Peripherally Inserted Central Catheter (PICC) Tip Detection with Deep Learning

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SUMMARY

A peripherally inserted central catheter is defined as a tube that used to give treatments, provide intravenous access, and prevent replayed procedure of needle sticks. The thin catheter is located from a vein in the arm to a safe window that the PICC tip should lie within, called superior vena cava (SVC). PICC malposition can cause pain, even serious complications. Chest radiograph analysis requires reading by radiologists to keep the tube in good position. Compared to high volume of radiographs, the number of experts is not enough to finish all images to be analyzed timely and correctly. In this study, we used FCN to make semantic segmentation for whole PICC line, with Mean IU score 0.53, which means a good prediction. This workflow is significant to clinical decision, and can help find PICC tip position and further be applied on detecting the PICC tip malposition.

INTRODUCTION

A peripherally inserted central catheter (PICC) is a thin, soft and flexible catheter that is frequently used for intravenous (IV) medications, nutrition supplementation, and blood draws. PICCs are important component of the device used to help and give treatment to more and more patients (Allen, 2000). The PICC is inserted percutaneously through antecubital vein with the tip lying within superior vena cava (SVC). The PICC line goes from patient's arm until a large vein of SVC. In general, PICC lines can stay in chest for months, which is similar with the way to input other kinds of tubes. Although it is popular and effective for treatment, it has some problems, such as infection, blocked line, clot of blood, and even splitting. Nurse needs to regularly clean PICC line with salt water to prevent infection or other risks.

PICCs malposition, typically caused by lack of real-time image leading (Yi, 2018), has significant consequences such as discomfort and pain to the patients, high cost, delayed treatment, that may result in serious complications such as cardiac arrhythmia (Lee, 2018). As such, it is of great importance to ensure proper positioning of the PICC. Insertion needs to be followed by an immediate chest radiograph so that radiologists can use chest radiography to interpret and verify if the tip placement is correctly positioned (Girgenti, 2014). Although diagnostic error rate of chest radiograph interpretation by expertise is very low (Fuentealba, 2012), a limited number of experts lead to delays in treatment due to a high volume of images (Yi, 2018). Therefore we hope that the applicability of Deep Learning system can help radiologists on improving accuracy and efficiency of interpretation of medical images and reducing errors.

Machine learning and deep learning recently have demonstrated potential to contribute to various medical applications (Yi, 2018). Deep learning technology have shown increased performance and accuracy of image interpretation (Lee, 2017), and it is the state-of-the-art approach with ability to extract hierarchical features from datasets, as opposed to manual feature selector (Shen, 2017; Lee, 2018). Tremendous success of deep learning applied in medical image analysis examples include tuberculosis (TB) detection on chest radiographs (Lakhani and Sundaram, 2017), pneumonia detection (Rajpurkar et al., 2017), segmentation on brain MRI (Milletari, 2016), kenn cartilage segmentation (Prasoon, 2013), etc.

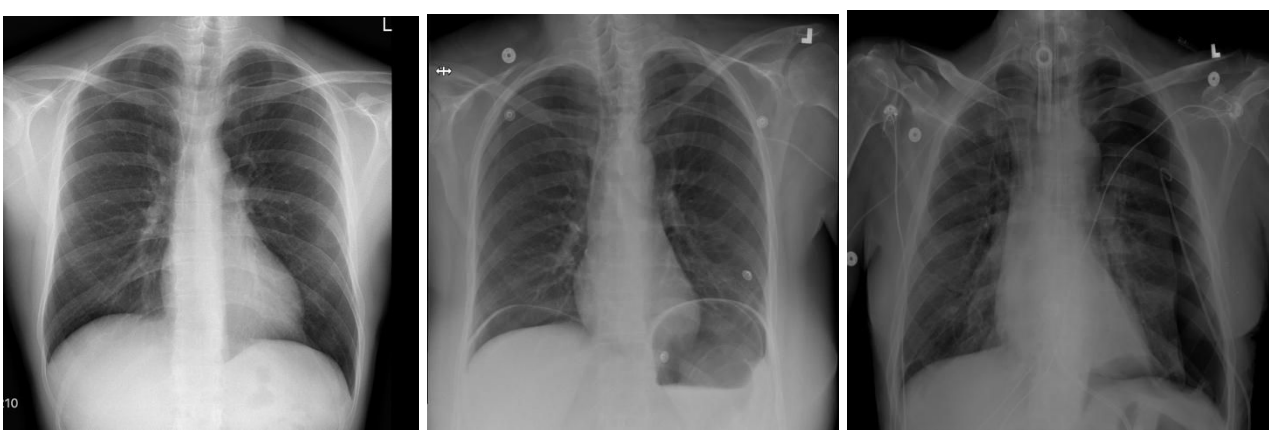
Thus, in this study, we propose automated semantic segmentation and localization deep learning methods to detect PICC tip placement, for subtle, we segment PICC line and localize catheter tip safe window, which consists of image normalization, faster R-CNN, and fully convolutional networks (FCNs). And ultimately estimate if the catheter tip is in the safe window by a post-processing approach. This deep learning system will reduce risk in treatment and aid in clinical-decision support.

METHODS

Dataset

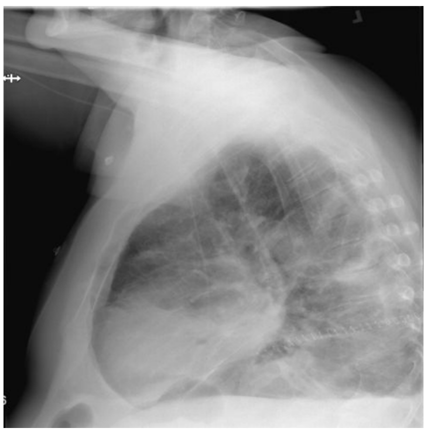
Digital Imaging and Communications in Medicine (DICOM) is one international and popular standard of 6 predominant medical image formats around the world. A file format and a network communications protocol in DICOM format are used to store and transmit medical information. We collected de-identified HIPAA-compliant (Health Insurance Portability and Accountability Act) DICOM dataset that contain PICCs that obtained from NYU Langone Hospital.

Each DICOM folder is composed with PA (posteroanterior), AP (anteroposterior), and lateral chest x-ray radiograph. Examples as shown in Figure. 1. The lateral file is the lateral projection of chest x-ray image. The frontal view includes PA and AP file. The PA film is taken while the x-ray passes from back of patients to anterior. The orientation of AP film is opposite with PA film. AP images are typically used for very ill patients who cannot stand to take PA radiograph. Due to enlarged heart size, superior mediastinum appears to be widened, and other modified structures taken by AP magnification, PA views perform better than AP films in quality and accuracy. As a result, we only use PA CXRs with the exclusion of other kinds of images.



a PA film

b AP film



c Lateral film

Figure. 1 Examples of three kinds of DICOM files for each patient. Typically, they are **a** PA film, **b** AP film, and **c** Lateral film

In addition, we collected notes on radiology reports for each CXR, which indicate the status of PICC line position, especially tip placement by radiologists. Notes was used to make sure the accuracy when we labeled the safe window for PICC tip placement, There are some examples in Table 1.

We collected unlabeled chest X-ray images in 3877 DICOM folders from a total of 3877 patients, and labeled 166 images with PICCs. Few images contain not only PICC line, but also lines of pacemaker, ECG line, etc. Details shown in Figure. 2. There are 147 CXRs be with only PICC line and 19 CXRs be without PICC line or having other kinds of line-shape tubes. For our segmentation study, we only choose the chest x-ray images with PICC line.

Table 1 radiology report

Notes for PICC tip position	Judgement
1. The PICC line tip in upper SVC	Right
2. Single-lumen PICC via the left basilic vein, with the distal tip left at the superior vena cava (SVC)	Right
3. The left PICC ends in the region of the distal left brachiocephalic vein, adjustment recommended	Wrong
4. PICC projecting over the cavoatrial junction	Right
5. There is a right upper extremity PICC line to the cavoatrial junction, new from prior exam	Right
6. A left-sided PICC line is in place with its distal tip within the cavoatrial junction	Right
7. Left PICC line has been repositioned with the tip now at the cavoatrial junction, previously in the azygos vein	Right
8. Right PICC inserted with tip projecting over right atrium	Wrong
9. The left subclavian PICC is stable in position, The cardiac silhouette is stable, mildly enlarged	Right

Data Labeling

For training and validation datasets, we set two labeling tasks, which are PICC line segmentation and PICC tip "safe window" localization. Under review of radiologists in NYU Langone Hospital, we used brush and rectangle functions in OsiriX (Chen et al., 2016) to manually perform the ground truth labels. For PICC line segmentation, the label line will be traced according to the PICC line. This step requires us to make the label line overlap with original PICC line as much as possible, so it takes much time for us to finish labeling with high accuracy. As drawing the safe window of PICC tip, we set a simple criteria to aid us to find the rectangle in line positioning. Since the PICC line tip should lie within superior vena cava (SVA), we found a simple matrix for guiding the insertion site, which provides a reproducible approach that the tip position should be within a rectangle range of a posterior rib height above the ridge at the windpipe base and two vertebral body units below the ridge at the windpipe base (Johnston, 2013). The ridge at the trachea is called carina, whose function is to separate left and right main bronchi. In this section, we found that the height criteria works pretty will while we compared our labeled safe window with radiologist record to check if the green zone is right. But width sometimes is not like the height, it is not always equals to the height, which means that the safe window is not always like a square, it is sometimes like a rectangle. So we read every radiologist recode for each chest x ray image we labeled to make sure the judge is precise. Figure 2 shows these two kinds of label images.

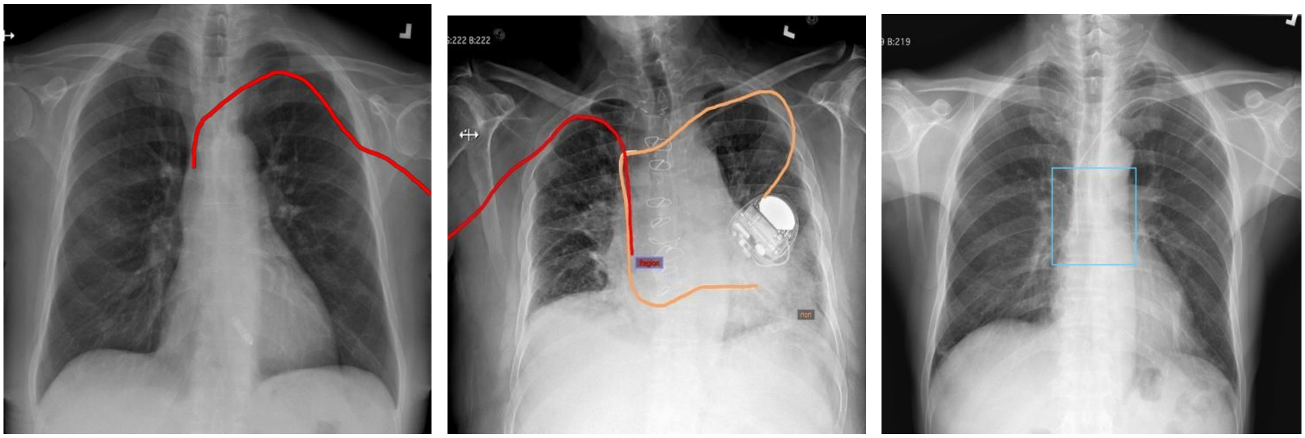
In addition, we differentiate PICC lines and other categories lines, such as ECK lines, pacemaker tubes, by name and color in PICC line segmentation task. Red color is distributed to PICC line and yellow represents all other lines. Name “Region” (default name) in OsiriX means PICC line, “non” means all other lines in the Chest X-ray images. And for safe window box labeling step, all box was named “Rectangle” in each chest x-ray radiograph. Details for description of labels are shown in Table 2.

Data Preparing

Because of the original data format is DICOM, we first used dcmj2pnm method to convert all labeled dicom to jpeg and png format. Then we transform all data into coco (Common Objects in Context) to help better research. COCO is used to annotate objects with not only bounding boxes, but also becomes a kind of standard to store information, which is convenient to open source. COCO convert need JSON (JavaScript Object Notation) file, which we got from OsiriX for each chest x ray image we labeled. In JSON, there are information about classes, image accession number, position of every point, and annotations, etc (Lin, 2014).

Data Preprocessing

All chest x-ray images were resized to 1024 × 1024 pixels, since we don’t want to miss important information of whole PICC line. And we distributed all dataset to train, test, and validation by proportion 8 : 1 : 1. In the end, we got 117 training data, 15 test data, and 15 validation data. During the process of labeling PICC line and safe window, we have ignored chest x ray images that were with low quality, including blurry, rotated CXRs.



a PICC line ground truth **b** PICC other lines ground truth **c** Safe window ground truth

d PICC line annotation **e** PICC and other lines annotation

Figure. 2 Labels of ground truth, respectively **a** PICC line ground truth, **b** PICC other lines ground truth, **c** Safe window ground truth, **d** PICC line annotation, and **e** PICC and other lines annotation

Table 2 Color and name used for PICC line and PICC tip safe window

Label	Color	Name of label	Description
PICC line segmentation			
PICC	Red	Region	PICC lines

Other lines	Yellow	non	ECG cables, pacemaker lines, any line-shaped objects
PICC tip safe window localization			
PICC tip safe window	Blue	Rectangle	Safe window within superior vena cava

Semantic Segmentation

Chest x ray radiographs are popular used for disease detecting by different conditions of patients, such as pneumonia, cardiac arrhythmia

congestive heart failure, etc. But there are few researches for devices detection in patients' organs, which are manually put by doctors and checked by radiologists. It takes much time for radiologists working on chest x ray image one by one. So that if there is malposition happen for patients, and is not found by experts in time, patients will feel uncomfortable, and dangers could happen even with life-threatening complications, such as heart failing (Ginneken, 2000).

For PICC tube segmentation, it is unfamiliar with the segmentation for lung, heart, or other organs. It is a line-shape devices, which can be difficult for models to learn and distinguish with rib or other line shapes devices, such as ECG lines and tubes of pacemaker, and any other tube-shaped lines. So we found materials for car lanes detection, which is similar methods as to PICC line.

We train an end-to-end PICC line detection as they predicting the lane. They make segmentation two tasks, one is binary segmentation, the other one is instance segmentation. What is more complicated than our PICC line detection is that their images may have 4 or more lanes per image. So it is necessary for them to use instance segmentation. Since we are going to only use the chest x ray radiographs with PICC line excluding other categories of tubes, we only chose the first part of their method, which is semantic segmentation.

FCN-based semantic segmentation can label and understand PICC line in pixel level, contrasted to region-based semantic segmentation, which is based on localization and followed by a classification step

(Guo, 2018). Also different classes could be recognized. Our prediction has 2 classes, one is PICC line, the other one is background. Fully convolutional network (FCN) takes advantage of convolutional neural networks (CNN) by converting the fully connected (FC) layers into 1 × 1 convolutional layers. Our semantic segmentation architecture includes a convolutional network and a deconvolutional network. Employing a VGG 16 architecture in convolutional network to generates a vector of features. Deconvolutional network make the output size larger, which is opposite of convolutional network getting the output size smaller, inputting the output of convolutional network, which are the vector of features then obtaining map of pixel-wise probabilities. Since spatial location information would lost when image size going smaller, the architecture combine deeper and shallower layers by fusing the output to produce new label map with larger spatial dimensions to enhance the result (Long, 2014). The convolutional network includes convolution, Batch Normalization (BN), and ReLU layers. Deconvolutional network is composed of deconvolution, unpooling, and ReLU layers. Workflow shown in figure. 3.

There are four advantages of using fully convolutional network. Firstly, we can input arbitrary-sized chest x ray radiographs as we want, instead of fixed input size for CNNs (Guo, 2018). Secondly, it allows us to make usage of transfer learning, we employed pre-trained LaneNet, which was used to predict lane for modern cars, protecting the car to properly driving between the lanes on the road (Neven, 2018). The network can be trained in a pixel-wise loss by this way, we use pixel-wise cross entropy loss to examine each pixel individually. Although with very small amount of dataset, the performance even can be good. Moreover, as mentioned above, upsampling allows us to translate the activations and to increase spatial information that was lost in convolutional network. Lastly, FCN can be used to predict and understand PICC line in pixel level in the whole and same size of original chest x ray images.

Loss function is pixel-wise cross entropy loss. It is common to be used for image segmentation. The score from the equation below will be repeated over all pixels and averaged.

$$-\sum_{classes} y_{true} \log\left(y_{pred}\right)$$

Also, another loss function, Dice coefficient, contribute to image segmentation a lot. It will calculate overlap between two samples. From 0 to 1, meaning bad to perfect overlap. This is the math for dice coefficient: |A∩B| represents the part in both A and B, A is the number of pixels in A, and the like.

$$Dice = \frac{2\,|A \cap B|}{|A| + |B|}$$

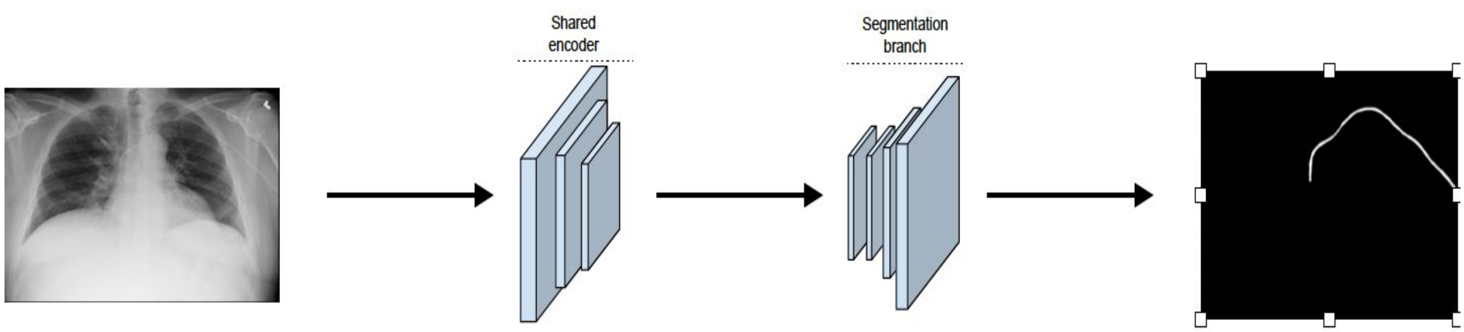


Figure. 3 The workflow for semantic segmentation for PICC line detection, which consists of an encoding and decoding steps

Training

We used pre-trained models in LaneNet lane detection Github (MaybeShewill - CV, 2019) to train our training data and tune model on validation dataset. Using stochastic gradient descent (SGD), we chose 0.001 as learning rate and used polynomial decay with power 0.9. the epoch is 80,000. We have used 6 hours finishing training process. Our study was run on rtx 2080 ti with 32 GB memory / GPU. All code were saved in Github repository (https://github.com/ShuyangDeng/PICC-line-tip.git).

Object Detection

We found material Github (Pkulzc, 2019) about object detection. What we are going to do after making segmentation of PICC line tip is PICC tip safe window localization. Object detection can not only recognize and classify all objects in an image, but also localizing them by drawing the bounding box around according objects. Faster R-CNN is made up of three parts, convolution layers, region proposal network (RPN), and classes and bounding boxes prediction. This model extract features of the original chest x ray radiograph, then region proposal network, which is a small neural network sliding on the last feature map, generating bounding box and pass it to following layers. For the last step, including ROI pooling, CNN, and two fully connected (FC) branches, which lead to a classifier and bounding box regressor. In RPN section, a 3 × 3 sliding window moves across the feature map and reduce the size. For each sliding-window location, it generates multiple regions, for each region proposal that is made up of a score for that part to represent the bounding box of the region.

In addition, there are other object detectors we can try for comparison, such as Single shot detectors (SSD), You only look once (YOLO). Single shot detectors (SSD) predict the bounding box and the class, using a VGG16 network to obtain vectors of features, which is similar to the convolution layers of Faster R-CNN. Then prediction part consists of edited convolution layers by ourselves after the VGG16 and following a filter. Also spatial information lost while going deeper, so independent object detections from feature maps before. Limits of SSD is that some small features of the image cannot be detected easily, so high resolution image should be input.

DarkNet is used in YOLO, which is little different with SSD. YOLO doesn't provide independent detections. It shifts the fully connected layers to 1 × 1 convolutional layer and then concatenates with the same size output from CNN to prevent the loss of spatial information. YOLOv3 is based on YOLO and make some changes in architecture. FPN is feature pyramid networks, which is an extractor used for improving precision and reducing time. It composes of two sections. One of them is the usual convolutional network to get the vectors of features from input image. But it is not good enough to detect small features in image. The other pathway is to fuse shallower layers from output of CNN. All these two sampling are semantic strong, and then a lateral connections between reconstructed layers and the feature maps would help the architecture to predict location for object with better performance. RPN could generate ROIs and select the feature layer with more fitting scale.

Post-processing

For PICC line segmentation, we will use function of opencv to link the PICC line and fit the curve which was predicted off and on. We will fit a polynomial line to the primary margin defined by the output of cv2. First of all, we can get the points of the primary edge. Then we get them pretty close to our target ones. And the array of coordinate pairs we get from above could be used to generate coefficients for a best-fit polynomial and to verify with plots generated. As above steps, we can get a successive PICC line for our prediction results.

But what is more important is that we need to try more pre-train models to improve the segmentation performance. After selecting the best model for our PICC line segmentation, we can make ROI (Region of interest), which was shown in figure. 4, to help us find where is the tip by finding the largest y value in ROI. By the way, figure. 4 shows what we referenced from PICC tip detection material, there might be some different from our architecture. For the preprocessing, we didn’t process blurred or rotated chest x ray images, because while we doing labeling, we have already filtered what we want and do not want. And as the small amount of the number of our labeled data, it is not necessary for us to make this section. Then upon the work of localization, we have got the safe window for PICC tip. Lastly, we only need to check if the tip is in the safe window to see whether our prediction is malposition or not (Lee, 2018).

RESULTS

Performance

We achieved an accuracy of almost 100% for training and 87% for validation in the whole 80,000 epochs. And both loss curve converge quickly smoothly. The loss of training and validation go to the lowest point before 10,000 epochs, and accuracy of both also goes high to the biggest number already at around 5,000 epochs.

The loss and accuracy curve shown in figure. 5, and some prediction examples for PICC line segmentation task shown in figure. 7.

We choose Mean IU to as segmentation measurement. Our mean IU score is 0.53, when the score is more than 0.5, it always considered a “good” prediction. Mean IU is an approach to calculate how much of the overlap between the target ground truth and output of our prediction. IU is intersection over Union, which is also named IoU and Jaccard index. During the process of training, it will generate different value for every chest x ray images as a loss function. Intersection is the pixels in both target and prediction, and the union represents all pixels together of prediction and mask. For each class, IoU will generate a score individually and then make average for all classes to get the final measurement score. Math details are performed:

$$IoU = \frac{target \cap prediction}{target \cup prediction}$$

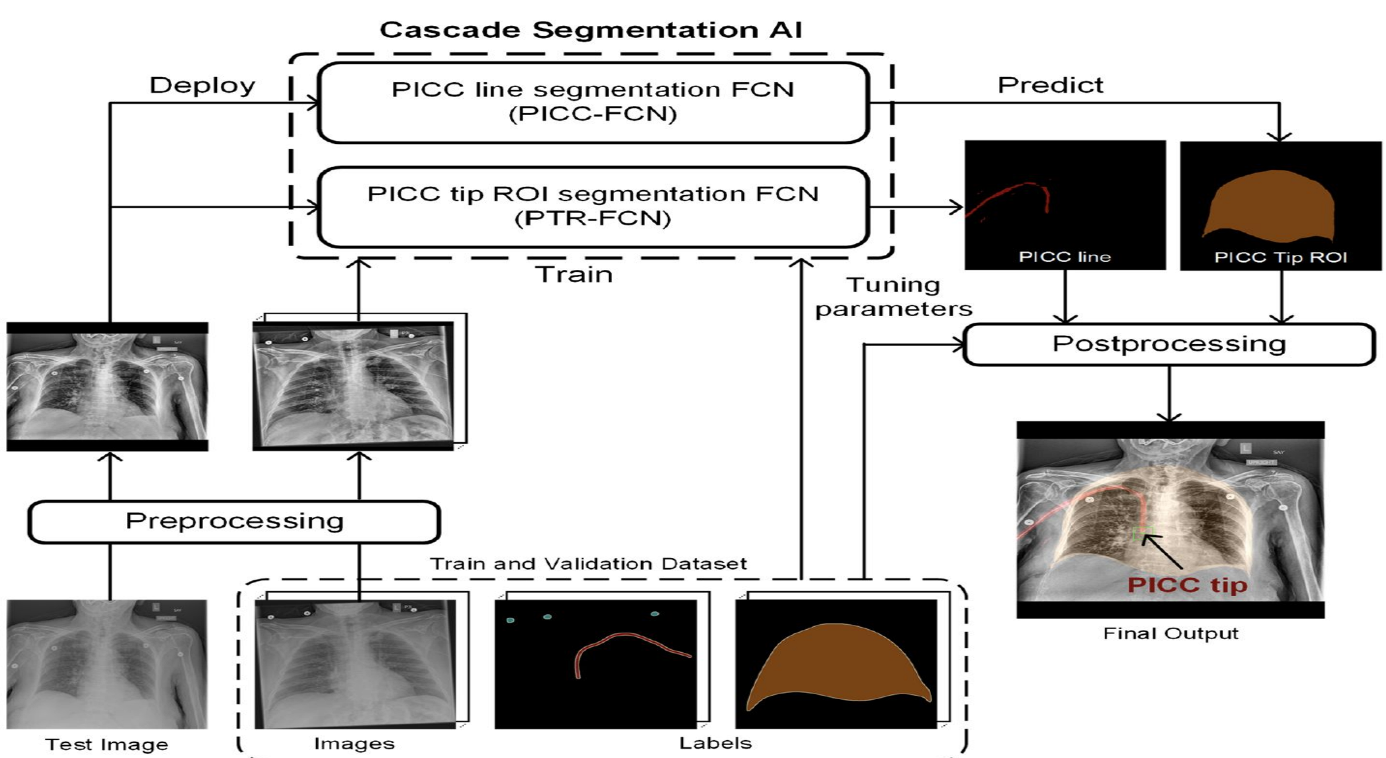
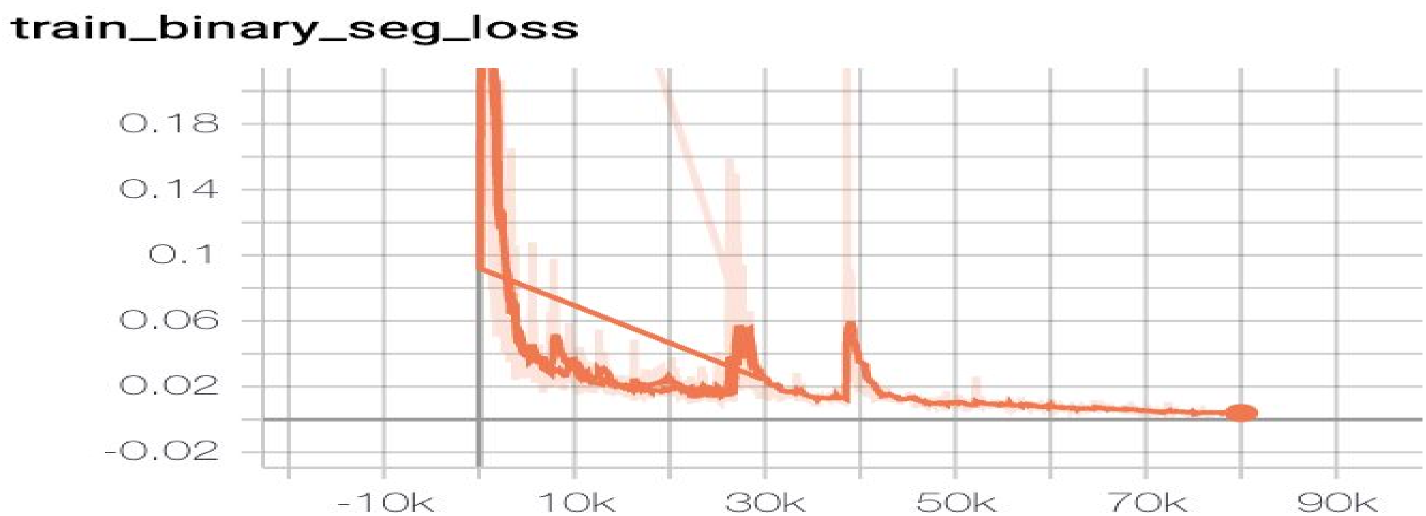


Figure. 4 Lee, H., Mansouri, M., Tajmir, S., Lev, M.H., and Do, S. (2018). A Deep-Learning System for Fully-Automated Peripherally Inserted Central Catheter (PICC) Tip Detection. Journal of Digital Imaging *31*, 393–402

A



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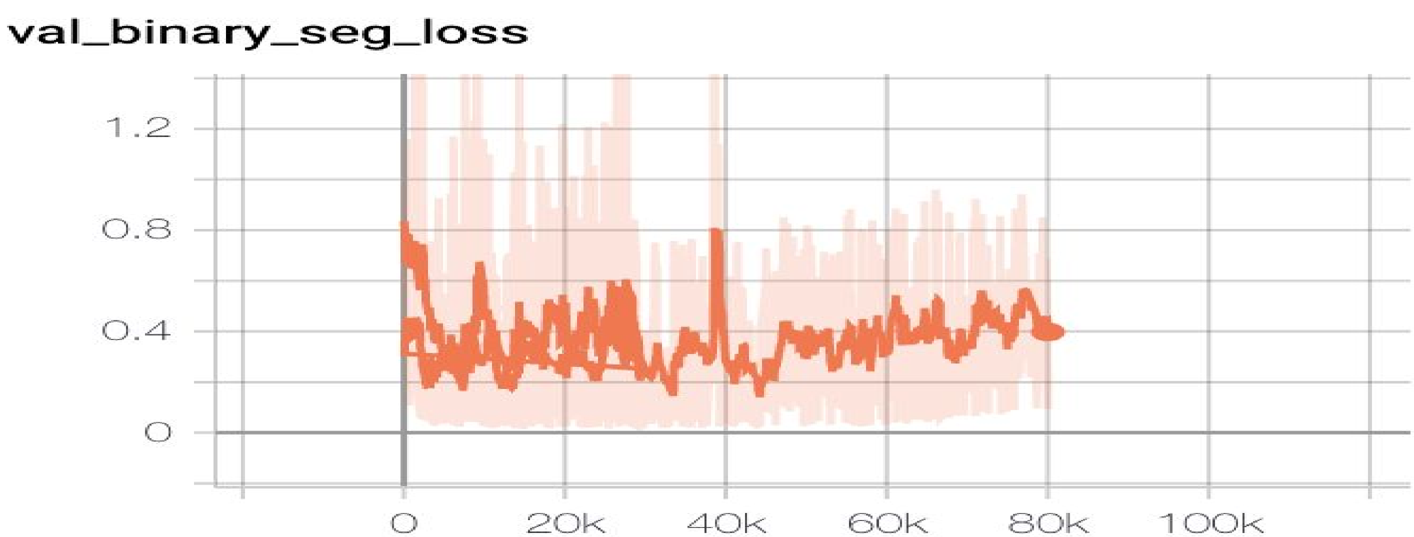

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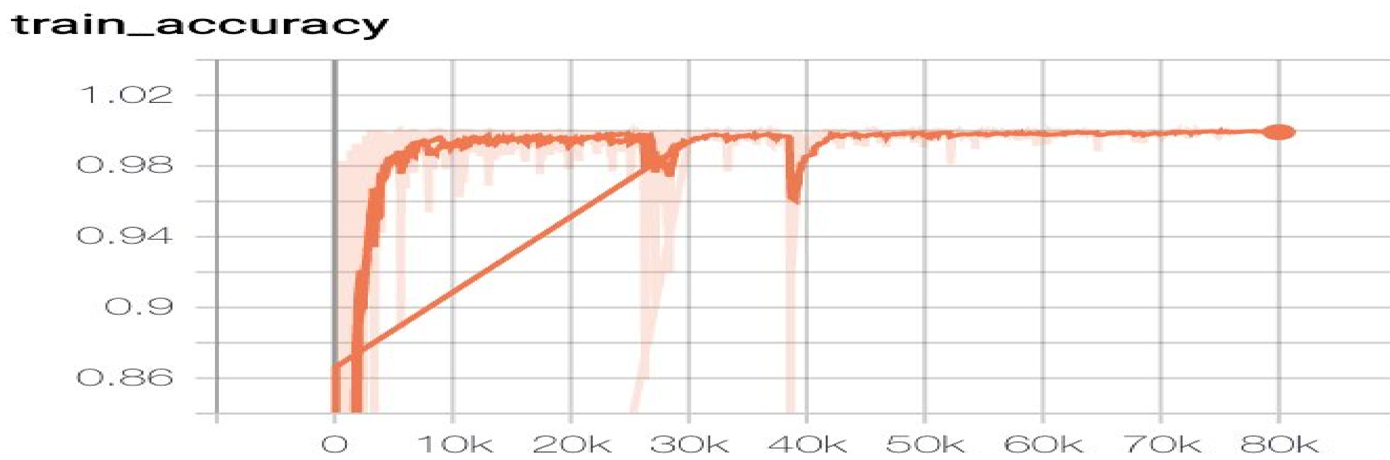

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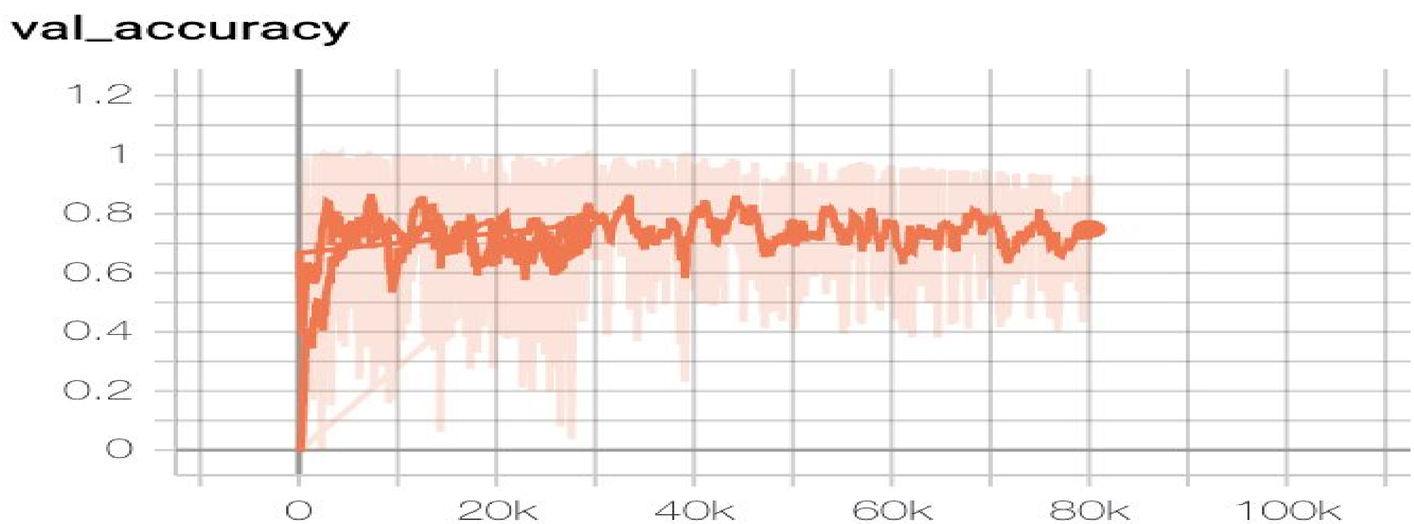

Figure. 5 The result of PICC line segmentation task. A. loss curve of training B. loss curve of validation C. accuracy curve of training D. accuracy curve of validation

DISCUSSION

In our study, we have made a workflow to predict PICC line tip position so that can see if malposition exists. Compared to PICC tip detection work of Lee (Lee, 2018), our system performs good enough even with little dataset. But we still have big space to improve, especially there are not much similar research for our direction.

We have achieved the first task, using semantic segmentation with convolutional and deconvolutional network and pixel-wise cross entropy loss to make PICC line segmentation with 0.53 Mean IU score. We reference the binary segmentation task in LaneNet (MaybeShewill-CV, 2019), and use pre-trained model of github to train our data. Since all data got from NYU Langone Hospital are unlabeled, it took lots of time for data labeling of PICC line and safe window at first. We didn't get too much data for our prediction. In the future, we can label more data to improve our model performance for both segmentation task and localization task. Also, we need to try more pre-trained models to compare and choose which model performs best. Lastly, MIMIC-CXR dataset can be used to add more data.

For semantic segmentation section, we have tried to use Mask R-CNN to make segmentation, but we only get the box accordingly of each PICC line, instead of showing and drawing the whole PICC line. Then we found LaneNet to achieve our goal. And some examples of prediction shown in figure. 7. We can see that our model can predict PICC line very accurately, but also there are some predictions have intervals. We need to use functions in opencv to link all the intervals to get our result picture more precise. Furthermore, to find the PICC tip point, we can make segmentation of ROI around the region of lung zone but not include the subphrenic areas (Lee, 2018), which was shown in figure. 4. By ROI segmentation and whole PICC line segmentation, we can find the largest y value in ROI, which is the tip location of PICC line. Thus, the measurement can be calculated the absolute distance for prediction and ground truth, such as RMSE (Lee, 2018).

In addition, there are ECG tube and other tube-shaped line in chest x ray image, we can distinguish them also when we get more data to be taken as background and improve our model prediction.

After we get the PICC tip segmentation, the following task is localization for safe window. Since we have labeled chest x ray image by a simple matrix, as we discussed before. We still need to improve the cariteria to make a more accurate safe window. We need to get the height information first and take height information into account (Johnston, 2013).

But this idea will lead to complicated learning process for model, because there is no reference for model to learn, we noticed the safe window placement may be a big difference between different chest x ray image while we labeling the safe window. So we can also try to make segmentation of lung, heart, to help model to learn how to find the PICC tip safe window. For the organ segmentation, we can use architecture shown in figure. 6, which also consists of an encode and decode parts. They provide InvertedNet to automatically detect lungs and hearts (Novikov,2017). There is an all-dropout architecture, since during the process of going deeper, we need to reduce the generalization test error. It is a popular and effective way to add dropout layer. In their research, they add drop layer following each convolutional layer after the activation (Novikov,2017). We can use Gaussian dropout as below:

$$\sigma = \sqrt{\frac{d}{1.0 - d}}$$

Another modification is all-convolutional, they shifted each pooling layer to a convolutional layer with kernel size, which is the same as the pooling size of the original pooling layer. And then they proposed the InvertedNet by reordering the number of feature maps from the layers output before.

Finally, we could simply detect the PICC tip placement by finding if x and y values are in safe window using functions in opencv, such as pointPolygon Test, etc.

All in all, we propose a workflow to help radiologists detect if the PICC tip placement is malposition or not, and has achieved PICC line segmentation task as a base to further goal. This AI process can reduce risk in treatment and aid in clinical-decision support.

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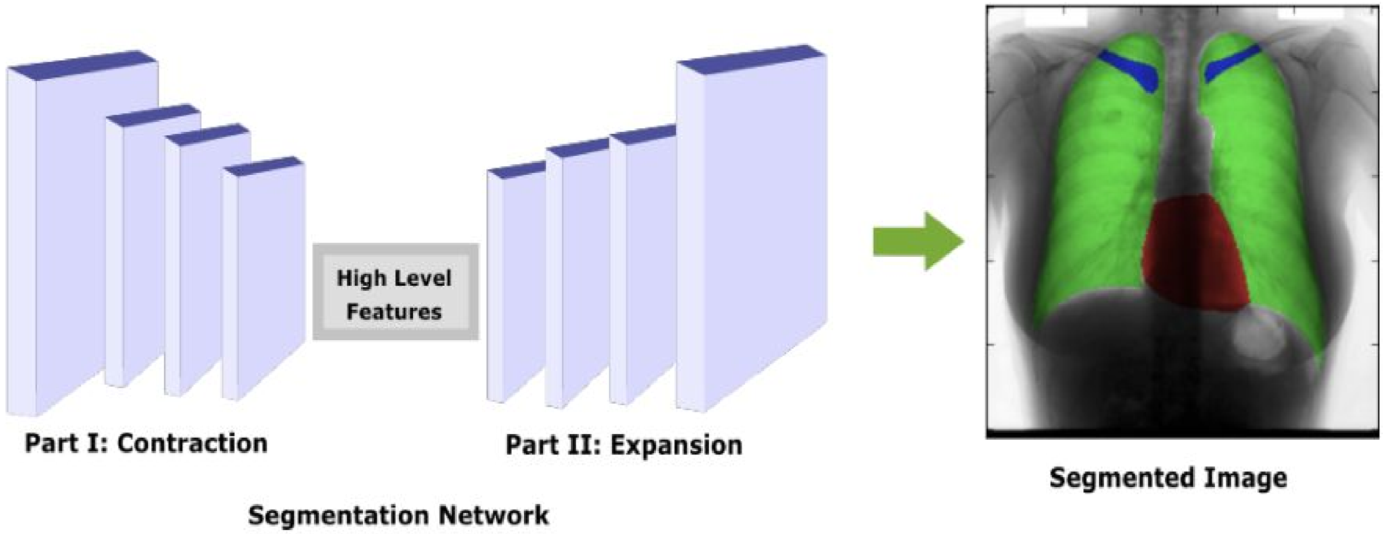
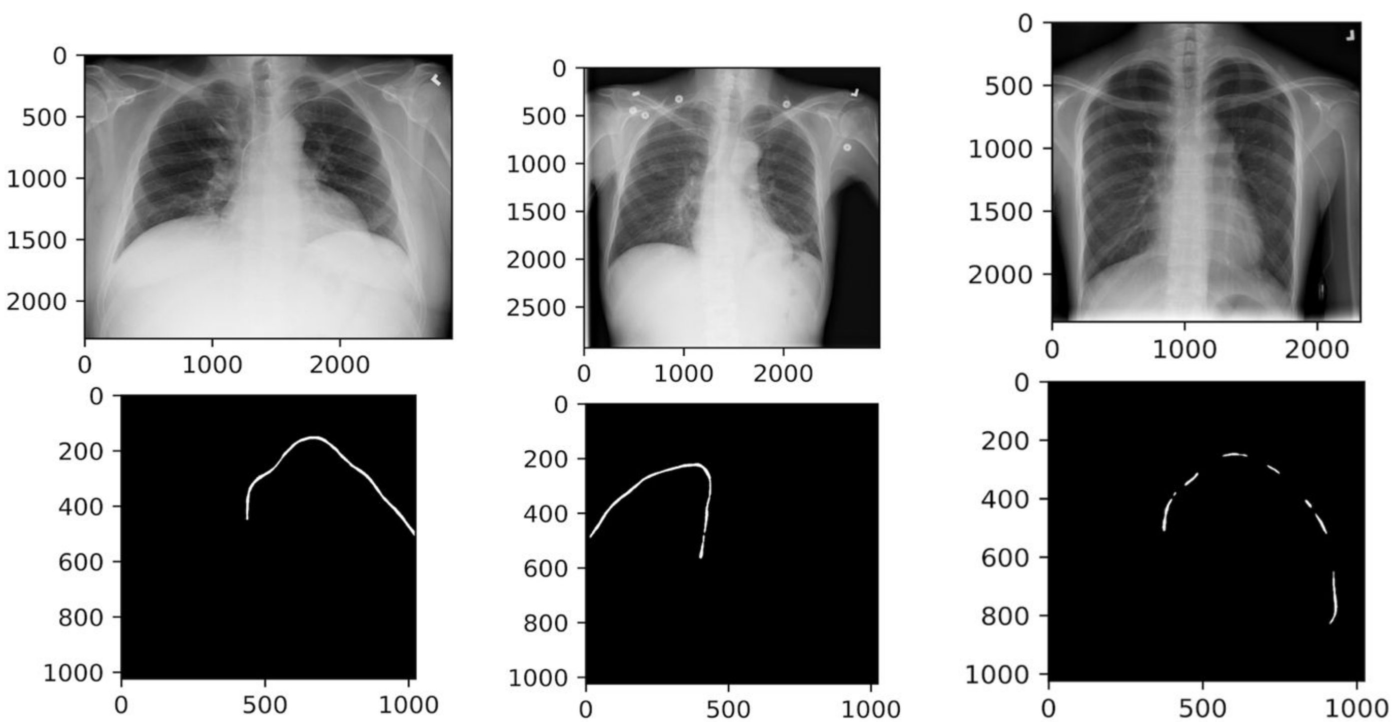


Figure. 6 Novikov, A.A., Lenis, D., Major, D., Hladůvka, J., Wimmer, M., and Bühler, K. (2017). Fully Convolutional Architectures for Multi-Class Segmentation in Chest Radiographs. ArXiv:1701.08816 [Cs].



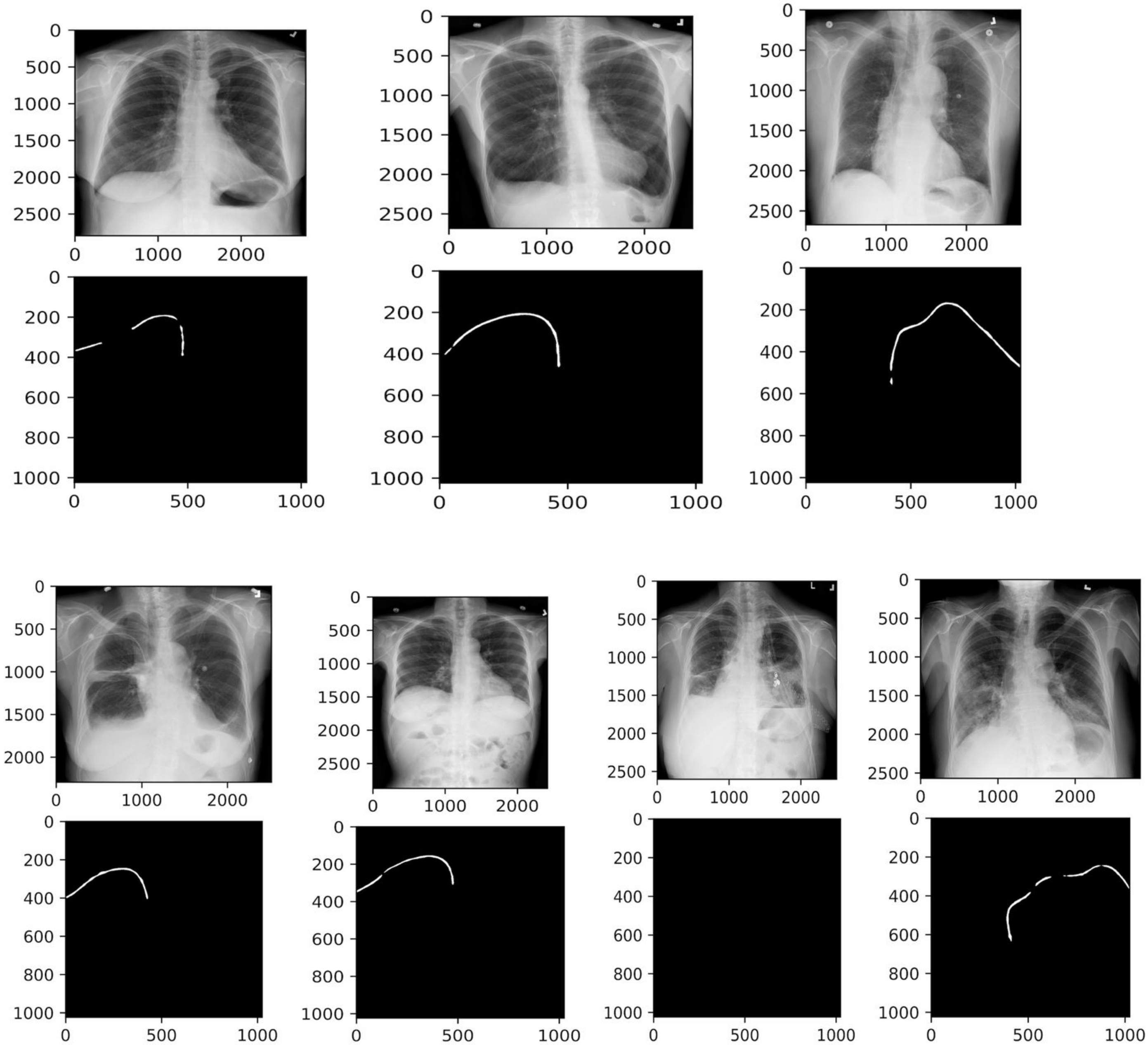


Figure. 7 Some examples for PICC line prediction

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