Auto find mispositioned catheters and lines by deep learning methods

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Abstract

In this paper, we propose a method that can label mispositioned catheters and lines on X-Ray images by using deep learning and image classification methods. We used different architectures like Resnet, EfficientNet, and DenseNet as the backbone of our solution to classify the line and tube from x-ray photos. We also applied different image augmentation methods to enhance our results. We introduced the learning rate scheduling method for fast convergence during the training, and we also employed mixed-precision training to accelerate the whole procedure while saving the GPU memory. The experiment result shows that the EfficientNet backbone significantly improves the classification accuracy compared to ResNet and DenseNet backbone.

1 Introduction

In hospitals, mispositioned lines and tubes would cause severe complications in patients. Nowadays, doctors and nurses frequently use traditional checklists to ensure they follow protocol in managing patients. These steps can be time-consuming and prone to human error, especially in stressful situations when hospitals are at capacity.

Nasogastric tube mispositioning into the airways has been reported in up to 3% of cases, with up to 40% of these cases demonstrating complications. Airway tube malposition in adult patients intubated outside the operating room is seen in up to 25% of cases. The likelihood of complication is directly related to both the experience level and specialty of the proceduralist. Early recognition of malpositioned tubes is the key to preventing dangerous complications (even death), even more so now that millions of COVID-19 patients need these tubes and lines.

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The gold standard for the confirmation of line and tube positions is chest radiographs. Once getting the chest radiographs (X-Ray images), a physician or radiologist must manually check these chest x-rays to verify the lines and tubes are correctly positioned. Not only does this leave room for human error, but delays are also common as radiologists can be busy reporting other scans. The delays would cause severe complications in most cases. Leveraging deep learning, we believe that we could develop algorithms that may detect mispositioned catheters and lines automatically and in a much sooner fashion. Once alerted from the model, clinicians can reposition or remove them immediately to avoid life-threatening complications, dramatically reducing the human resources involved.

Under the COVID-19 pandemic, almost all the hospitals are at capacity, and more patients require correctly positioned catheter lines and tubes. If successful, our efforts may help clinicians save lives and release many human resources on other emergencies. Quick feedback on catheter and line placement could help clinicians better treat these patients. Even beyond COVID-19, detection of line and tube position will always be required by many ill hospital patients.

The Royal Australian and New Zealand College of Radiologists (RANZCR) is a not-for-profit professional organization for clinical radiologists and radiation oncologists in Australia, New Zealand, and Singapore. The group is one of many medical organizations worldwide (including the NHS) that recognizes mispositioned tubes and lines as preventable. To label mispositioned tubes by deep learning methods, we use the dataset with X-Ray images and handcrafted labels published by RANZCR on Kaggle[1].

2 Related Work

Paras Lakhani [6] evaluated the efficacy of deep convolutional neural networks (DCNNs) in differentiating subtle, intermediate, and more obvious image differences in radiography. In the paper, three different datasets were created, which included presence/absence of the endotracheal (ET) tube (n = 300), low/normal position of the ET tube (n = 300), and chest/abdominal radiographs (n = 120). The datasets were split into training, validation, and test. Both untrained and pre-trained deep neural networks were employed, including AlexNet and GoogLeNet classifiers, using the Caffe framework. Data augmentation was performed for the presence/absence and low/normal ET tube datasets.

In[8], Hongyu Wang and Yong Xia proposed a model called ChestNet. It consists of two branches. The first classification branch is a universal feature extraction-classification network, which would, to some extent, free users from troublesome handcrafted feature extraction. The second branch is an attention branch to exploit the correlation between class labels and the locations of pathological abnormalities. By introducing the attention branch, the pathologically abnormal regions could be adaptively concentrated by the model. Using the proposed model, they achieved SOTA on the Chest X-ray 14 dataset.

In [2], Maayan and etc. suggest a method for training the network, first with synthetic data and then with real X-ray images in a fine-tuning phase, which allows the network to train on thousands of cases without annotating any data. The proposed method was tested on 477 real chest radiography from a public data set and reached AUC of 0.99 in classifying the presence vs. absence of the ET tube, along with outputting high quality ET tube segmentation maps, which could give us more hints on how the training should go on.

3 Method

3.1 Dataset

In this paper, we would like to detect the presence and position of catheters and lines on chest x-rays. We use 40,000 images as inputs to train and test our model.

The dataset has been labeled with a set of definitions to ensure consistency with labeling. The normal category includes lines that were appropriately positioned and did not require repositioning; The borderline category includes lines that would ideally require some repositioning but would in most cases still function adequately in their current position; The abnormal category included lines that required immediate repositioning. Since there can be multiple tubes in an X-Ray image and different tubes have different usages, the dataset labels are further separated into different tube categories. There are four categories for tubes in the dataset: PAC stands for Pulmonary artery catheter; ETT stands for endotracheal tube; NGT stands for Nasogastric tube; CVC stands for central venous catheter. The model will output if any kind of tubes are mispositioned.

3.2 Architecture

Convolutional neural network (CNN) is one of the most popular architectures to solve the image classification problem. ResNet[3] is one of the most widely used CNN architectures. ResNet features residual learning blocks that help fight against vanishing gradients problem by introducing skip connections. DenseNet[4] connects each layer to every other layer in a feed-forward fashion. The traditional convolutional networks would have L layers with L connections, but the DenseNet has L(L+1)/2 direct connections. Each layer in the DenseNet takes all proceding layers' feature-maps as the inputs, and the feature-maps would be used as the inputs into all subsequent layers. The DenseNets alleviate the vanishing gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the parameters. EfficientNet[7] is a recently introduced convolutional neural network. The authors of EfficientNet first design a new baseline network using neural architecture search and later scales it up using a new scaling method that uniformly scales the properties of CNNs using a highly effective compound coefficient. The EfficientNet series archives state-of-the-art accuracy in the ImageNet dataset as of 2020.

We choose ResNet, DenseNet and EfficientNet as the backbone CNN for our classification model in our experiments. Most of the published experiments on this dataset use ResNet as their image classification backbone. ResNet series are great models and are used widely in image classification tasks. However, from the paper and experiments published recently, EfficientNet performs better than ResNet on ImageNet classification. Therefore, we believe changing the CNN backbone from ResNet to EfficientNet can improve the accuracy of mispositioned tube detection.

Since there are multiple tubes, we proposed a multi-head image classification network for poorly placed tube detection. In our model, we have four different heads. Each of them receives the same flattened CNN features as input and uses a single linear layer for classification output. We use different loss functions for different heads. For ETT and SGC heads, we applied a standard Softmax layer and cross-entropy loss on them. For NGT and CVC heads, we applied a Sigmoid layer and Binary cross-entropy loss on them. We use Binary cross entropy loss on NGT and CVC heads because there could be more than one NGT or CVC tubes in one X-Ray image. Therefore, the result can be both in the Normal category and Abnormal Category. The traditional Softmax layer does not fit this situation, so we use a sigmoid layer and Binary cross-entropy loss.

One of the critical properties of CNN is that the shallow layers in CNN learn general features. In contrast, the deep layers in CNN learn specific features. Using this property, we also propose a new kind of header with an extra CNN layer and a linear layer. The CNN layer is the same as the last layer of the CNN backbone. In training, the heads receive features from the second to last layer of the CNN backbone and extract features using the last CNN layer with its own weights. We believe this kind of head can perform better because it can only learn the specific feature it wants.

3.3 Image augmentation

Image augmentation is a common technique used in image classification tasks. To archive higher accuracy, deep learning methods require many samples. However, the samples available for training are usually limited. We can use image augmentation to create new training samples artificially by rotation, crop, and flip the images to solve the problem. In our settings, we first scale the images by a random multiplier with a range of 0.08 to 1.0; then, we crop the image to 256x256. The cropping process reduces the GPU memory usage in training and ensures that image processing is fast since the original images are large. After random rotation and random flip are applied to the image, we normalize the image to the mean and the standard deviation from the ImageNet dataset. The normalizing process solves the imbalance samples problem and ensures smooth training as we apply weights pre-trained on ImageNet to our CNN backbones.

3.4 Learning rate scheduling

To archive the best accuracy, we dynamically reduce the learning rate during training. We use a method called reducing learning rate on plateau. As the name tells, half of the learning rate will be reduced if the validation set's overall accuracy has stopped increasing for 10 epochs. We use this method to accelerate the initial learning by using a slightly larger learning rate and fine-tuning the model automatically by reducing the learning rate.

3.5 Mixed precision training

As recent CNN models become deeper and deeper, GPU memory requirement increases, and the training speed decreases. We use a new training method called mixed-precision training to accelerate the training speed and reduce GPU memory usage. During training, all convolution and matrix multiplication will be performed under float 16 precision, significantly reducing GPU memory usage by half and increasing training speed. When calculating loss, the precision is scaled back to float 32 to prevent underflow or overflow for loss calculation.

4 Experiments

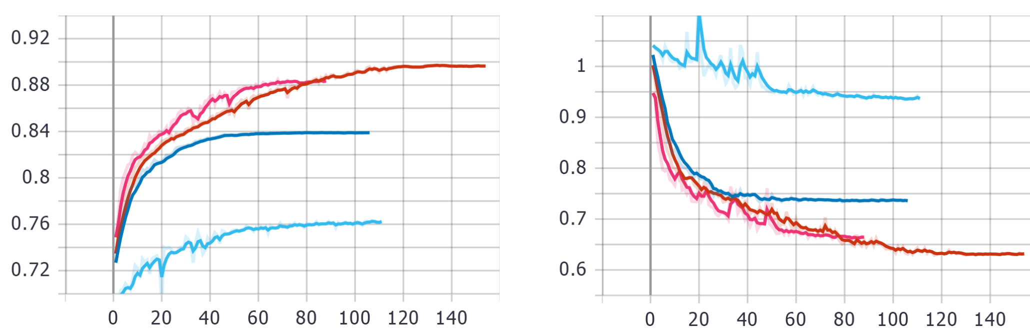
We split the official dataset into the training set and validation set, and use a fixed random seed to ensure the result is reproducible. 80% percent of data becomes training set, 10% of data becomes validation set, and 10% of data becomes test set. During the training, we use SGD as the optimizer, set the batch size to 32, initial learning rate to 0.001 and momentum to 0.9. We use PyTorch as our training framework and use Tensorboard to monitor and record our training results.

4.1 Metrics

Instead of looking at the results' accuracy, we use area under ROC curve (AUC) as our metrics. A ROC curve (receiver operating characteristic curve) shows the true positive rate and false positive rate of a binary classification model at all classification thresholds. AUC is the area under the ROC curve, which is classification threshold invariant. Since people can set a threshold based on their needs (more false positive or false negative), the AUC metric can better reflect a binary classification model's overall performance.

4.2 Results

Compare between different CNN models The overall Loss and AUC is shown in Figure 1. All of the models use CNN + Linear head.



(a) Overall AUC (b) Overall loss

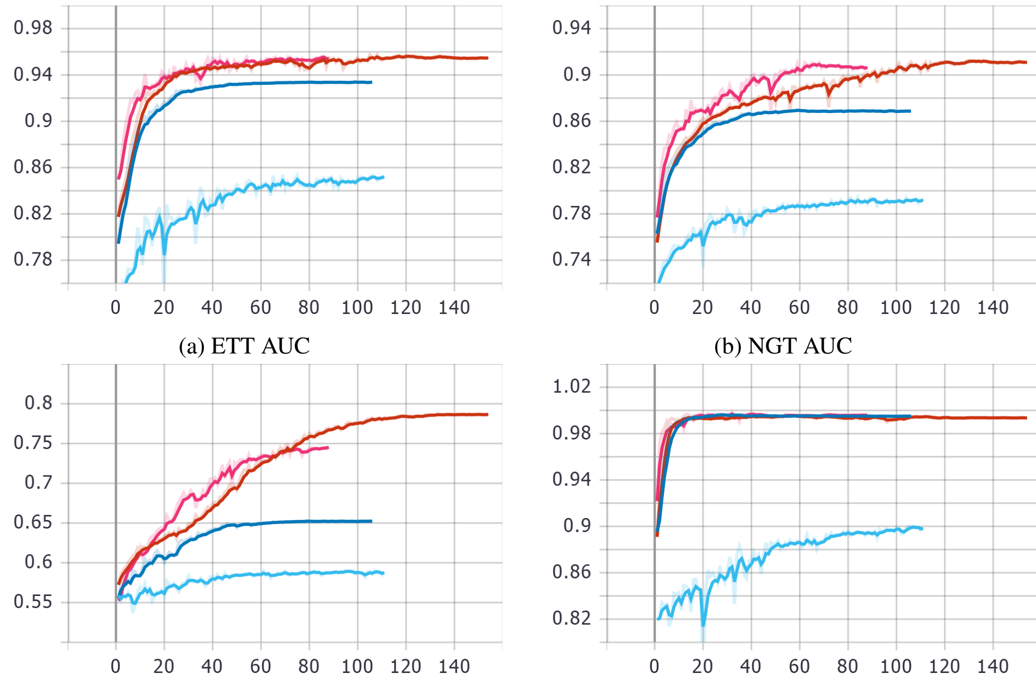
Figure 1: Overall Loss and AUC for different CNN backbone. Pink line: Model with ResNet50 backbone. Red line: Model with EfficientNet-b5 backbone.Blue line: Model with EfficientNet-b4 backbone. Aqua line: Model with DenseNet201 backbone.

The validation AUC for different categories is shown in Figure 2.

The test AUC for different CNN models is shown in Table 1.

Compare between different heads The overall AUC for differrnt heads is shown in Figure 3.

The test AUC for different CNN models is shown in Table 2.



(a) ETT AUC

(b) NGT AUC

(c) CVC AUC

(d) SGC AUC

Figure 2: Validation AUC for different tube categories. Pink line: Model with ResNet50 backbone. Red line: Model with EfficientNet-b5 backbone.Blue line: Model with EfficientNet-b4 backbone. Aqua line: Model with DenseNet201 backbone.

Table 1: AUC on test set for different CNN models

Model	Testset AUC
Resnet-50	0.8835
EfficientNet-b4	0.8389
EfficientNet-b5	0.8973
DenseNet201	0.7622

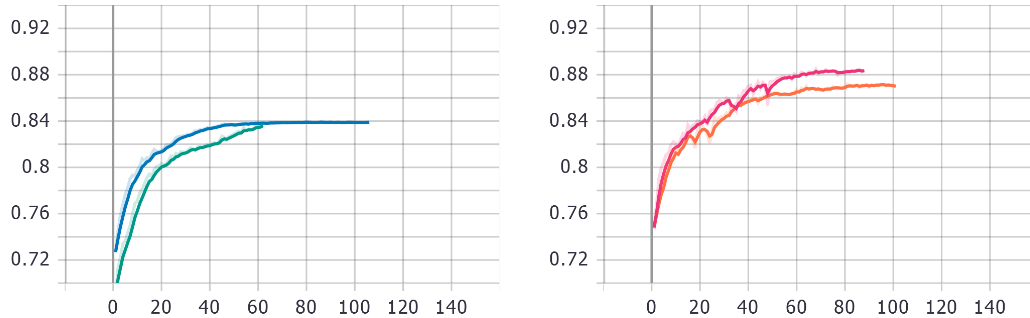
5 Discussion

5.1 Different backbones

In this report, we tried four different backbones: ResNet50, DenseNet201, EfficientNet-b4 and EfficientNet-b5. From Figure 1, we can see that EfficientNet-b5 has the highest AUC. It is expected since it is the largest model among all of the four models. The ResNet-50 performs better than we expected. It has almost the same performance as EfficientNet-b5 on ETT, and outperforms EfficientNet-b4 on all categories. Recent work has shown that convolutional networks can be more accurate and efficient to train if there are more short connections in and between layers. DenseNets take this into consideration and develop the architecture. But from this experiment, we could see that the AUC for DenseNet is the lowest. One possible reason is that these skip connecctions in DenseNet destory the layer structure and the individual CNN layers in the heads are actually affecting each other.

5.2 Different headers

We tried two different headers: one with Linear layer and the other with CNN + Linear layer. Comparing AUC for different heads using data in Figure 3, we can see that CNN + Linear layer head works better for both models. The result is consistent with what we expected before: shallow CNN



(a) EfficientNet-b4 AUC. Blue line: CNN + Linear layer. Green line: Linear layer.

(b) ResNet-50 AUC. Pink line: CNN + Linear layer. Orange line: Linear layer.

Figure 3: Overall AUC for different heads.

Table 2: AUC on test set for different head

Head-Model	Testset AUC
Linear-Resnet-50	0.8698
CNNLinear-Resnet-50	0.8835
Linear-EfficientNet-b4	0.8389
CNNLinear-EfficientNet-b4	0.8377

layers learn general features; deep CNN layers learn specific features. With one layer more flexibility of learning, the whole model will work better.

5.3 Different types of tubes

From Figure 2, we could see that, we achieved a relatively high accuracy on ETT, NGT and SGC (above 90% accuracy, some of them even above 95% accuracy). But for the CVC, the highest accuracy we could achieve is around 79%. From Figure 4, we could see that CVCs are the most complicated tubes. The tubes can be at the the left side, right side or even at the both sides of the body. It would be hard for the network to correctly detect different CVC tubes at all positions. The other types of tubes are relatively straightforward, and so get higher accuracy for these tubes.

6 Individual contributions to the project

Fangzhou Ai Fine tuning.

Yue Qiao ResNet and EfficientNet model. Multi-Head design.

Zunming Zhang DenseNet model.

Code `https://github.com/arition/CSE251B-PA/tree/master/Project`

References

[1] Royal Australian and NZ College of Radiologists. Ranzcr clip - catheter and line position challenge | kaggle. `https://www.kaggle.com/c/ranzcr-clip-catheter-line-classification`, 2021. (Accessed on 03/12/2021).

[2] Maayan Frid-Adar, Rula Amer, and Hayit Greenspan. Endotracheal tube detection and segmentation in chest radiographs using synthetic data, 2019.

[3] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015.

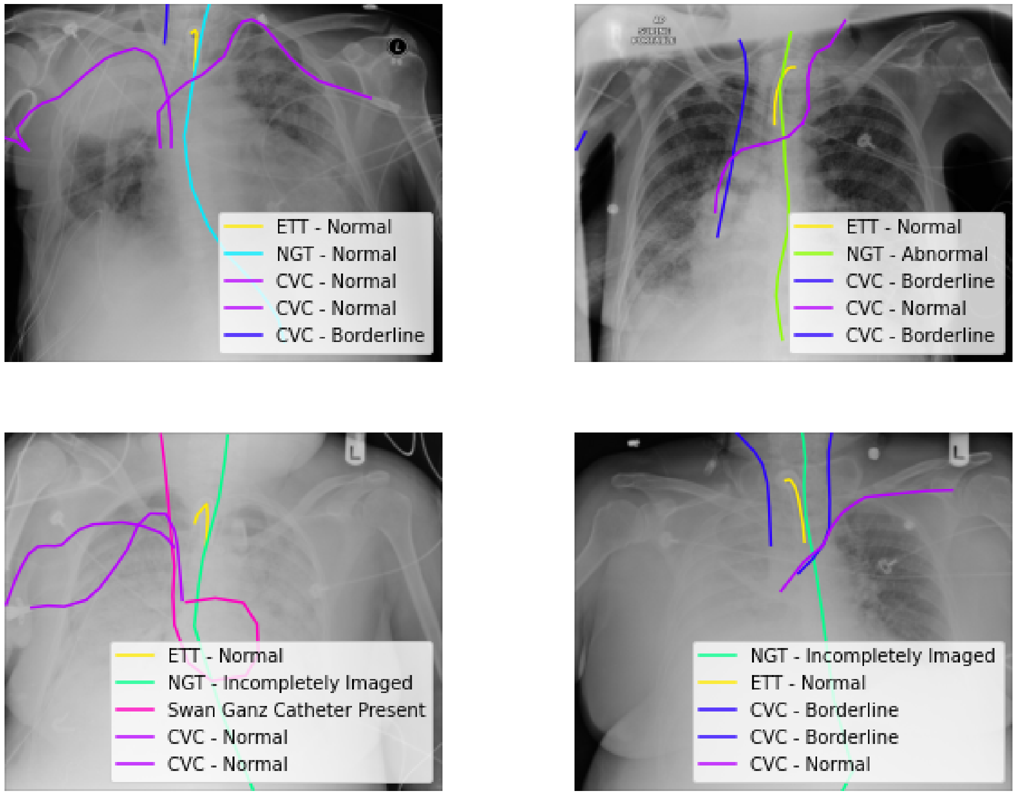


Figure 4: Visualization of different types of tubes.[5]

[4] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4700–4708, 2017.

[5] Nick Kuzmenkov. Making sense from annotations | kaggle. `https://www.kaggle.com/c/ranzcr-clip-catheter-line-classification/discussion/222630`, 2021. (Accessed on 03/20/2021).

[6] Paras Lakhani. Deep convolutional neural networks for endotracheal tube position and x-ray image classification: challenges and opportunities. *Journal of digital imaging*, 30(4):460–468, 2017.

[7] Mingxing Tan and Quoc V. Le. Efficientnet: Rethinking model scaling for convolutional neural networks, 2020.

[8] Hongyu Wang and Yong Xia. Chestnet: A deep neural network for classification of thoracic diseases on chest radiography, 2018.