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.

Preprint. Under review.

The gold standard for the confirmation of line and tube positions is chest radiographs in the real world. 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. Leveraging deep learning, we believe that we could develop algorithms that may be able to detect mispositioned catheters and lines automatically. Once alerted, clinicians can reposition or remove them to avoid life-threatening complications, which will dramatically reduce 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. Earlier detection of mispositioned catheters and lines is even more critical as COVID-19 cases continue to surge. 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 [5] 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[7], Hongyu Wang and Yong Xia proposed a model called ChestNet, which consists of two branches: a classification branch serves as a uniform feature extraction-classification network to free users from troublesome handcrafted feature extraction, and an attention branch exploits the correlation between class labels and the locations of patholog-ical abnormalities and allows the model to concentrate adaptively on the patholog-ically abnormal regions.With this 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. Whereas traditional convolutional networks with L layers have L connections (one between each layer and its subsequent layer), DenseNet network has L(L+1)/ 2 direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. DenseNets have several compelling advantages: they alleviate the vanishing-gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters. EfficientNet[6] 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.

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

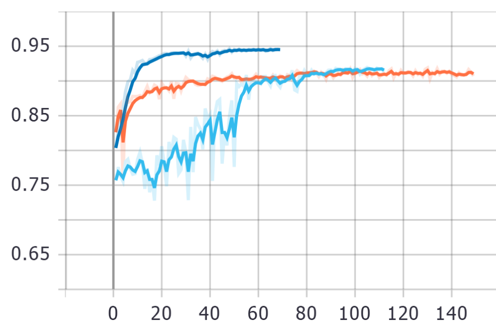
As recent CNN models become deeper and deeper, GPU memory requirement increases, and the training speed decreases. We use a new training method called mixed-precision training to accelerate the training speed and reduce GPU memory usage. During training, all convolution and matrix multiplication will 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

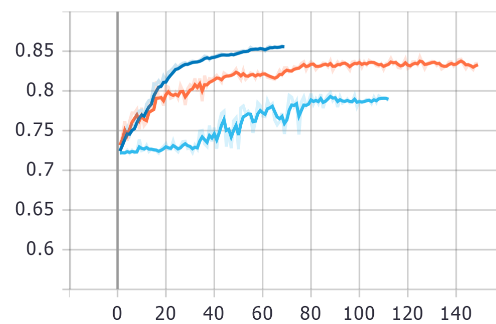
We split the official dataset into the training set and validation set, and use a fixed random seed to ensure the result is reproducible. 80% percent of data becomes training set, 10% of data becomes validation set, and 10% of data becomes test set. During the training, we use SGD as the optimizer, set 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 Results

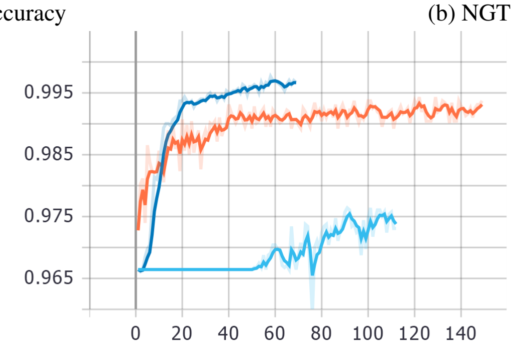
The validation accuracy for different categories is shown in Figure 1.



(a) ETT Accuracy



(b) NGT Accuracy



(c) SGC Accuracy

Figure 1: Validation accuracy for different tube categories. Orange line: Model with ResNet50 backbone. Blue line: Model with EfficientNet-b5 backbone. Aqua line: Model with DenseNet101 backbone.

More experiments in progress...

5 Discussion

We can see that for ETT, NGT and SGC, EfficientNet outperforms ResNet a lot from the Figure 1. That's expected since EfficientNet also outperforms ResNet in ImageNet classification.

Recent work has shown that convolutional networks can be substantially deeper, more acurate, and efficient to train if they contain shorter connections between layers close to the input and those close to the output. DenseNets take this into consideration and develop the architecture. But from this experiment, we could see that the accuracy is lower than EfficientNet.

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