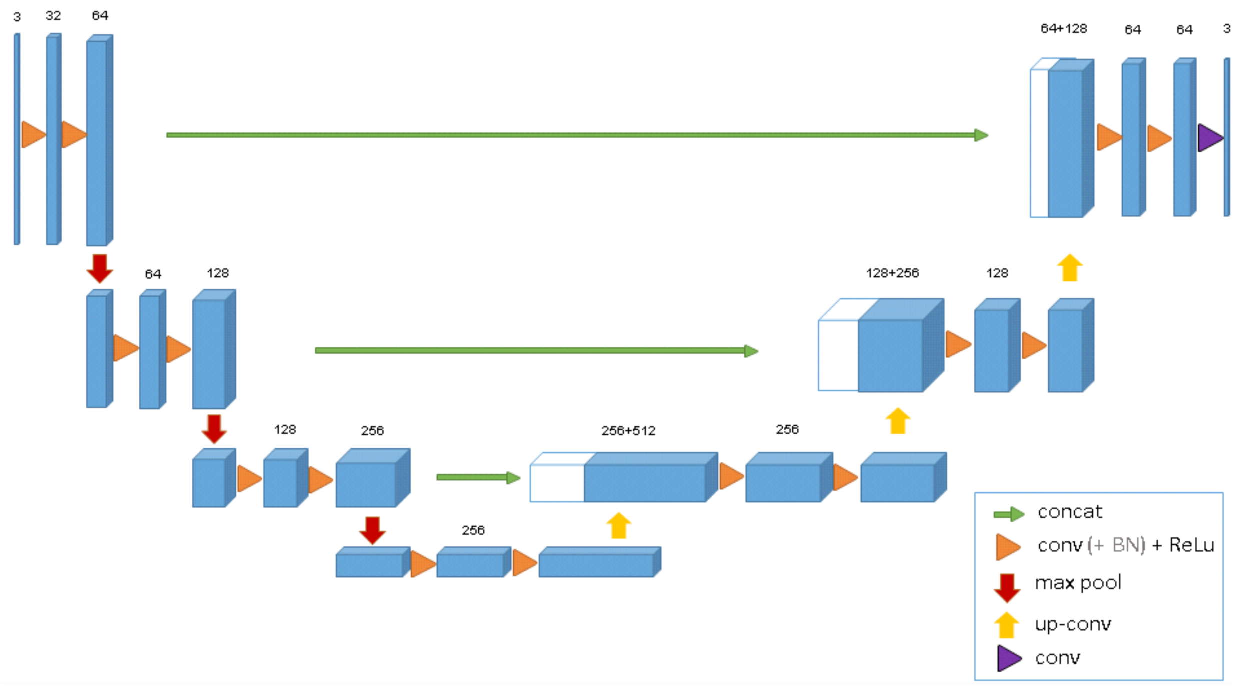

Fig. 5. 3D U-net architecture as implemented in Cicek et al. [2]. Downsampling path followed by upsampling generating an output equal in dimension to the input generating sciatic nerve probabilities for each voxel. Number corresponds to number of 3D activation maps.

- Training took ~120 hours on a Nvidia Titan X GPU on Vanderbilt's Advanced Computing Center for Research and Education (ACCRE) GPU cluster

RESULTS

- Seg. accuracy determined by binary label Dice Similarity Score (DSC):

$$DSC = \frac{2TP}{2TP + FP + FN}$$

where true positives (TP) are correct CNN-predicted SN voxels in reference to the manually expert-defined SN.

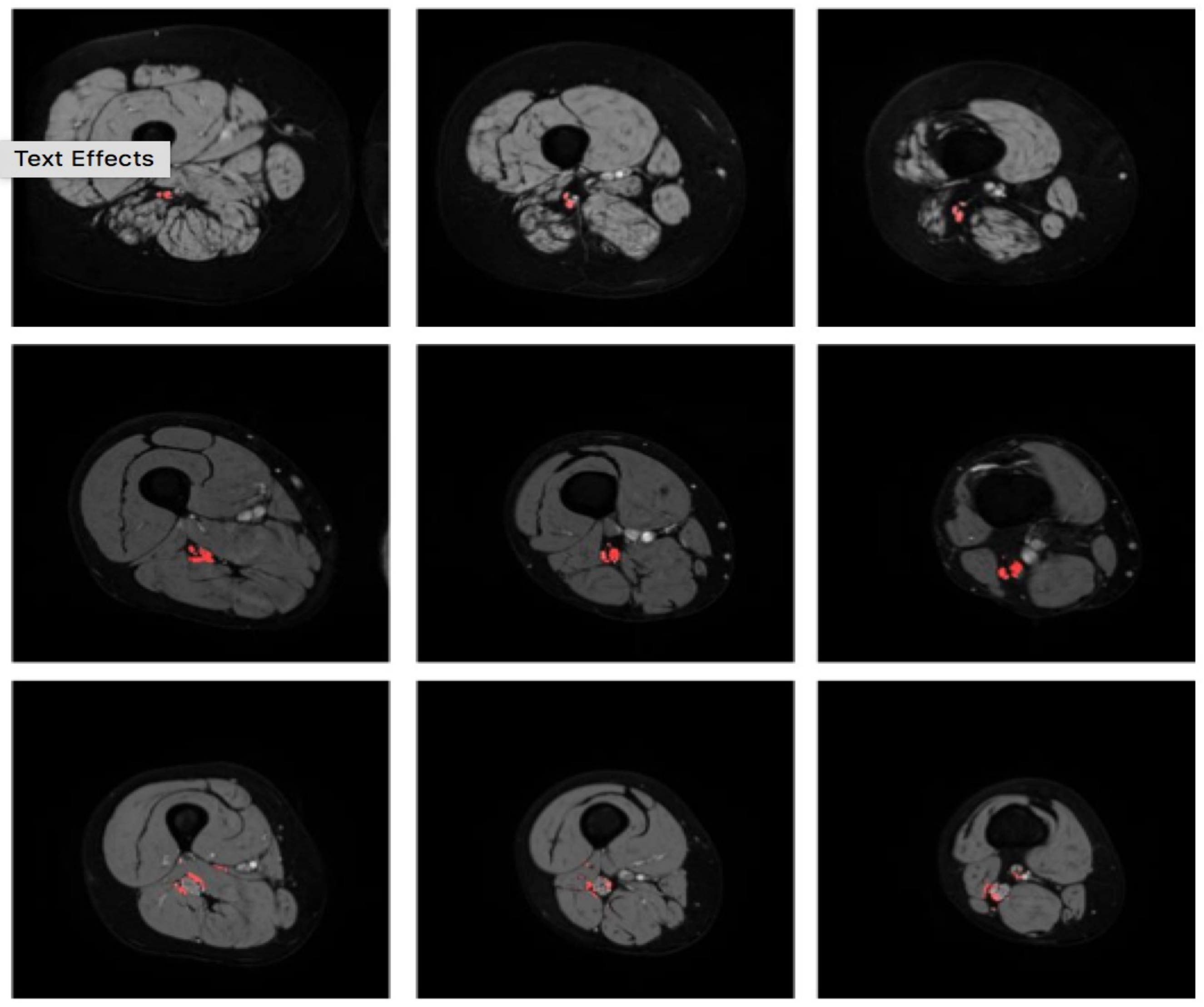

Fig. 6: Proximal, medial, and distal slices of batch normalizing 3d CNN generated SN ROIs over MRI from CMT1A patients. Top row: dice-coefficient = .973. Middle row: dice-coefficient = .874. Bottom row: dice-coefficient = .184.

Overall Automated Segmentation

	Net 1		Net 2		Net 3		Net 4	
	DC	No. Failures	DC	No. Failures	DC	No. Failures	DC	No. Failures
Trial 1	0.712	2	0.762	1	0.801	1	0.511	8
Trial 2	0.758	2	0.824	0	0.854	0	0.489	7
Trial 3	0.747	1	0.815	0	0.836	0	0.558	4
Average	0.739	1.67	0.800	0.33	0.830	0.33	0.519	6.33

CMT Patients Automated Segmentation

	Net 1		Net 2		Net 3		Net 4	
	DC	No. Failures	DC	No. Failures	DC	No. Failures	DC	No. Failures
Trial 1	0.682	2	0.743	1	0.783	1	0.532	5
Trial 2	0.740	2	0.838	0	0.850	0	0.449	6
Trial 3	0.670	1	0.830	0	0.848	0	0.581	2
Average	0.697	1.67	0.804	0.33	0.827	0.33	0.521	4.33

Figure Legend

Net 1	2D CNN w/ Non Linear Data Augmentation
Net 2	3D CNN w/ Non Linear Data Augmentation
Net 3	3D CNN w/ Batch Normalization and Non Linear Data Augmentation
Net 4	3D CNN w/o Non Linear Data Data Augmentation

CONCLUSIONS

- The CNN-based segmentation algorithm provided an accurate and objective method of segmenting the sciatic nerve from the MR images in many cases; however, further refinement may be required for a acceptable segmentation in all cases
- The improvement in dice coefficient in networks employing on-the-fly non linear elastic deformations also demonstrates the necessity for generating unseen, but structurally similar MR images while training the network to prevent it from becoming dependent on the precise structures of the limited training data set and thus unable to correctly classify the unseen testing MR images.
- Dice score demonstrates capabilities of CNN-based algorithm to perform peripheral nerve segmentation despite variable truth voxels
- Further work includes:
  - Automate SN image-cropping to create end-to-end autonomous analysis of MRI acquisitions
  - Analyze capability of CNN model to autonomously predict CMTNS for expected CMT patient debilitation prognosis

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