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Automatic Detection of Misplaced Tubes and Catheters Using EfficientNet B7

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Abstract

Tube misplacement can lead to complications in patients together with serious medical malpractice cases. Intubation and the insertion of various medical tubes are employed to safeguard the airways of critically ill patients. Critically unwell patients undergo intubation, with the insertion of various medical tubes to safeguard their airways. The nasogastric tube serves the purpose of providing nutrition, while the central venous catheter finds application in a range of medical procedures. The significant challenge lies in doctors adhering to medical protocols to ensure the correct installation of these tubes. The implementation of medical protocols by physicians to guarantee the correct placement of tubes presents a significant challenge. Misplaced tubes increase the probability of complications in patients and, in the worst of cases, even lead to mortality. So, identifying the proper positioning of tubes before starting the procedure is crucial. In this paper, we propose identifying the misplaced tube and catheters detection using deep learning approach with accurate outcome.

Keywords: Tube misalignment, EfficientNet B7, central venous catheter, deep learning, nasogastric tube, EfficientNet model

INTRODUCTION

During surgical operations, intubation is commonly essential, particularly when the patient is in critical care. Doctors follow medical guidelines to ensure that tubes are placed correctly. Human mistake, however, is a possibility, especially when hospitals are overburdened. As a result, any tube that is misplaced can cause a catastrophic problem. To avoid these problems, chest X-rays (CXRs) are carefully and precisely reviewed on a regular basis to verify appropriate tube insertion. However, physical examination of CXRs takes time and frequently ends in misinterpretation. Automatic computer-assisted interpretations that are quick and accurate could potentially lower the cost of these surgical procedures, reduce radiologists' workload, and improve patient care quality. The endotracheal tube (ETT), the nasogastric tube (NGT), the central venous catheter (CVC), and the Swan–Ganz Catheter are all examined in this study. In severely ill patients, placement of an ETT is the primary technique of airway protection and management. Incorrect ETT placement is reported in 8% of patients, with 2% of them having major consequences. The nose is connected to the stomach via a tube called a nasogastric tube (NGT). For severely ill patients who are unable to feed themselves, enteral nutrition (EN) via feeding tubes is the most prevalent method of nutritional supplementation. NGT malposition occurs in 1.3% to 2.4% of patients. In critical care settings, CVCs are routinely used to monitor body functions and give drugs; 55% of CVC issues are due to health care workers, while 12% are caused by device

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failure. Swan–Ganz thin tubes are inserted into the heart's right side. Swan–Ganz catheterization is a procedure that is used in perioperative treatment and heart surgery. In 0.1% of cases, significant problems associated to Swan–Ganz catheterization and placement were discovered. Thousands of CXR images are taken in hospitals to examine the proper positioning of tubes and catheters, making a computer-aided diagnosis (CAD) crucial. Utilizing computer-assisted assessments of post-procedure CXRs to objectify decision-making in high-pressure situations can assist in case prioritization and reduce the potential for human errors.

LITERATURE REVIEW

As per literature survey, we are going to briefly describe the concepts of detecting and categorizing accurate catheter and tube placement from CXRs using a convolutional neural network–based EfficientNet model.

Mallon et al. [1] describe that the enteric tubes, such as nasogastric, are commonly used to deliver nutrition, fluid, and medication. Safe enteric tube positioning can be confirmed by a CXR as the reference standard. Radiologists categorized the CXRs of adult patients into two groups: one indicating a correct enteric tube position and the other signifying a misplaced enteric tube. In this study, they used 121-layer Dense Net on a private CXR dataset collected from Imperial College Healthcare NHS Trust. They used AUC (area under the curve) as a metric in this study and achieved achieved an AUC of 0.82.

Limitations: The study was performed only on NGT placement and used a small-scale dataset of 4600 CXR images.

Jung et al. [2] describe that the CXRs are used in the intensive care unit (ICU) to examine and monitor critically ill patients on life-supporting devices. The American College of Radiology advises conducting a CXR after intubation to verify the proper positioning of the ETT in order to ensure airway patency and adequate lung ventilation. In this study, the authors proposed models for the classification of the ETT position as correctly placed or incorrectly placed. CXRs are a valuable tool in the ICU for assessing and tracking the condition of critically ill patients who are reliant on life-supporting equipment. Among these patients, ETTs play a crucial role in maintaining open airways and ensuring proper lung ventilation. To ensure the safety and effectiveness of these procedures, the American College of Radiology recommends the performance of a CXR immediately after intubation to verify the correct placement of the tube. The data consisted of 1985 images that consisted of proper, improper placement, and absence of ETTs.

They used the EfficientNet model to classify the position of ETT and achieved an overall values of 0.892 for accuracy, 0.843 for precision, 0.843 for sensitivity, 0.922 for specificity, and 0.843 for F1-score.

Limitations: It is specific to only one type of tube, that is, ETT and dataset consisted of only 1985 images.

Ridouani et al. [3] describe that tubes and catheters are very important devices for saving patients' lives. There are a variety of tubes and catheters; those especially used during this study are ETT, NGT, and Swan–Ganz catheter. Errors in positioning these kinds of devices, if not detected early, may cause crucial complications (even death). Doctors and nurses use checklists to make sure the medical procedure goes smoothly, but these steps take a long time and require more resources with the possibility of human errors during verification protocols especially when hospitals are at full capacity. The main advantage of using a single deep convolutional neural network (DCNN) to detect abnormal positioning of several lines based on CXR processing is to avoid the complexity caused by using a DCNN network for each type of line. Efficient DCNN can detect abnormal positioning in real time and immediately notify doctors to adjust tube position. After testing several networks (ResNet50v2, DenseNet121, InceptionV3) during this work, they got the AUC scores of 77.54%, 75.92%, 75.52%, respectively, with ResNet at the best.

Limitations: Although they used a large dataset of 30,000 images the AUC can be improved by classification using other models.

Problem Statement

Intubation misplacement is a common medical error that can occur during emergency intubation procedures, where the tube or catheter is accidentally misplaced. Analyzing CXRs images manually is a time-consuming process that often results in misinterpretation. Human mistakes, however, are a possibility especially when hospitals are overburdened. As a result, any tube that is misplaced can cause a catastrophic problem [4].

Objective of the Work

The main objective of this work was to improve the accuracy in identifying the misplaced tube detection and improve the patient care quality.

Proposed Work

To solve this issue, we proposed an automated tube detection system using deep learning algorithm that can automatically detect the correct position of various tubes and helps reduce the probability of tube misalignment, preventing risky complications and reduce radiologist's workload.

METHODOLOGY

Numerous approaches for the automatic detection of tubes and catheters from CXR images have been proposed in the literature in which researchers have previously used deep learning to detect and classify tubes and catheters using CXRs. However, the vast majority of their applications are restricted to a single tube or catheter. The majority of the researchers trained deep learning models to detect tubes and catheters using a small dataset, which is insufficient for healthcare systems [5]. These studies incorporate diverse images and datasets sourced from various origins. Furthermore, numerous ways to evaluate performance have been applied. Earlier, it was done on small-sized dataset and used to detect only a single tube-like system: ETT, NGT, or CVC. The system may not possess the ability to detect all categories of intubation simultaneously [6].

To solve this issue, we proposed an automated tube detection system using deep learning that can automatically detect the correct position of various tubes and helps reduce the probability of tube misalignment, preventing risky complications and reduce radiologist's workload [7].

The depicted in Figure 1 illustrates the system architecture, which comprises the following modules.

Image Loading

Loading dataset is the first step, next the loaded dataset is given to the pre-processing. Here the dataset used is Catheter Line Position dataset.

Pre-processing

Pre-processing has the following steps to make data set cleaner and get better results. They are:

Noise Removal

Noise removal is a critical step in digital image processing to enhance image quality, and it holds particular significance in the field of medical imaging. Image noise can originate from a variety of sources, encompassing both external factors within the transmission system and environmental elements, such as Gaussian, Poisson, Blurred, Speckle, and salt-and-pepper noise [8]. In medical imaging applications, noise removal methods have gained paramount importance, and some of the most commonly employed filters are the median filter, Weiner filter, and Gaussian filter, each tailored to yield optimal results for specific types of noise. Here we use Gaussian filter for noise removal.

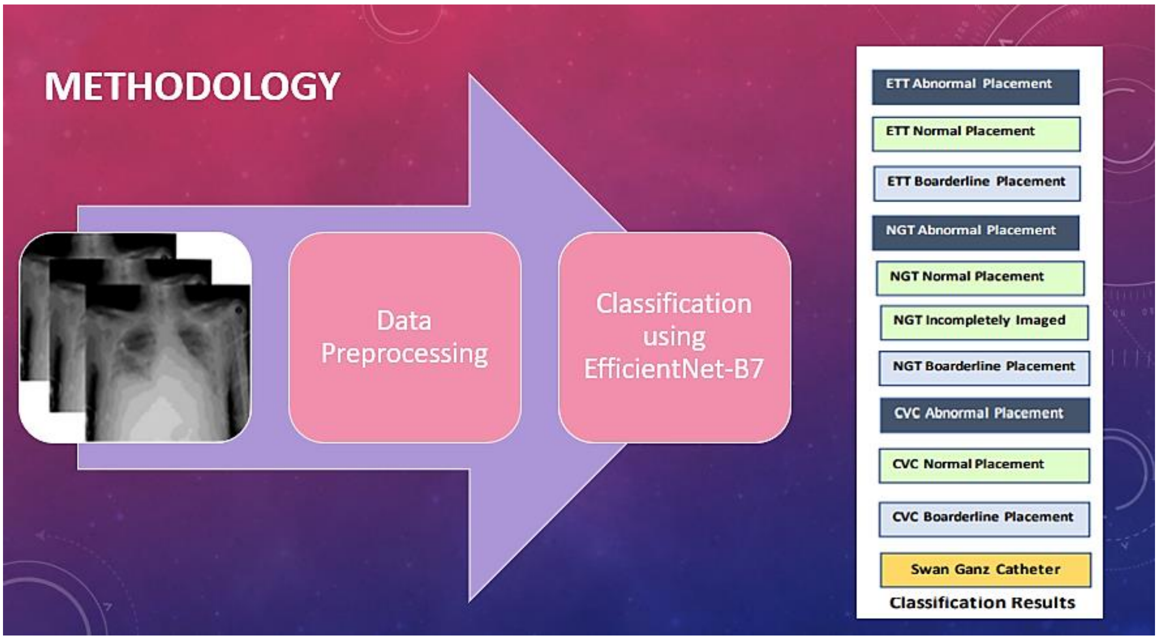

Figure 1. System architecture of proposed system.

Image Enhancement

Image enhancement involves improving the quality and content of original data before additional processing, with the main goal being to enhance the clarity and understandability of information in images for human viewers or to provide better input for automated image processing techniques. Here we apply the CLAHE algorithm for enhancing the quality of images [9].

Augmentation

Image count disparities can be rectified by employing image augmentation techniques. Image augmentation involves the artificial generation of additional training images by applying various forms of processing or combinations of multiple processes, including random rotations, shifts, and shearing, among others [10]. This helps to balance the number of images in different categories or classes, thereby improving the performance of machine learning models and reducing bias caused by imbalanced datasets. It can help overcome the increasingly large requirements of deep learning models.

Histogram Equalization

Histogram equalization is a simple yet effective technique for improving the visual quality of images.

- It adjusts the contrast of an image.
- Detecting important features like tubes in CXR images can pose a challenge when they are not distinctly visible. Histogram equalization can enhance the visibility of these tubes, improving the accuracy of diagnosis.

Dataset

The dataset is publicly available and taken from Kaggle. The dataset consists of three categories, normal class, abnormal class, and borderline. The dataset consists of three types of tubes represented in Table 1: NGT, ETT, and CVC. NGT is a medical device inserted through the nose and down into the stomach for enteral feeding, medication administration, or to remove gastric contents. ETT is a medical device inserted through the mouth and down into the trachea to maintain an open airway during general anesthesia or respiratory distress and can be used for mechanical ventilation. CVC is a type of catheter that is placed in a large vein in the neck, chest, or groin to allow for the administration of medications, fluids, blood products, or nutrition. Each tube is labeled into three categories: normal, abnormal, and borderline as shown in Table 1.

Table 1. Labels present in the dataset.

ETT	Abnormal	Endotracheal tube placement abnormal
ETT	Borderline	Endotracheal tube placement borderline abnormal
ETT	Normal	Endotracheal tube placement normal
NGT	Abnormal	Nasogastric tube placement abnormal
NGT	Borderline	Nasogastric tube placement borderline abnormal
NGT	Incompletely imaged	Nasogastric tube placement inconclusive
NGT	Normal	Nasogastric tube placement borderline normal
CVC	Abnormal	Central venous catheter placement abnormal
CVC	Borderline	Central venous catheter placement borderline abnormal
CVC	Normal	Central venous catheter placement normal
Swan–Ganz catheter present		

CVC, central venous catheter; ETT, endotracheal tube; NGT, nasogastric tube.

DEEP LEARNING MODEL

EfficientNet: EfficientNet is a deep neural network architecture introduced by Google researchers in 2019. EfficientNet was conceived with the aim of attaining top-notch performance on a range of computer vision tasks, all while maintaining computational efficiency. The central concept underpinning EfficientNet involves a methodical approach to harmonizing model depth, model width, and resolution through a technique known as compound scaling. This approach helps in optimizing the model architecture for both accuracy and efficiency.

EfficientNet models are known for achieving excellent results on image classification tasks with significantly fewer parameters compared to earlier architectures like ResNet or Inception. They have become popular in the field of computer vision due to their ability to achieve high accuracy while being more resource-efficient, making them suitable for deployment on devices with limited computational resources.

EfficientNet models are available in various iterations, denoted as EfficientNet B0 through B7, each progressively increasing in size and capability compared to its predecessor. Researchers have used EfficientNet as a backbone architecture for various tasks, including object detection, image segmentation, and more, achieving state-of-the-art results in many of these domains.

It is designed to provide a highly efficient and effective solution for image classification tasks, while minimizing the computational resources required during training and inference. EfficientNet achieves its efficiency by using a novel scaling method that balances the dimensions of depth, width, and resolution. The architecture scales these dimensions uniformly and proportionally, thereby achieving better performance than traditional scaling methods. The EfficientNet architecture consists of several convolutional layers, followed by a set of auxiliary layers that are designed to improve the network's performance. It includes a series of blocks, each of which contains a combination of convolutional layers, normalization layers, and activation functions. These blocks are responsible for extracting features at a different level of abstraction. One of the key features of the EfficientNet architecture is the use of a compound scaling method (represented in Figure 2) to determine the optimal dimensions of the network. This method involves scaling the network's depth, width, and resolution in a principled and efficient manner, resulting in a network that is both accurate and efficient. EfficientNet stands as a cutting-edge deep neural network architecture, delivering exceptional performance across various image classification tasks, all the while optimizing computational resource usage during both training and inference stages.

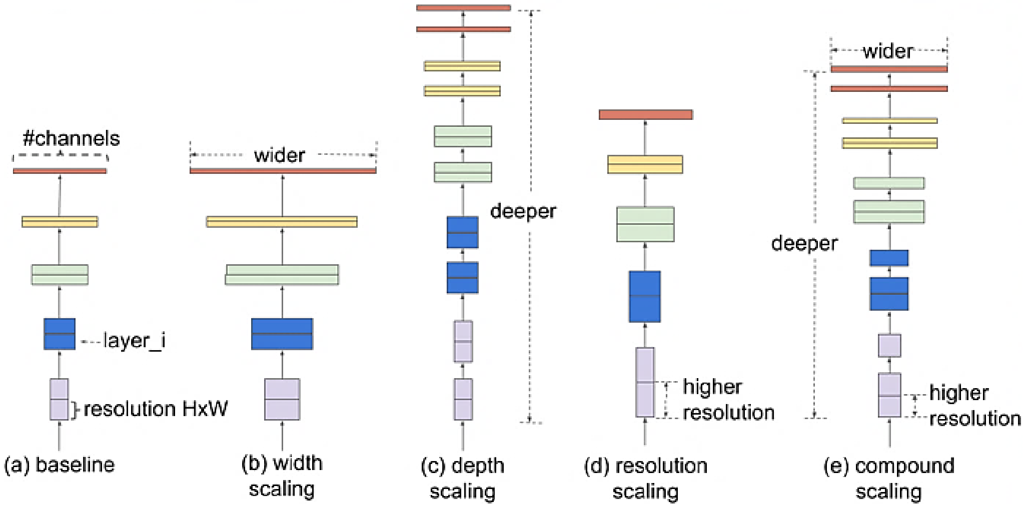

Figure 2. Compounding scaling.

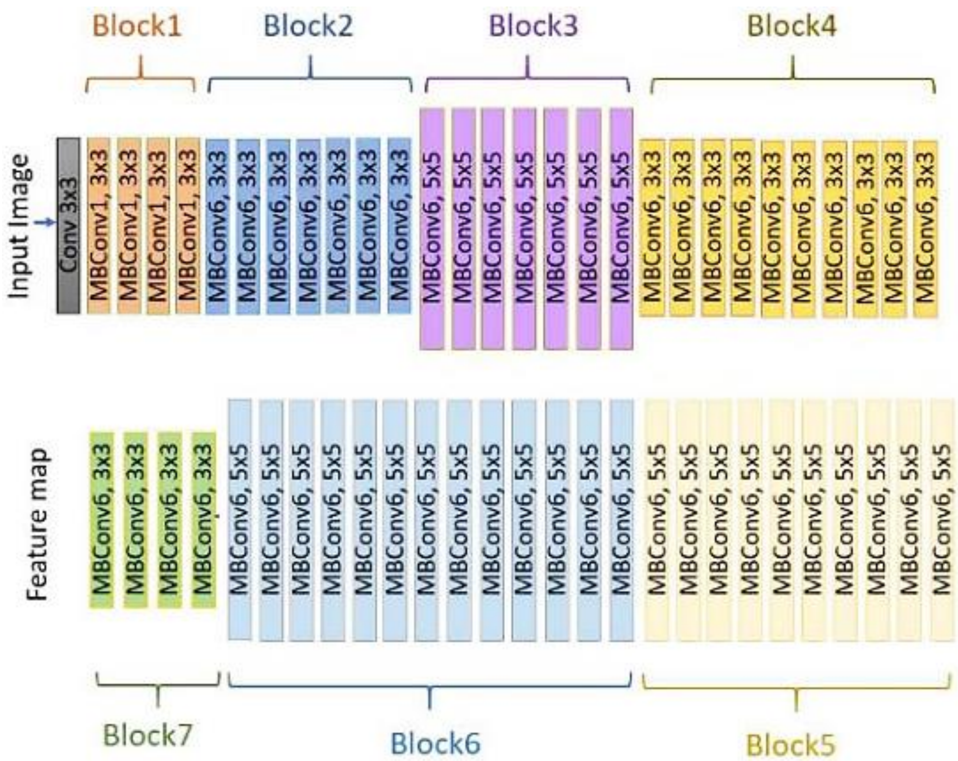

Figure 3. Architecture of EfficientNet B7.

Architecture of EfficientNet

EfficientNet models come in different variants, such as EfficientNet B0, B1, B2, ..., B7, with each variant being larger and more powerful than the previous one represented in Figure 3.

The MBConv (Mobile Inverted Residual Bottleneck) block is a key building block of the EfficientNet architecture. It is designed to increase the network's depth while keeping the number of parameters and computations low.

The MBConv block comprises multiple layers, as shown in Figure 4, with the initial layer being a pointwise convolution responsible for reducing the channel count in the input tensor. This layer has a small number of filters, typically less than 100.

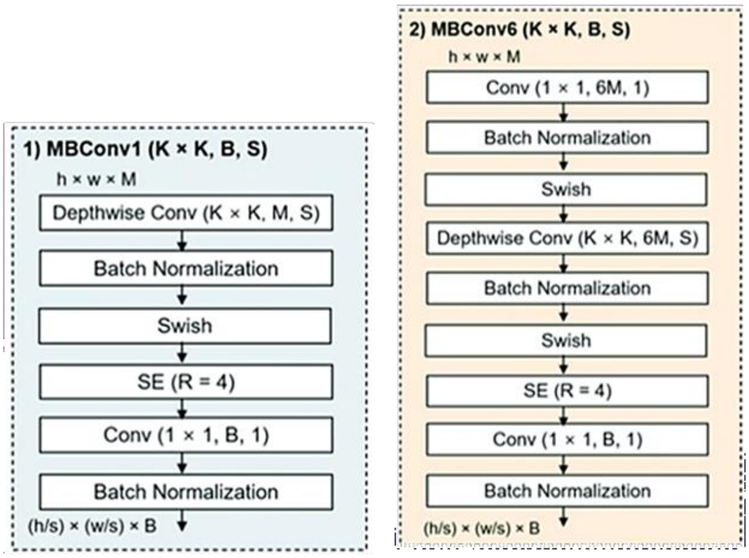

Figure 4. Layers in EfficientNet B7.

Table 2. Result analysis of the EfficientNet model.

Epoch	Loss	AUC	Val Loss	Val AUC	Learning Rate
1	0.062	0.780	0.054	0.849	0.001
2	0.051	0.859	0.052	0.883	0.001
3	0.047	0.891	0.044	0.911	0.001
4	0.044	0.909	0.043	0.921	0.001
5	0.042	0.921	0.041	0.925	0.001
6	0.04	0.930	0.041	0.931	0.001
7	0.038	0.937	0.039	0.932	0.001

AUC, area under the curve.

The second layer is a depth-wise convolutional layer. In deep neural networks, especially in models like MobileNet and EfficientNet, depth-wise convolutions are used to process the input in an efficient manner. Depth-wise convolutions typically use a compact kernel size, typically either 3 × 3 or 5 × 5.

The third layer involves a pointwise convolution operation, which increases the tensor's channel count. This layer has a larger number of filters than the first.

The fourth layer is a squeeze-and-excitation block, which enhances the network's expressiveness by selectively focusing on important features. The squeeze-and-excitation block consists of a squeeze operation, which reduces the spatial dimensions of the feature map, followed by an excitation operation, which weights the feature map based on its importance.

The final layer is a pointwise convolution that projects the tensor back down to the original number of channels. The EfficientNet model is used to extract features from CXR images. Finally, the probabilities of the 11 independent classes are predicted using the last dense layer with the sigmoid activation function.

The MBConv block is in turn made up of combination of some other layers. They are: (1) depth-wise convolution layer, (2) batch normalization layer, (3) swish activation function, and (4) squeeze-and-excitation block.

RESULTS

AUC is a robust metric for evaluating the performance of models, especially in situations where the classes are imbalanced. We have obtained an AUC of 93.7% (results depicted in Table 2).

Figures 5 and 6 depict the outcome analysis, specifically focusing on the accuracy of training data across different training epochs.

```
Epoch 1/12
188/188 [==============================] - 1062s 4s/step - loss: 0.0627 - auc: 0.7807 - val_loss: 0.0541 - val_auc: 0.8499 -
lr: 0.0010
Epoch 2/12
188/188 [==============================]  272s 1s/step  loss: 0.0514  auc: 0.8594  val_loss: 0.0521  val_auc: 0.8836  l
r: 0.0010
Epoch 3/12
188/188 [==============================] - 270s 1s/step - loss: 0.0473 - auc: 0.8920 - val_loss: 0.0441 - val_auc: 0.9118 - l
r: 0.0010
Epoch 4/12
188/188 [==============================] - 269s 1s/step - loss: 0.0442 - auc: 0.9093 - val_loss: 0.0430 - val_auc: 0.9216 - l
r: 0.0010
Epoch 5/12
188/188 [==============================] - 269s 1s/step - loss: 0.0422 - auc: 0.9212 - val_loss: 0.0413 - val_auc: 0.9255 - l
r: 0.0010
Epoch 6/12
188/188 [==============================] - 265s 1s/step - loss: 0.0403 - auc: 0.9303 - val_loss: 0.0414 - val_auc: 0.9312 - l
r: 0.0010
Epoch 7/12
188/188 [==============================] - 273s 1s/step - loss: 0.0386 - auc: 0.9378 - val_loss: 0.0398 - val_auc: 0.9325 - l
r: 0.0010
```

Figure 5. Epochs of training data accuracy.

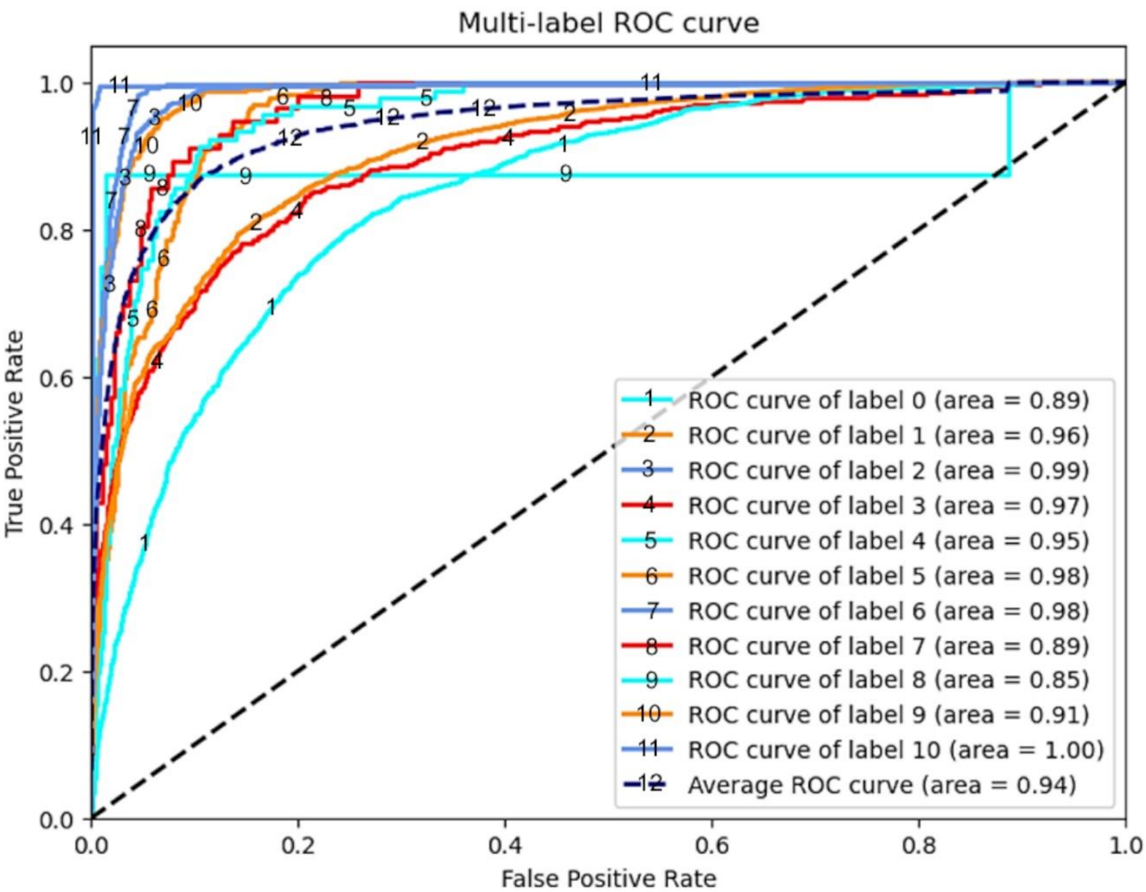

Figure 6. Area under curve.

CONCLUSION AND FUTURE WORK

There are several techniques to detect malpositioned tubes in CXRs. But based on the existing methods and future requirements we are considering EfficientNet B7 model to detect the position of tubes and catheters in CXRs. It achieved 93.4% AUC. However, it could be increased by a larger number of train images or through model hyperparameter tuning.

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