



A novel deep learning based cloud service system for automated acupuncture needle counting: a strategy to improve acupuncture safety

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ABSTRACT

Objective The unintentional retention of needles in patients can lead to severe consequences. To enhance acupuncture safety, the study aimed to develop a deep learning-based cloud system for automated process of counting acupuncture needles.

Methods This project adopted transfer learning from a pre-trained Oriented Region-based Convolutional Neural Network (Oriented R-CNN) model to develop a detection algorithm that can automatically count the number of acupuncture needles in a camera picture. A training set with 590 pictures and a validation set with 1 025 pictures were accumulated for fine-tuning. Then, we deployed the MMRotate toolbox in a Google Colab environment with a NVIDIA Tesla T4 Graphics processing unit (GPU) to carry out the training task. Furthermore, we integrated the model with a newly-developed Telegram bot interface to determine the accuracy, precision, and recall of the needling counting system. The end-to-end inference time was also recorded to determine the speed of our cloud service system.

Results In a 20-needle scenario, our Oriented R-CNN detection model has achieved an accuracy of 96.49%, precision of 99.98%, and recall of 99.84%, with an average end-to-end inference time of 1.535 s.

Conclusion The speed, accuracy, and reliability advancements of this cloud service system innovation have demonstrated its potential of using object detection technique to improve acupuncture practice based on deep learning.

1 Introduction

Forgetting to remove needles after acupuncture treatment is a well-known hazard for patients and healthcare providers. Needles that are accidentally left in patients may cause serious damages such as internal organ penetrations, cardiac tamponade, pneumothorax, and spinal cord injury^[1–3]. The injuries would grow worse when the needles are left in unconscious or demented patients, as

it is almost impossible for them to notice the forgotten needles. Furthermore, neglectation of acupuncture needles in hospitals and clinical settings may cause complications by negligent caregivers, increasing the risks of patients being infected with blood-related diseases^[4,5]. Even though the incidence of forgotten needles has been rare because of strict operational rules on safety considerations, precautionary measures should be planned out to minimize the risks.

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In places like the USA and Hong Kong of China, most clinics and hospitals use form paper to record the number of needles used in acupuncture treatment, as advised by the Council of Colleges of Acupuncture and Herbal Medicine [6]. The numbers of needles inserted and needles removed are recorded on the paper. After treatment, the removed needles are counted in a container and compared to the pre-treatment record. Any mismatch in number indicates that some needles are left in the patient. However, counting the removed acupuncture needles manually is not only a tedious and time-consuming task, but also prone to human error [3]. A fast, convenient, and accurate solution for automatic acupuncture needle counting with electronic records is essential to protect patients from getting injured by forgetting needles.

The application of deep learning has been a rapidly developing research topic in the field of medical image analysis [7]. Researchers have demonstrated the potential of this technique in skin lesion classification [8], pulmonary nodules detection [9], and liver tumor segmentation [10]. However, few studies concentrate on enhancing patient care. Repetitive tasks, such as counting surgical tools or dispensed drugs, are prone to human errors. Therefore, research on automated counting in these daily clinical tasks is useful and necessary for improving patient safety.

However, research on automated counting of acupuncture needles has been lacking because acupuncture needle is a thin and long target which is difficult to be identified under the traditional axis-aligned detection. Horizontal box detection struggles to accurately pinpoint diagonally positioned needles, while the counting requirement further adds to the complexity because of the demand for successive detections in multiple instances. The overall accuracy is exponentially relative to the per-instance accuracy, which then determines the clinical utility of the detector. These challenges of detecting diagonal objects have spurred researchers to develop oriented object detection, incorporating the object's angle relative to the vertical axis in the bounding box parameter. These approaches lead to a more precise fit for, elongated objects [11, 12]. Therefore, we have transitioned from traditional axis-aligned detection to embrace oriented object detection, culminating in the development of our solution, “AcuCount”. This innovative system, derived from “Acupuncture” and “Count”, is specifically designed to accurately detect a wide array of acupuncture needle brands.

The construction of the “AcuCount” solution began with the creation of an image set of acupuncture needles with oriented box annotation, then implemented transfer learning to fine-tune the Oriented Region-based Convolutional Neural Networks (Oriented R-CNN) algorithm. To provide fast and mobile access to our algorithm, we also built an adjunctive telegram bot interface script for the

algorithm to be hosted on cloud platforms. Simply by installing a popular messaging application, telegram messenger, users could easily connect our cloud service platform on their own devices.

The ultimate goal of the “AcuCount” solution is to provide a cloud service system for automatically counting acupuncture needles and reduce the incidence of forgotten needles in acupuncture practice.

2 Data and methods

In this study, we first developed a deep learning algorithm for counting needles, then we programmed the “AcuCount” Telegram bot by combining the mobility of Telegram Messenger in the workflow (Figure 1).

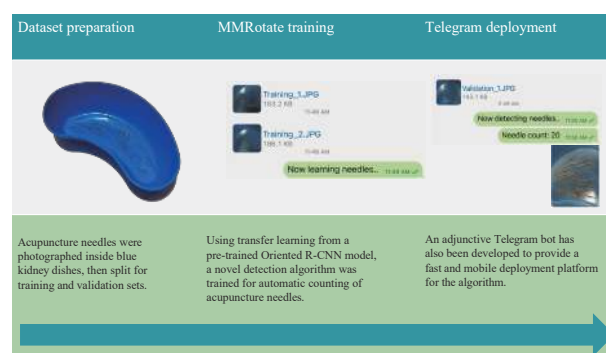


Figure 1 A graphical workflow of the study

2.1 Dataset preparation

2.1.1 Data collection Four types of acupuncture needles were included in the datasets. They are copper needles of the Hwato brand (Suzhou Medical Appliance Factory Ltd., China) with dimensions of 0.25 mm × 30 mm and 0.25 mm × 40 mm, and silver needles of the MOCM brand (Wuxi Jiajian Medical Instrument Co., Ltd., China) with dimensions of 0.25 mm × 30 mm and 0.25 mm × 40 mm.

For the background containers, two types of blue kidney dishes were used. The dishes with graduation markings were purchased from the Warwick Sasco Ltd., and measured 20 cm in length, while the dishes without graduation markings were purchased from the Capecraft Hospital Ware and measured 25 cm in length. The blue kidney dishes were selected as the background due to their universal availability in acupuncture clinics, and therefore could promote the universal adoption of the model created. Furthermore, using a blue kidney dish as a simple background could help reduce the size of image files, which could save training time and better fit into memory constraints.

Images were captured by an Apple iPhone 7 at a resolution of 4 032 × 3 024 pixels. To increase the generalizability of our “needle-in-dish” dataset, we took multiple measures while capturing these images. First, the container was shaken a few times to mimic a random

distribution of needles. Second, the pictures were taken at various distances, angles, lighting conditions, and with different brands of blue kidney dishes as well. Third, some needles were bent beforehand to simulate the wear and tear experienced after usage.

2.1.2 Oriented ground truth box annotation Oriented box detection has a few advantages over the traditional horizontal box detection, especially when the object of interest is a long and thin needle (Figure 2). On one hand, a horizontal bounding box may include more background regions or multiple objects, which are irrelevant to the detection, hence confusing the model in training, particularly when the needle is placed diagonally. On the other hand, an oriented box can precisely identify the object in the bounding box, thus reducing the interference of information irrelevant to training. Therefore, the oriented boxes are less likely to trigger non-maximum suppression (NMS) and retain more detection boxes than horizontal boxes [11, 12].

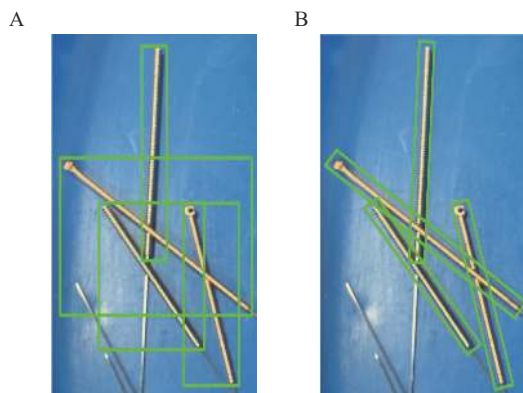


Figure 2 Comparison of needle detection between in horizontal and oriented boxes
A, horizontal boxes. B, oriented boxes.

2.1.3 Data preprocessing All the photos captured by the Apple iPhone 7 camera were processed to 960×1280 pixels (height $\times$ width), in order to match the default photo dimension in Telegram bot. The resolution was set to 96 dpi, the bit depth was set to 24 bits, and the red, green, and blue (RGB) colors were normalized. Vertical, horizontal, diagonal flip and random angle rotation were applied to the training dataset to create a more diverse distribution of needles for learning. Moreover, the pictures were augmented by random brightness and contrast variation to simulate the fluctuation in illumination, which in turn allowed the detection algorithm to better adapt to the variance in lighting, reflections, and image quality.

A total of 1 615 photos were taken and split into a training set and a validation set. The number of photos and needles in each set is shown in Table 1. The number of needles in the photos of the training set varied in the range of 1 – 20, but the number of needles in the photos of the validation set was constant at 20.

Table 1 The numbers of photos and needles in the training and validation sets

Dataset	Number of photos	Number of needles
Training set	590	9 511
Validation set	1 025	20 500

2.2 Detection algorithm

Oriented R-CNN was selected as the backbone network due to its state-of-the-art (SOTA) performance and native support from mmdet. The workflow is illustrated in Figure 3 [13]. The Oriented R-CNN was designed as a two-stage detector. The image first underwent feature extraction by the backbone ResNet-50-Feature Pyramid Network (FPN), a feature pyramid network that produced five levels of features. Then, the feature maps were sent to the Oriented Region Proposal Network (RPN) for further convolutional training. Eventually, both the feature maps and the RPN proposals were passed to the Oriented R-CNN head for rotated region of interest alignment, resulting in the classification and regression output.

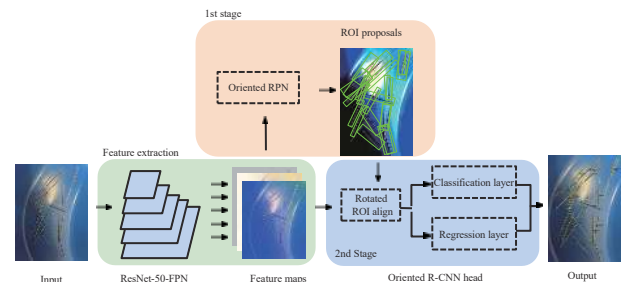


Figure 3 The workflow of the two-stage Oriented R-CNN model

2.3 Training configurations (implementation details)

Ablation experiments were carried out to determine the optimal hyperparameters with regards to our needle dataset.

First, we increased the NMS threshold compared with the baseline in the Oriented R-CNN paper. Unlike the aerial images in dataset for object detection in aerial images (DOTA) dataset [14], where vehicles and ships were not stacked upon together, it is very common to see needles overlapped with each other in our needle dataset. Increasing the NMS threshold from 0.25 to 0.30 could avoid pruning of these closely packed detection boxes, while avoiding multiple boxes being spawned on the same target, as in the case of increasing NMS threshold to 0.35. Second, we tweaked the settings of aspect ratio from (0.5, 1.0, 2.0) to (0.0625, 0.125, 0.25, 0.5, 1.0, 2.0, 4.0, 8.0, 16.0), so more elongated anchor boxes could be generated. The lengthened boxes could fit better into the shape

of acupuncture needles, thus increasing the intersection over union (IoU) overlap during the training process. For simplicity, we trained both copper and silver needles under one single label.

2.4 Telegram bot (remote counting service system)

The trained detection algorithm was further integrated into a Telegram bot using the python-telegram-bot library [15]. The architecture of the Telegram bot is outlined in the below sections, along with its workflow.

2.4.1 Client To use our Telegram bot for automatic needle counting, the users are only required to have a camera phone, and a constant internet connection. Then, download the Telegram Messenger from Apple App store or Google Play store for installation and subscription (@AcuCount_bot). After initiating a new chat with our bot, the user simply needs to send the needle picture to the Telegram bot for each instance of needle counting.

2.4.2 Server The captured images were transmitted to the telegram server and then forwarded to our Telegram bot script for processing. The image was resized by bilinear interpolation to match its dimensions to the trained dataset. Subsequently, the image was fed into the inference graph, yielding the coordinates of bounding boxes and detection scores for the detection box drawings on the result image. Finally, the resultant image, together with the number of the needles, was sent back to the user interface via the telegram server. To facilitate easy reference and future analysis, the needle count, timestamp, and the username are embedded within the filename of the result image.

Our GitHub demonstration (https://github.com/Deadfish-hk/AcuCount_Imageset) was operated on Google Colab (https://colab.research.google.com/github/Deadfishhk/AcuCount_Imageset/blob/main/MMrotate_training_github.ipynb#) as the cloud computing platform, where Google Drive also served as the cloud data storage. Our lightweight Telegram bot script also allows transplantation from cloud platforms to local systems with few modifications.

2.5 Experimental setup

The training process was carried out on Google Colab with NVIDIA Tesla T4 as the graphics processing support. MMRotate library 0.3.4 was used for the experiments [16]. All training models were pre-trained on the ImageNet dataset before the training was initiated on our customized dataset. The other training parameters are specified in Table 2.

Table 2 The training parameters of Oriented R-CNN model

Attribute	Parameter
Backbone	ResNet-50-FPN
Image resolution (pixel)	960 × 1 280
Anchor aspect ratio	(0.0625, 0.125, 0.25, 0.5, 1.0, 2.0, 4.0, 8.0, 12.0, 16.0)
First stage max proposals (number)	2 000
First stage NMS threshold (score)	0.8
Second stage NMS threshold (score)	0.3
Detection threshold (score)	0.5
Batch size (image)	2
Training epochs (number)	80
Learning rate [value, (epoch)]	0.01 (0), 0.001 (53), 0.000 1 (72)
Momentum (μ)	0.9
Data augmentation	Random horizontal, vertical, diagonal flip poly random rotation random brightness, and saturation

The measurement of the end-to-end counting time was simulated by hosting the Telegram bot on Google Colab, and then sending the validation images via the desktop application, as if it was in actual practice. The time at which an incoming image was received as well as a detected image was sent forward was logged as the end-to-end counting time in a log file. This time may be interpreted as a brief representation of the processing time required for internal inference and visualization, and external network transmission.

2.6 Reporting metrics

The results are presented in terms of accuracy, precision and recall to verify the clinical efficiency of the model. An image is classified as accurate if it has no misclassified needle-head (false positive) or missing needle-head (false negative).

$$\text{Accuracy} = \frac{\text{Number of accurate pictures}}{\text{Total number of pictures in the validation set}} \times 100\%$$

$$\text{Precision} = \frac{\text{Number of correct bounding boxes (TP)}}{\text{Total number of detected boxes (TP + FP)}}$$

$$\text{Recall} = \frac{\text{Number of correct bounding boxes (TP)}}{\text{Total number of objects presented (TP + FN)}}$$

TP, true positives. FP, false positives. FN, false negatives.

3 Results

3.1 Model evaluation

As illustrated in Table 3, our Oriented R-CNN model achieved an overall accuracy of 96.49%, successfully identifying the correct needle count in 989 out of 1 025 images in the validation set. Additionally, our model demonstrated similar detection performance with copper and silver needles, even in mixed scenarios. The average end-to-end counting time is approximately 1.535 s for processing one image under the Tesla T4 environment.

Table 3 The detection results of our Oriented R-CNN model

Object	Accuracy	Precision	Recall
Copper needle	95.85% (231/241)	99.98% (4 810/4 811)	99.79% (4 810/4 820)
Silver needle	97.22% (245/252)	100.00% (5 033/5 033)	99.86% (5 033/5 040)
Mixed copper and silver needle	96.43% (513/532)	99.96% (10 625/10 629)	99.86% (10 625/10 640)
Overall	96.49% (989/1 025)	99.98% (20 468/20 473)	99.84% (20 468/20 500)

3.2 Ablation experiments

In order to support our proposed changes in the NMS threshold and aspect ratio, we have conducted a series of ablation experiments to investigate the optimal settings. The results has generally correlated well with our argument presented in section 2.3. Higher settings of the NMS threshold and an increased number of aspect ratios have demonstrated superior performance compared with others (Table 4).

Table 4 Results of the ablation experiments on NMS threshold and aspect ratio

Parameter	Value	Overall accuracy (%)
NMS threshold	0.25	94.04
	0.30	96.49*
	0.35	92.98
Aspect ratio	0.5, 1.0, 2.0	91.31
	(0.0625, 0.125, 0.25, 0.5, 1.0, 2.0, 4.0, 8.0, 12.0, 16.0)	96.49*

*Best in class.

Some of the example detection have been selected for demonstration (Figure 4).

The datasets used during the current study are available in the following repository: https://github.com/Deadfish-hk/AcuCount_Imageset.

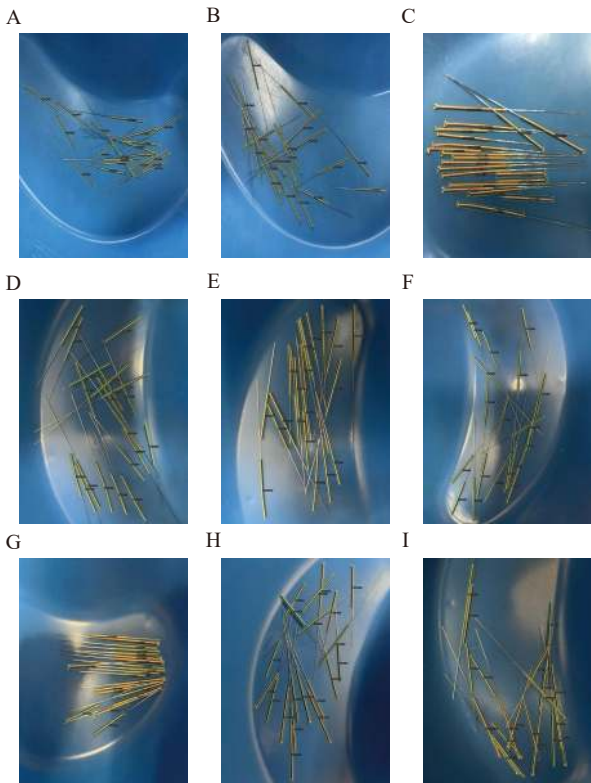


Figure 4 Some selected examples generated by Oriented R-CNN model in the validation dataset

A – C, copper needles. D – F, silver needles. G – I, mixed copper and silver needles.

4 Discussion

To our knowledge, this is the first manuscript to utilize artificial intelligence in counting acupuncture needles. Our method requires no specialized equipment and minimal financial investment for adoption. As evidenced in this and other studies, object detection algorithms have demonstrated superior performance in daily counting tasks [17, 18]. By using telegram messenger as the communication interface, users are offered a robust level of security and a range of synchronization capabilities [19]. The synchronization feature across multiple devices allows the resultant image to be simultaneously displayed at both the bedside and the nurse station, streamlining the double-checking process. When the Telegram bot is connected to a dedicated cloud drive, every resultant image generated can be immediately uploaded and safeguarded as a reliable medical record of each acupuncture treatment. These advancements in speed, accuracy, and reliability offered by an automated service system could significantly enhance acupuncture safety and efficiency.

In the near future, we will continue improving the accuracy and usage of the needle detector by expanding the dataset with multiple sources, encompassing needles of different sizes, brands, and containers with various appearance. Although our model is trained on images exclusively with needles from brand Hwato and MOCM,

other brands of acupuncture needles (such as Aright and DLM Master) which share a similar appearance could also be detected using this algorithm. Though it was not reported, we have observed a considerable improvements in speed by using a more advanced graphics card for inference. In view of the rapid evolution of artificial intelligence computing and the less modern graphics card we used for inference, it is believed that there is still room for reducing computing time. The speed and accuracy offered by this model could be comparable or even superior to its human counterpart in future development.

Beyond acupuncture needles, other small and diagonal objects, such as sharp surgical tools and drugs, are also frequently counted in daily practices in hospitals^[20]. By modifying the detection model in our telegram script, the detector could be customized to count these objects of interest after appropriate transfer learning. Our Telegram bot offers features such as bounding box visualization, cloud recording, and synchronous monitoring, which could provide additional assistance to medical personnel in their daily counting tasks. We hope this pilot study could replace some of the present manual counting procedures in clinical settings and could eventually be incorporated into daily practice for improvements in safety and efficiency in the future.

A significant limitation of this study is the limited availability of Telegram Messenger in the China region. To address this issue, we plan to explore opportunities for transferring our cloud service system to WeChat in the future. This will enable us to provide this service to the greatest user base of acupuncture practitioners^[21].

5 Conclusion

This study presents the first application of artificial intelligence for counting acupuncture needles, demonstrating its potential for enhancing safety and efficiency in acupuncture practice in terms of speed, accuracy, and reliability improvement. This method requires minimal investment, and by utilizing Telegram Messenger for communication and synchronization, it offers practitioners a secure and streamlined electronic system for double-checking and record-keeping, paving the way to digitalize traditional practice.

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Competing interests

The authors declare no conflict of interest.

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一种基于深度学习的新型针灸针自动计数的云服务系统： 提高针灸安全性的策略

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【摘要】目的 病人针灸治疗时，漏针可能造成严重后果。为增强针灸安全性，本研究将开发一个基于深度学习的自动云端数针系统。**方法** 本研究利用拍有针灸针的手机图片为曾预先训练的定向目标检测模型（Oriented R-CNN）进行转移学习，以开发一种能够自动计算图片中针灸针数量的目标检测算法。我们首先拍摄了一个包含 590 张图片的训练集以及一个包含 1 025 张图片的验证集。随后在带有 NVIDIA Tesla T4 图形处理器（GPU）的 Google Colab 环境中部署了 MMRotate 工具箱为模型进行训练。我们将训练的模型与 Telegram bot 手机小程序界面集成，并评估模型的准确率、精确率和召回率。本小程序中云端数针系统的速度则以端到端处理时间计算。**结果** 在每张图片 20 根针的验证集情景中，我们的定向检测模型在准确率、精确率和召回率上分别达到 96.49%、99.98% 和 99.84%，平均端到端处理时间为 1.535 秒。**结论** 这项云服务系统在速度、准确性和可靠性上的提升展示了深度学习物体检测技术改进针灸实践的潜力。

【关键词】 人工智能；电脑视觉；目标检测；针灸；病人安全