# Utilizing a convolutional neural network for tool detection in central venous catheterization

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Purpose: Convolutional neural networks (CNNs) have proven to be a powerful tool for various different tasks in computer vision. As their prominence has grown, so too has the availability of resources to utilize their capabilities. One important use of CNNs is in medical simulation training. Simulated training has been shown to improve residents' skills significantly, decreasing complication rates by as much as 10% [1]. Central Line Tutor is a simulated training environment that guides users through central venous catheterization (CVC), providing real-time instructions and feedback [2]. Central Line Tutor utilizes MobileNet, a CNN, to identify the tools of CVC as they are being used. This tool detection provides an indication of proper adherence to the procedure's workflow. The robustness of the network at recognizing tools is dependent on variation in training set images. Higher variation allows for better recognition of the tools in different environments, providing a more robust classifier. This study evaluates the accuracy of a MobileNet after applying transfer learning using a high variation training set composed of the tools used in CVC. The accuracy of the retrained network may be used to indicate the usefulness of applying transfer learning to an off-the-shelf CNN for recognizing various tools used in CVC.

Methods: To effectively retrain a neural network, many training images with high variation are needed. 17,500 images of each of the 7 tools used in CVC were gathered. These tools consist of a scalpel, dilator, syringe, catheter, anesthetic syringe, guidewire, and the guidewire's casing (Fig. 1). Additionally, 25,000 images of the workspace without tools were collected. This totalled to 147,500 training images. To maximize variation, these images were taken with the tools in various positions, lighting conditions and camera angles.
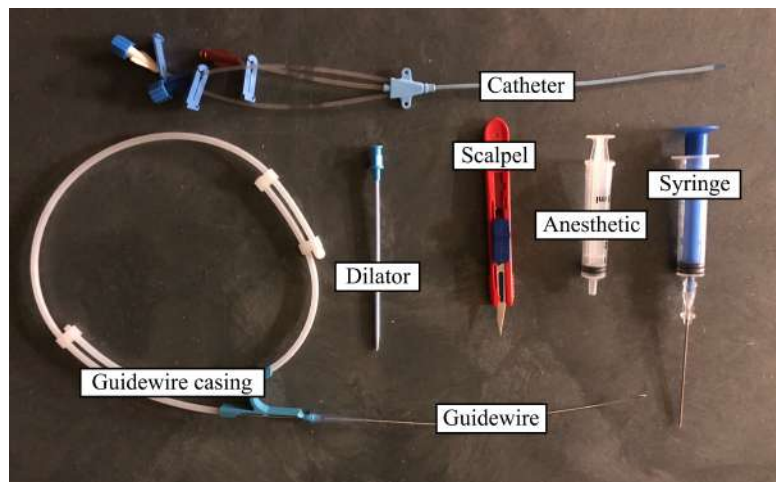
Fig 1. Tools used in CVC

Furthermore, images were collected with and without medical gloves, and the tools were handled with both left and right hands. These variations are illustrated in 5 sample images from the scalpel training set (Fig. 2). The initial layers of a MobileNet network were pretrained on the ImageNet dataset. This pretrained network was provided by tensorflow. The final layer of the network was replaced with a fully connected layer that was trained on the collected training set using 100,000 training steps. To test the accuracy of the retrained network at identifying tools, 5 trials of the CVC procedure were recorded using Central Line Tutor. These recording were separated into 4,376 total frames. These images were completely separate from the training images, and were not available to the network at the time of training. The recording frames were then classified both manually and by the retrained network. The manual classifications represent the ground truth. The performance of the MobileNet was evaluated by comparing the manual and retrained network classifications. The accuracy of the network was measured across all frames, and the precision of each tool was computed. The precision is the percentage of correct classifications out of total classifications for a given tool. The accuracy is defined by the percentage of correct classifications from all of the recorded frames.

Fig 2. Sample images from scalpel training set

Results: The retrained network correctly classified 2,732 of the recorded frames, providing an overall accuracy of 62.4%. The best identified tool was the scalpel with 95.7% precision. The least was the guidewire casing, with a precision of 21.7%. Tools fell into two distinct groups, and either had high precision (70-100%) or low precision (20-40%) classification. High precision tools consisted of the scalpel, catheter, anesthetic and syringe. Low precision tools were the guidewire casing, guidewire and dilator. The results are displayed in the table (Table 1).

Conclusions: These results indicate that the network retrained with a high variation training set was effective for the identification of some tools used in CVC. Tools that were small in size with non-distinct colour, such as the guidewire or dilator, were classified less accurately. Tools with distinct shape and colour like the scalpel or catheter were reliably classified with the retrained network. A limitation may have stemmed from only one person gathering training images. Multiple people would have introduced more variation in the training set would improve the classifier. Further improvements can be made by increasing variation and size of the training set for low precision tools. The high precision classification of certain tools suggests that with an optimized training set, the utilization of transfer learning on an off-the-shelf CNN is useful for the detection of the various tools used in CVC.

Tool	Precision (%)
Anesthetic	72.4
Catheter	81.0
Dilator	27.2
Guidewire	35.6
Guidewire Casing	21.7
Nothing	60.3
Scalpel	95.7
Syringe	77.3

Table 1. Resulting precision for all tools used in CVC

References:

[1] Barsuk JH, McGaghie WC, Cohen ER, O'Leary KJ, Wayne DB (2009) Simulation-based mastery learning reduces complications during central venous catheter insertion in a medical intensive care unit. Critical Care Medicine 37(10):2697-2701.

[2] Hisey R, Ungi T, Holden MS, Baum ZM, Keri Z, McCallum C, Howes DW, Fichtinger G (2018) Real-time workflow detection using webcam video for providing real-time feedback in central venous catheterization training. SPIE Medical Imaging 2018.