Detection of Spinal Ultrasound Landmarks Using Convolutional Neural Networks

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Purpose: Scoliosis, an excessive curvature of the spine, affects approximately 1 in 1,000 individuals. Scoliosis is usually discovered in adolescents and it progresses until the spine reaches full development. Bracing decreases the progression of high-risk curves and significantly reduces the probability of needing surgery. For bracing to be effective, early referral is critical, but it requires systematic screening, which is currently prevented by the lack of a safe spinal curvature measurement method. Scoliosis is more prevalent among girls, and because the most common spinal measurement method is x-rays, developing girls are exposed to high levels of radiation. Ultrasound is a method that can alleviate this potentially harmful radiation exposure.

Spinal curvatures can be accurately computed from the location of spinal transverse processes, by measuring the vertebral angle from a reference line [1]. A scoliosis measurement system based portable ultrasound may enable wide-scale deployment for scoliosis screening. A major practical difficulty is that ultrasound scanning of the spine requires considerable practice. The acquisition of image frames that contain transverse processes is a difficult skill. In order to aid the sonographer in the scanning process, we should automatically detect the presence (or absence) of transverse processes in the ultrasound frames and provide feedback to the sonographer. Convolutional neural networks have emerged as a powerful tool for computer vision and image classification [2]. We present a method using a deep convolutional neural network for the detection of spinal transverse processes in ultrasound.

Methods: A total of 2,752 ultrasound images were recorded from a spine phantom to train a convolutional neural network. Subsequently, another recording of 747 images was taken to be used as testing images. In total, there were 2,037 images used for training, 715 used for validation, and 747 used for testing. All the ultrasound images from the scans were then segmented manually, using the open source 3D Slicer (www.slicer.org) software. Next, we fed the images through a convolutional neural network, created based on a modified version of the Inception v1 (GoogLeNet) deep convolutional neural network. The Inception network was chosen because it promised to provide a balance between accurate performance and time-efficient computation.

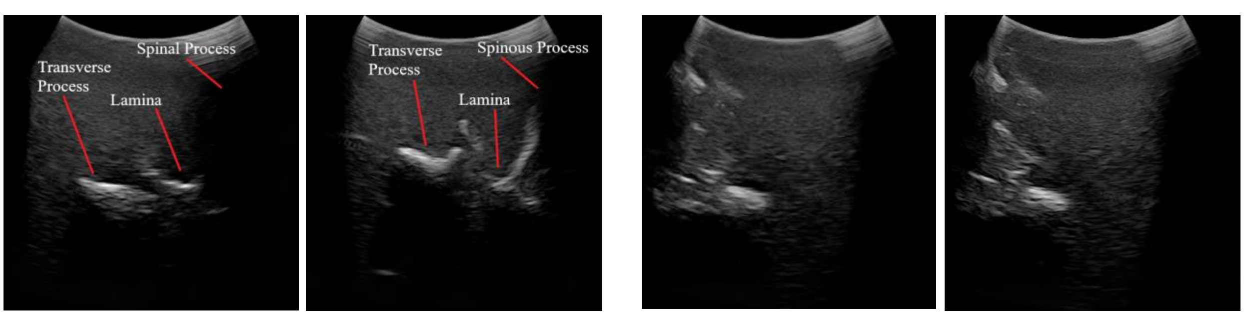

Fig. 1. Pairs of ultrasound scans containing transverse process (left) and no transverse process (right)

Inception v1 contains 22 layers and 9 modules; each module involves operating filters of size 1x1, 3x3, and 5x5 at the same level, then concatenating the outputs and sending them to the next inception module. While this network is able to classify over 1,000 different image classes, our ultrasound images only belonged to two classes, and so we created a simpler network based on the same premises using only 2 linearly stacked inception modules, rather than retraining an existing instance of the Inception network.

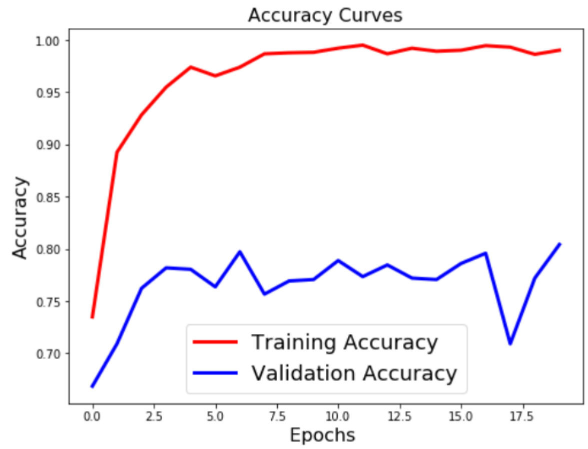

Fig. 2 Accuracy of classification for training (red) and validation (blue)

Results: Deep learning classification using the modified version of the Inception convolutional neural network was successful in detecting the presence of spinal processes, with an accuracy rate of 84%. Out of the 454 testing images that contained transverse processes, 405 were correctly identified; out of the 293 testing images that did not contain a transverse process, 224 were correctly identified.

	Predicted	
True	Present	Absent
Present	405	49
Absent	69	224

Fig. 3 The results of the network in classifying the 747 testing images

Conclusions: The classification model performs with considerable accuracy. Better accuracy can be achieved with more data and improvements in the classification model. Our data was rather limited, as only one spine phantom was scanned using constant setting on the ultrasound machine. Nevertheless, our results suggest that with appropriate refinements of the training process, deep convolutional neural networks are a viable tool for the detection of spinal transverse processes in ultrasound imagery.

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