Detection of the Malpositioned Catheters and Endotracheal Tubes on Radiographs using Deep Learning Methods

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Detection of the Malpositioned Catheters and Endotracheal Tubes on Radiographs using Deep Learning Methods

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Abstract

Deep learning advancements have resulted in wonderful outcomes for a range of recent image processing research studies in medicine. Chest X-Rays are the most often performed radiological examination and are an particularly important modality that is being researched extensively for a variety of purposes. One of them is tube and line placement, which is usually verified by a radiologist because of the significant problems that might occur from incorrect placement. Delays are to be expected when radiologists are engaged with other scans, which offers an opportunity for human error. As COVID-19 accelerates, it will become increasingly critical to detect misplaced catheters and lines more quickly and accurately as more individuals are intubated and linked to a ventilator. Deep learning systems can help prioritize radiographs to interpret potentially misplaced catheters and lines. As a result, knowledge of contemporary algorithms was gained, as well as the major problems associated with creating a viable deep learning model for identifying catheter and tube locations on radiographs. This paper proposes a unique technique for classifying normal and malpositioned tubes on chest radiographs using EfficientNet CNN along with CBAM (Convolutional Block Attention Module) as a novel approach and EfficientNet CNN as a baseline approach. This investigation will assist in developing the machine learning techniques for this critical application.

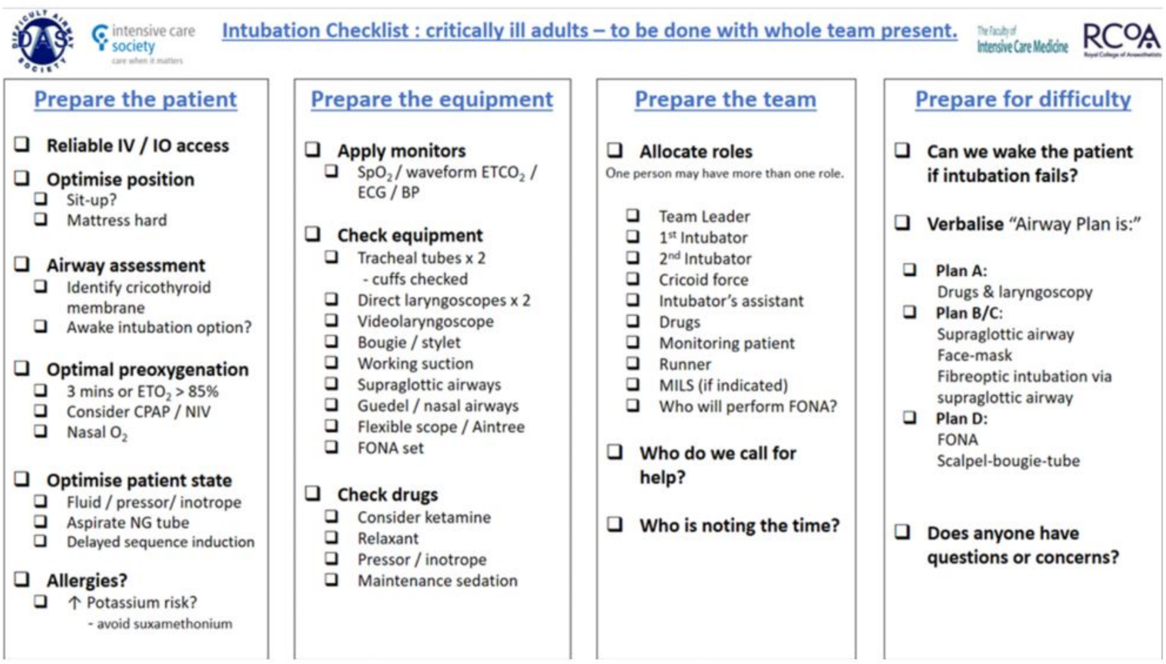
1 Introduction

For decades, X-ray imaging of the chest has been a cornerstone of radiology and is currently the topmost conducted radiological test worldwide, with nations getting an average of 238 erect-view chest X-ray pictures per 1000 people yearly (United Nations, 2008) (Çallı et al.; 2021). Chest X-rays are used for a variety of purposes, including determining the placement of catheters and tubes.

To aid the patient's breathing, different tubes and lines are used, as shown in Figure 1. A plastic tube called an ETT (Endotracheal tube) seen in Figure 1a is inserted via the mouth into the windpipe (trachea). After insertion, the ETT is linked with the ventilator, which provides oxygen to the lungs. Similarly, a tracheostomy tube (NGT) seen in Figure 1b is a curved tube that is placed into a tracheostomy stoma, which is a hole in the neck and windpipe. In terms of design, there are several kinds of tracheostomy tubes that differ regarding their various characteristics for various reasons. Also, a central venous catheter (CVC) seen in Figure 1c, sometimes referred to as a central line, central venous line, or central venous access catheter, is a catheter that is inserted into a large vein. It is a method of obtaining venous access. For more dependable vascular access, it is frequently necessary to place bigger catheters in more centrally placed veins in critically sick patients or those requiring extended intravenous therapy. These catheters are frequently put into neck veins, chest veins, groin veins, or arm veins (also known as a PICC line, or peripherally inserted central catheters).These are used if it is required to sedate and "rest" a severely ill patient or to maintain the patient's life. In hospital patients, lines and tubes may be incorporated, and improper position of these might cause significant problems. Medical practitioners use checklists as shown in Figure 2 to verify that they adhere to the procedure for treating patients while placing tubes (Higgs et al.; 2018). However, these stages are lengthy that are certain to mistakes (Yi et al.; 2020), which is especially true in difficult scenarios involving overcrowded hospitals.

(a) Endotracheal Tube (b) Tracheostomy Tube (c) Central Venous Catheter

Figure 1: Different Tubes and Lines



Intubation Checklist : critically ill adults – to be done with whole team present.

Prepare the patient
- Reliable IV / IO access
- Optimise position
  - Sit-up?
  - Mattress hard
- Airway assessment
  - Identify cricothyroid membrane
  - Awake intubation option?
- Optimal preoxygenation
  - 3 mins or $ETO_2 > 85\%$
  - Consider CPAP / NIV
  - Nasal O_2
- Optimise patient state
  - Fluid / pressor/ inotrope
  - Aspirate NG tube
  - Delayed sequence induction
- Allergies?
  - ↑ Potassium risk?
    - avoid suxamethonium

Prepare the equipment
- Apply monitors
  - SpO_2 / waveform $ETCO_2$ / ECG / BP
- Check equipment
  - Tracheal tubes x 2
    - cuffs checked
  - Direct laryngoscopes x 2
  - Videolaryngoscope
  - Bougie / stylet
  - Working suction
  - Supraglottic airways
  - Guedel / nasal airways
  - Flexible scope / Aintree
  - FONA set
- Check drugs
  - Consider ketamine
  - Relaxant
  - Pressor / inotrope
  - Maintenance sedation

Prepare the team
- Allocate roles
  One person may have more than one role.
  - Team Leader
  - 1st Intubator
  - 2nd Intubator
  - Cricoid force
  - Intubator's assistant
  - Drugs
  - Monitoring patient
  - Runner
  - MILS (if indicated)
  - Who will perform FONA?
- Who do we call for help?
- Who is noting the time?

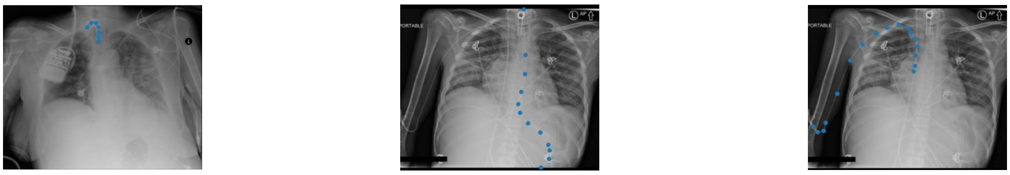
Prepare for difficulty
- Can we wake the patient if intubation fails?
- Verbalise "Airway Plan is:"
  - Plan A:
    Drugs & laryngoscopy
  - Plan B/C:
    Supraglottic airway
    Face-mask
    Fibreoptic intubation via supraglottic airway
  - Plan D:
    FONA
    Scalpel-bougie-tube
- Does anyone have questions or concerns?

Figure 2: Intubation CheckList

1.1 Motivation

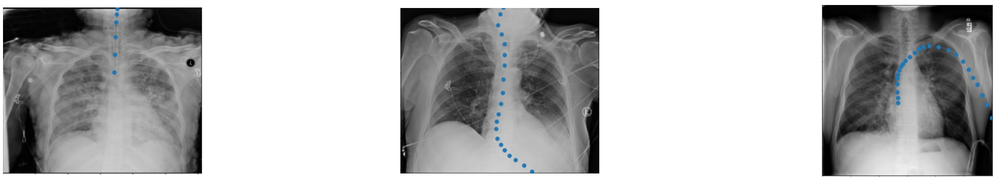
A nasogastric tube malposition has been observed in the airways of 3% of patients; up to 40% of these instances have problems. 25% of aged patients who had intubation away from the operation theater, endotracheal tube malposition is seen. In 30% of the radiogram, central venous catheters are misplaced (Jain; 2011). The early detection of misaligned tubes and lines on the chest X-Ray, which is particularly essential because millions of COVID-19 patients now need such tubes and lines, is the key to avoiding severe consequences (including death).

A Chest radiograph is the usual method for verifying the placement of the line and tube (Sakthivel et al.; 2020). However, these chest x-rays must be carefully inspected by a radiologist to ensure that the catheters and endotracheal tube are positioned properly. Not only would this introduce the possibility of mistakes, but delays are also a possibility, since radiologists may be distracted by other scans. Algorithms based on deep learning may identify misaligned catheters and lines. After being notified, clinicians should relocate or remove them to avoid potentially deadly consequences. The normal, borderline and abnormal positions of tubes and lines (annotated points of tubes and lines on chest radiograph) on chest X-rays from the labeled dataset are depicted in Figure 3, Figure 4 and Figure 5, respectively.



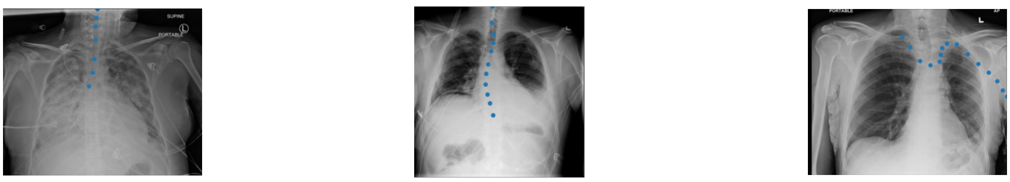
(a) ETT Normal (b) NGT Normal (c) CVC Normal

Figure 3: Normal Position of Tubes and Lines in Chest Radiograph



(a) ETT Borderline (b) NGT Borderline (c) CVC Borderline

Figure 4: Borderline Position of Tubes and Lines in Chest Radiograph



(a) ETT Abnormal (b) NGT Abnormal (c) CVC Abnormal

Figure 5: Abnormal Position of Tubes and Lines in Chest Radiograph

As COVID-19 spreads, it is critical to identify misplaced catheters and lines as soon as possible. Numerous hospitals are at capacity, and more individuals than ever before require these tubes and lines. Physicians and radiologists can handle these patients more effectively if they can promptly monitor catheter and line insertion. Apart from COVID-19, determining the location of lines and tubes will continue to be critical in the treatment of so many suffering hospital patients. Early diagnosis would help prevent deaths caused by malpositioning and would also provide a benefit to the radiology department.

1.2 Research Question

To what extent deep learning algorithms can detect the malpositioned tubes and lines on chest radiographs?

1.3 Research Objective

This study will look for tubes and lines that are incorrectly located on the chest radiograph. Incorrectly positioned endotracheal tubes and lines in hospital patients might cause significant problems. Deep learning systems may locate missing catheters and lines. In order to avoid serious acute problems, deep learning can realign or eliminate them.

- Detecting lines and ETT on the chest X-Rays(radiographs).
- Using image augmentation to improve detection accuracy.
- Using CLAHE to enhance the contrast of the picture.
- To construct model using CNN in combination with CBAM (convolutional block attention module).
- Training of the model and evaluation of the model's detection accuracy for misplaced catheters and tubes.

Section 1 of this paper outlines the research field, motivation (1.1), goal(1.2), and objective of this study(1.3). Section 2 delves further into earlier and related work. Section 3 discusses the suggested methodology of this research. Section 4 describes the research design specification, while Section 5 discusses the details regarding the research implementation, as well as the assessment procedure . Section 6 provides the comprehensive analysis of the results along with the discussions and findings of the research. Following that, section 7 provides with the conclusion and future work. At last, the report ends with the references.

2 Related Work

This section discusses and analyses relevant work on tubes and lines misalignment. This section is split into several subsections. Each section looks at the efficacy of a certain technique. To diagnose malposition, it is necessary to first examine the existence of tubes and lines on the chest radiographs, followed by further information, such as the catheter tip's placement. These bits of information can determine the kind and characteristics of the object. Finally, the tube and line positions may be determined.

2.1 Detection of the inserted catheter and endotracheal tube

In the first place, radiographs of the chest should be taken to check if the tubes and lines are detectable. It may be possible to train a model to distinguish between chest X-ray images with and without tubes by building two labeled datasets: one for chest X-rays with tubes and lines and one without them.

Kao et al. (2015) develop an automated technique for identifying tubes and positions of their tip in pediatric chest radiography. A seed point was located along the line going through the cervical region, and then the direction of the line was traced from the seed point. 528 pictures were obtained using endotracheal tubes and 816 images without them in this technique. Overall, 99.1 percent accuracy was achieved in identifying chest X-Rays with or without tubes. The accuracy of chest X-rays with tubes was 94.3% in that research, which may be increased by training the model on a bigger dataset. The ROC curve was used to evaluate the results.

A completely automated technique for segmenting catheters in live 2D X-ray fluoroscopic pictures using CNNs is proposed, with execution times of less than 125 milliseconds (Ambrosini et al.; 2017). The segmentation of the research data produced a median tip distance error of 0.9 millimeters and a median centreline distance error of 0.2 millimeters, with 85 percent of frames having a centreline distance error of less than 1 millimeter. Distance errors are measured in millimeters on the X-ray detector scale. Actual distance inaccuracies are lower on a patient-by-patient basis. Very few pictures contain false positives following CNN segmentation. The primary limitation of extracted catheters is that false negatives might result in significant segmentation gaps. As a result, the proximal end of the catheter may occasionally be missing. With a bigger training set, the model should be more generic.

Deep convolutional neural networks (DCNN) are extremely effective at differentiating images variations in radiography (Lakhani; 2017). DCNN and pre-trained networks are used in the research. They got an AUC of 0.99, which is a reasonable degree of precision given the conditions, but having small dataset of 180 pictures, there is a danger of overfitting. DCNN (AlexNet and GoogLeNet) also performed well with limited training data in recognizing pictures with a high degree of apparent variation, such as chest vs. abdominal radiographs, with an AUC of 1. DCNN, on the other hand, performed poorly in detecting the location of lines and tubes, having an AUC of 0.81; this suggests that there is room for improvement and that it may be enhanced further with high precision, as this is an important component of medical research. Identifying the catheter's position in the radiograph needs a large quantity of data to train the model, which would be insufficient with a relatively limited dataset. Additionally, high locations of the ET tube can be monitored that were not examined in this study.

The idea of sparse representation is brought into the architecture of the deep learning network, and its widespread use to represent superior multidimensional data linear decomposition capability and substantial architectural benefits of multilayer nonlinear mapping are presented (Liu and An; 2020). To solve the low classifier efficiency issue, a sparse representation classifier with kernel function optimization is presented. This sparse representation classifier can help enhance the accuracy of image categorization. Additionally, this article offers a deep learning model based on stacked sparse autoencoders that is applied to the fundamental issue of image classification. The technique is evaluated against various traditional image classification systems utilizing a public database, a medical database, and the ImageNet database. Not only does the suggested technique have better average accuracy than other traditional approaches, but it also adapts well to diverse image datasets, as demonstrated by testing findings. This technique is more accurate with big datasets and could be less accurate with biomedical image analysis, as the datasets related to it are comparitively smaller.

2.2 Detection of the tip of the catheter and tube

Along with identifying the existence of the tube, other method is to find the location of the tip which is necessary for detecting the location of the tube. Kao et al. (2015) evaluated each pixel value to the preceding average value repeatedly, ending at the point when the pixel value abruptly declined. The amount of the pixel value decrease at the tip position varies across images due to picture contrast or noise, and employing a fixed threshold may cause difficulties. Multiple criteria were utilized to choose positions of the tip, and the most appropriate candidate was picked to solve these concerns.To determine the accuracy of the indicated sites, a radiologist confirmed the position of the tip in chest x-rays with tubes. The difference in distance was utilized to determine the detection precision of the suggested technique. The average error was 2.01 mm in situations where the presence of an endotracheal tube was recognized satisfactorily.

This study proposes a method for identifying the edge of an implanted catheter using supervised deep learning (Lee et al.; 2018). After segmenting the lung areas and the PICC, the tip was defined as the PICC's lowest terminus inside the lung area. In addition to PICCs, these approaches may be used to find the tips of other types of catheters, such as central venous catheters and tunneled catheters linked to ports. On 150 test examples, the model with mean, SD, and RMSE of 3.10 mm, 2.03 mm, and 3.71 mm, respectively, estimated absolute distances from ground truth after being trained on 400 training cases and 50 validation cases on a case-by-case basis. Winding up the catheter and placing it irregularly in respect to anatomical landmarks, such as when the tip is elevated to the lungs, are two variables that may lead to the failure of these techniques. As a result, a more precise approach for determining the tip placement is necessary.

This article provides an in-depth review of deep learning-based object recognition systems that solve a number of sub-problems, including occlusion, clutter, and poor resolution, using different degrees of R-CNN modification (Zhao et al.; 2019). Direct regression, which is extensively used in deep learning for generic object recognition, is another approach with the most promise for recognizing catheter tips. Instead of the four corners of the bounding box, which are utilized for general object recognition, the tip location will be used as the regression goal for catheter tip detection.

The tip of a peripherally inserted catheter (PICC) was identified and segmented on chest X-ray images in this research utilizing a multi-task deep learning model (Yu et al.; 2020). To determine appropriate catheter placement on radiographs, the catheter tip must be identified. They conducted the study on a limited dataset of 348 X-ray pictures, given the application's criticality. As a result, further study in this sector is necessary to increase the overall accuracy of position detection.

To determine catheter placement, the catheter tip must be found. To guarantee effective operation of the catheter tips and to minimize the risk of issues, they should be positioned in certain anatomic areas. To minimize the risk associated with bronchial intubation, the tip of the ETT should be high above the tracheal carina (Yi et al.; 2020).

2.3 The type of catheter present in the Radiograph

In this study, preliminary tests were used to differentiate between the NGT, ETT, Tracheostomy, Drainage Tube, Central Venous Lines, and Swan-Ganz Catheter (Jain; 2011). Due to the fact that the nasogastric tube is used to feed patients or aspirate gastric contents, its tips should be placed in the stomach. It can penetrate the small intestine to a depth of 10 to 12 cm. The endotracheal tube provides ventilation for the lungs while also avoiding aspiration. The tip of the collar should be 5-7 cm above the carina in the neutral position. The tracheostomy point should be approximately midway between the stoma and the carina. In contrast to the ET tunnel, it maintains its position during neck flexion and extension. Central venous lines (catheters) are used for a number of purposes, including hemodynamic pressure management, medication delivery, nutritional support, and fluid administration. The patient may experience heart perforation and arrhythmias as a result of improperly positioned catheters. The Swan-Ganz is a catheter for the pulmonary artery that features a flow-directed balloon tip. It should be no more than one centimeter lateral to the mediastinum.

2.4 Position of the catheter in the Radiograph

Another study used the TensorFlow framework for Inception V3, ResNet50, and DenseNet to classify feeding tube malposition on chest and abdomen radiographs as critical (bronchial insertion) or non-critical (i.e., a feeding tube in the esophagus, stomach, or duodenum) (Singh et al.; 2019). The highest AUC of 0.877 was obtained by categorizing radiographs as vital or non-critical intestinal tube locations using Inception V3. In this study, the use of imbalanced data sets resulted in a poor AUC, which may be improved by expanding the size of the training data. The incorporation of more DCNNs into future models has the potential to enhance performance. Pre-trained networks consistently outperformed untrained networks in all scenarios. With the assistance of convolutional neural networks, critical feeding tube malpositions may be recognized and conveyed more readily.

The data set utilized in this work was used to train CNNs to classify chest radiographs as normal or abnormal following their evaluation of a collection of 533 pictures manually labeled by radiologists (Dunnmon et al.; 2019). The impacts of network design on end performance were quantified using standard binary classification measures, as well as a comprehensive error analysis that included visualization of CNN activations. The mean area under the receiver operating characteristic curve (AUC) for a CNN trained with 200000 pictures was 0.96. This AUC value was greater than that obtained when the model was trained with 2000 pictures (0.84) but not significantly higher than that obtained when the model was trained with 20000 images (AUC = 0.95). While CNNs trained on such a big dataset are beneficial, they might be more accurate because the dataset used for training is so vast and the AUC can be increased to enhance segmentation accuracy. Radiograph classification must be precise in order to advance this field further and discover misplaced catheters and tubes.

2.5 Attention Mechanism

This paper presents a Residual Attention Network with an encoder-decoder module (Wang et al.; 2017). The Residual Attention Network is made up of attention-aware features. Different modules' attention-aware features adjust as layers deepen. Within each Attention Module, the feed-forward and feedback attention processes are combined into a single feed-forward process.

Attention residual learning is used to train incredibly deep Residual Attention Networks with hundreds of layers. An alternative to directly calculating the 3D attention map was proposed by Woo et al. (2018). Because the separate attention generation method for 3D feature maps is less computationally intensive, it can be easily integrated into current CNN architectures.

This work adaptively calibrates channel-wise feature responses by modeling interdependencies between channels. Hu et al. (2018) show how to stack these components to build SENet topologies that generalize well across datasets. For current state-of-the-art CNNs, SE blocks increased output considerably with minimal computational expense. As in the previous module, global averaged characteristics are utilized to calculate channel-wise attention. To infer fine channel focus, Woo et al. (2018) suggest using max-pooled features instead. Hu et al. (2018) study missed spatial attention, which is essential in deciding where to focus.

Woo et al. (2018) examine the aspect of attention in architectural design. Attention not only guides concentration but also assists in the expression of interests. They propose a novel network module named "Convolutional Block Attention Module" in this study to increase representation power by focusing on relevant characteristics while suppressing irrelevant ones. Convolution procedures extract insightful characteristics by combining information across both the channel and spatial module. They created channel and spatial attention modules for each branch to learn what and where to pay attention. By understanding which knowledge to emphasize or conceal, their module successfully facilitates network information flow. They found that by adding their lightweight module, network speed increased considerably on several benchmarks (ImageNet-1K, MS COCO, and VOC 2007). They also observed that the module causes the network to correctly focus on the target item.

This article focused on the influence of attention on deep neural networks. The BAM is a simple and efficient attention module that can be used with any feed-forward convolutional neural network (Park et al.; 2018). From two different routes, their module produces an attention map. They put it where the feature maps are downsampled in each model. The module may be trained end-to-end for any feed-forward models and creates hierarchical attention at bottlenecks. They tested its efficacy on three different benchmark datasets. They found a hierarchical thinking system. Adaptive feature refining at the bottleneck may be observed in various vision tasks.

Using the self-attention mechanism, this research (Fu et al.; 2019) obtains a wide range of context-dependent connections. The Dual Attention Network (DANet) was suggested to adaptively integrate local and global characteristics. Two attention modules were integrated on the FCN , one for modeling spatial semantic interdependencies and the other for modeling channel semantic interdependencies. The location attention module aggregates the features at each position into a weighted average of all positions. The channel attention module highlights interdependent channel maps by combining relevant characteristics across all channel maps. Dual attention modules efficiently collect context and offer better segmentation data. An analysis of four scene segmentation datasets shows that our attention network regularly beats the competition. Also, reducing computational complexity and improving model resilience are essential and will be studied in future studies.

This article offers a Spatial Group-wise Enhance (SGE) system that may modify each sub-feature's value by establishing a factor of attention for each spatial location in each semantic category (Li et al.; 2019). When SGE is coupled with standard CNN backbones, image recognition efficiency may be substantially improved. Using ResNet50 backbones, SGE improves accuracy by 1.2 percent on the ImageNet test. The SGE module will greatly improve feature groups' capacity to convey various meanings. Despite its simplicity, SGE has demonstrated its practical value by consistently progressing in image classification and detection tasks.

Self-attention is viewed as an alternative to convolutions in this article (Bello et al.; 2019). Using relative self-attention in two dimensions outperforms convolutions as an image categorization computational primitive. So they suggest concatenating convolutional feature maps with self-attention feature maps to enhance convolutional operators with self-attention. In the fully attentional environment, future research may examine how different attention mechanisms balance computing efficiency and representational power. By removing downsampling and average pooling, a computational method based on local attention might be developed.

This article classifies current CNN architectural advances into seven groups based on intrinsic taxonomy observed in newly published deep CNN architectures (Khan et al.; 2020). Each of the seven categories is described below. Also addressed are basic CNN components, current issues, and CNN applications. CNN's block-based design simplifies and clarifies architecture, allowing for modular learning. The block concept will continue to be employed, and CNN's performance will improve. In addition to spatial information, attention and channel information manipulation will be increasingly relevant in deep learning model building.

2.6 Research Gaps and Proposed Solution

Previous work on evaluating radiographs using pre-trained networks has been conducted on a very limited and unbalanced dataset, which does not meet the requirements of this essential application of medical research. Many studies conducted in this field demonstrate that segmenting or categorizing radiographs based on specific criteria (Normal or Abnormal, Et tubes present or absent) is rather accurate, with an AUC (ROC curve) of about 0.99. Additionally, while detecting the tip of the tubes is performed with satisfactory precision, there is room for improvement by using the tip position as the regression goal for catheter tip detection rather than the four corners of the bounding box, which is utilized for general object recognition (Zhao et al.; 2019). However, detecting the tubes and lines in such radiographs remains a study topic, and no research has achieved the level of precision necessary in this sector.

Malpositioning can result in a variety of problems, including death. Convolutional procedures on position determination extract insightful characteristics by combining cross-channel and spatial information, which may result in the loss of many critical and target aspects in biomedical pictures. The purpose of this paper is to propose the use of the "Convolutional Block Attention Module". A successful technique that relies on acquiring certain features from an input image and applying them to the network, which leads to the network locating the targeted objects, as experimentally shown by Woo et al. (2018). Further, in-depth investigation is conducted on various datasets in order to establish the viability of this approach to image analysis, as reported in the paper proposed by Woo et al. (2018).

2.7 Summary details of the related work

In Table 1 summary of the previous works are provided.

Author(s)	Objectives	Research Design	Keywords	Findings
Kao et al. (2015)	Identifying ETT and their tip positions	Used a seed point and utilized numerous line paths threshold to determine the candidate position	Seed point, threshold, cervical region, Lmax & C	99.1% in locating the ETT on chest radiographs
Ambrosini et al. (2017)	Segmenting catheters in live 2D X-ray fluoroscopic images	Automated techniques using CNN	Fluoroscopic Images, CNN, segmentation	Few images contain false positives and false negatives are resulting in significant segmentation gaps
Lakhani (2017)	Differentiated Image variations using DCNN & Pretrained networks	Based on AlexNet and GoogLeNet	AlexNet, GoogLeNet,DCNN, ETT	AUC of 0.99 but over-fitting is possible due to very small dataset
Wang et al. (2017)	Using attention residual learning and train Residual Attention Networks	Residual Attention Network with an encoder-decoder	Residual Attention, encoder-decoder, feed-forward	Directly calculated the 3D attention map
Lee et al. (2018)	Identifying the edge of an implanted catheter using supervised deep learning	Segmented the lungs area and defined the tip area	PICC, deep learning, CVC	Mean, standard deviation, and root mean square error of 3.10 mm, 2.03 mm,and 3.71 mm, respectively. A more precise approach is required.
Hu et al. (2018)	Calibrated channel-wise feature responses	SENet topologies by modeling interdependencies between channels	SENet,channel-wise, CNN	SE blocks increased output with minimal computational expense
Woo et al. (2018)	Examine aspect of attention in architectural design	Used features from both channel and spatial attention modules using "CBAM"	CBAM, channel axis, spatial axis, attention	Network speed increased on several benchmark dataset using CBAM architecture.
Park et al. (2018)	Using BAM with any feed-forward CNNs to see the influence of attention on deep neural networks	BAM with deep neural networks	BAM, neural networks, attention	Found a hierarchical thinking system
Zhao et al. (2019)	Review of deep learning-based object recognition systems	Designed to solve a number of sub-problems using different degrees of R-CNN modification	Occlusion, Clutter,R-CNN	Using tip location instead of bounding box in object recognition
Singh et al. (2019)	Used tensorFlow framework to classify feeding tube malposition on chest and abdomen radiographs as critical or non-critical	Used Inception V3, ResNet50, and DenseNet in classification	Inception V3, ResNet50, DenseNet, DCNNs	AUC of 87.7% in classifying the radiographs
Dunnmon et al. (2019)	Classified chest radiographs as as normal or abnormal	Trained CNN and used binary classification for error analysis	CNN, Radiographs, AUC	AUC 84%(With 2000 images), AUC 96%(with 200000 images)
Fu et al. (2019)	To obtain a wide range of context-dependent relations	Used Dual attention network to integrate local and global dependencies	DANet, FCN, attention modules, semantic	efficiently collected context relations and offered better segmentation data.
Li et al. (2019)	Established a factor of attention for each spatial location in each semantic category	Spatial Group-wise Enhance (SGE) system that modified the value of each sub-feature	SGE, CNN, ResNet50, ImageNet	SGE module greatly improved feature groups capacity to convey various meanings
Bello et al. (2019)	Concatenating convolutional feature maps with self-attention feature maps to enhance convolutional operators with self-attention	Used self-attention with CNN	self-attention, CNN, average pooling	Removed downsampling and average pooling in order to satisfy the objective
Yu et al. (2020)	Tip of a peripherally inserted catheter (PICC) was identified	Segmented on chest X-ray images in this research utilizing a multi-task deep learning mode	Deep learning, PICC, RPN, ROI pooling route	Identifed the location of the tip using 348 chest X-Rays
Yi et al. (2020)	Determined catheter placement	Used various medical technicalities to decide the placement	Catheter, anatomic	Tip of ETT should be positioned higher
Khan et al. (2020)	Classified current CNN architectural advances into seven groups based on intrinsic taxonomy	Used CNN architecture	CNN, spatial information	Spatial information,attention and channel information manipulation will be increasingly relevant in deep learning model building

Table 1: Summary details of the related work to detect the position of catheter and tubes on chest radiographs

3 Methodology

This study employs the Knowledge Discovery in Databases (KDD) methodology. This technique was chosen because it enables the project's developers to go back to a previous stage if necessary.. Figure 6 illustrates the flow of chest radiographs that would be used to train a deep learning model for predicting whether tubes and lines are placed correctly or incorrectly. The data, which consists of chest radiographs, would be pre-processed in order to be used in later phases and to make the model more accurate. Following that, it would be enhanced by using Python's Albumentation package. The purpose of augmentation is to generate more training data from the current chest radiographs. Due to the high level of noise in the radiograph pictures, the dataset will be modified using

CLAHE (Contrast Limited Adaptive Histogram Equalization) to increase its contrast in order to more precisely detect the implanted tubes and catheters.

After pre-processing and transformation, the data is model-ready and can be input into the suggested modeling approach to generate a reliable model which is capable of detecting misplaced tubes and lines and implementation of it is explained in a detailed manner in section 5. CBAM is used in combination with CNN in modeling to improve the sensitivity of identifying catheters that have been misplaced. Design of the CBAM along with CNN approach used in this research is explained in section 4. Numerous literature reviews in subsection 2.5 demonstrate the efficacy of attention mechanisms in image analysis, and Woo et al. (2018) proposed technique of integrating CBAM with CNN architecture has demonstrated tremendous results, and several experiments on various datasets demonstrate the efficacy of CBAM in image analysis. As a consequence, in this critical field of medical science, we suggest this approach to increase the precision of detecting misplaced tubes and lines and informing doctors automatically, rather than depending on manual human involvement.

Following the model's development, we split data into train and test folds using stratified group k-Fold cross-validation to maintain the percentage of samples for each class and to guarantee that the same group does not occur in both folds. This model would be trained on misplaced tubes and lines and evaluated using the procedures explained in 6. Successfully developing this model and increasing its accuracy will assist doctors in automatically spotting misplaced tubes and lines and would be less error-prone owing to reduced manual labor by radiologists, particularly during these tough times of COVID-19.

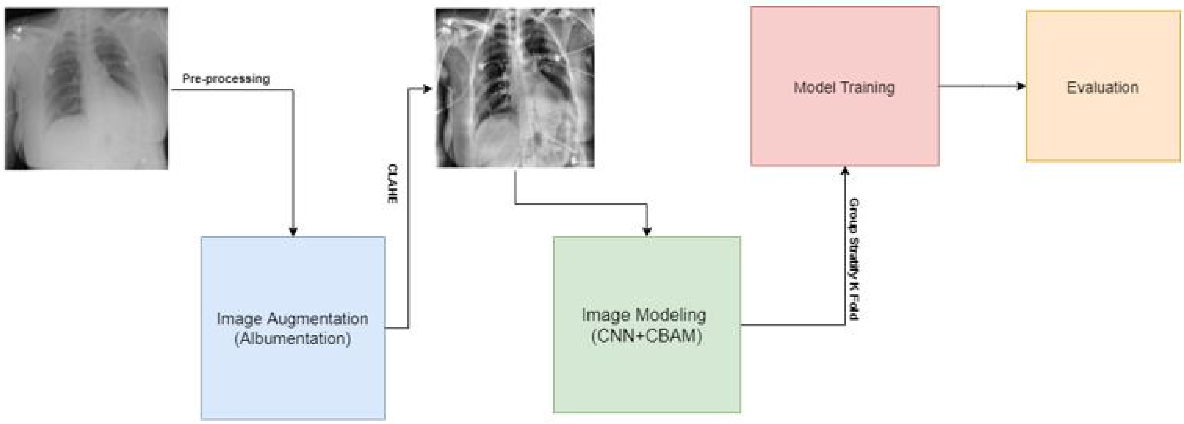


Figure 6: Research methodology for detecting the malpoistion of Catheters on Chest Radiographs

3.1 Dataset Collection

The dataset used in this study was made freely available on Kaggle by RANZCR (Royal Australian and New Zealand College of Radiologists). The dataset is sufficiently big having 30.1K chest radiograph images excluding test dataset to undertake the analysis, and this is likely the first time that a dataset of this size has been utilized to determine the position of lines and tubes. The data publisher has taken into account the privacy concerns of patients and has concealed the patients' identities in this dataset. This dataset contains images of normal, borderline, and abnormal ETT (Endotracheal Tube), NGT

(Nasogastric Tube), and CVC (Central Venous Catheter) placements on chest radiographs that were hand labeled by radiologists. Along with the images file, a CSV file is present which contains image IDs, binary labels and patient IDs. Below is the binary labels present in the dataset.

- ETT - Abnormal
- ETT - Borderline
- ETT - Normal
- NGT - Abnormal
- NGT - Borderline
- NGT - Incompletely Imaged
- NGT - Normal
- CVC - Abnormal
- CVC - Borderline
- CVC - Normal
- Swan Ganz Catheter Present

Additionally, this dataset includes a CSV file including data annotations for the lines and tubes on the chest radiograph to assist non-medical individuals in tracing them as shown in Figure 3, Figure 4 and Figure 5.

3.2 Dataset Preparation

In this process, chest radiograph data goes under pre-processing techniques and is cleaned to prepare it for the subsequent phase in the applicable methodology. Because this study is focused on biological images, the implemented machine learning method must be very accurate. To improve the model's accuracy in categorizing radiographs as well-positioned or malpositioned, an image augmentation approach (Albumentation) is used. To achieve augmentation, a funtion named "image_augment" is built for augmenting the image horizontally (random_flip_left_right) and vertically (random_flip_up_down) which is called when dataset is created on the function call of "dataset_creation". Figure 7 shows the images before and after augmentation.

(a) Images before Augmentation (b) Augmented Images

Figure 7: Images before and after augmentation

After albumentation, Chest radiographs were processed to enhance contrast in the images. CLAHE is used to equalize the data and avoid over-amplifying the images. The CLAHE procedure on a chest radiograph is demonstrated in Figure 8 from the RANZCR dataset, enhancing the image's contrast. It would be incredibly beneficial for identifying tube and line locations and categorizing radiographs as misplaced or correctly aligned.

Figure 8: CLAHE applied on a Chest Radiograph

4 Design Specification

Convolutional Neural Networks (CNN) are combined with the CBAM module provided by Woo et al. (2018) to construct a deep learning model that classifies radiographs as normal (properly positioned tubes and lines) or abnormal (mispositioned tubes and lines). As seen in Figure 9 by Woo et al. (2018) the CBAM is connected to the CNN and receives the input as intermediate features F including information from both the channel and spatial axes of the CNN block. CBAM then highlights distinct properties along the channel (F) and spatial axes (F) by concentrating on "what" and "where" to attend. As a consequence, it learns which knowledge should be highlighted and which should be repressed, resulting in an improvement in the accuracy of recognizing misplaced catheters and tubes. Channel and Spatial attention module are explained in subsection 4.1 and 4.2 respectively.

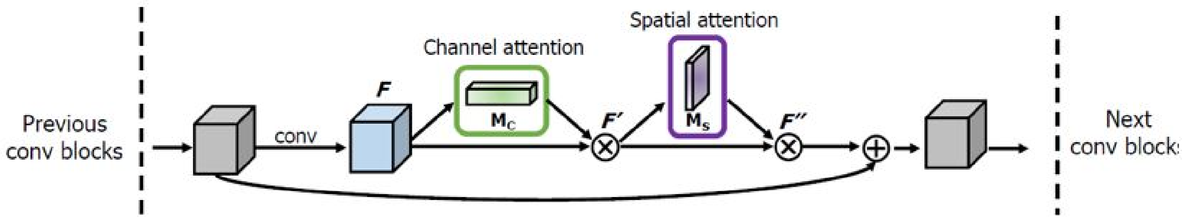


Figure 9: CBAM integrated with CNN (Woo et al.; 2018)

4.1 Channel Attention Module

The focus in the channel attention module of CBAM is on 'what' is significant in the context of an input chest radiograph. This channel attention module aggregates the spatial information included in the feature map using max-pooling and average-pooling. The average and maximum pooled features are sent into a shared multi-layer perceptron (MLP) that has a hidden layer. After applying MLP to each feature, the result is merged using element-wise summation, as seen in Figure 10 of the channel attention module.

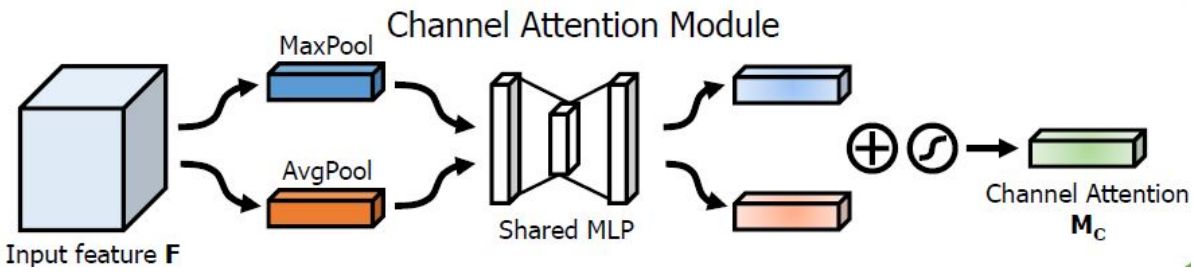


Figure 10: Channel Attention Module (Woo et al.; 2018)

4.2 Spatial Attention Module

The spatial attention module of CBAM puts a focus on determining ”where” is significant in relation to an input chest radiograph. The channel refined feature is subjected to average and maximum pooling, which is then merged to create an effective feature, as seen in Figure 11 . A convolutional layer is used to this produced feature to construct spatial attention that learns which characteristics should be emphasized and which should be hidden.

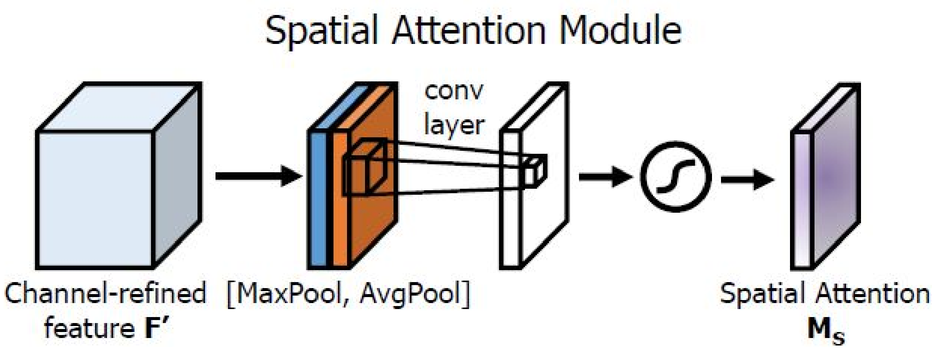


Figure 11: Spatial Attention Module (Woo et al.; 2018)

5 Implementation

Once pre-processing and transformation have been done, the data is model-ready, and it can be used to build a model and implementation of it is discussed in great depth in this section. We used pre-trained model such as EfficientNet (EfficientNetB3) in the baseline approach and the different EfficientNet Model with the CBAM (Convolutional Block Attention Module) in the novel approach. Concept of transfer learning is shown in Figure 12,

5.1 Baseline Approach

The study of the literature established that convolutional neural networks were successful at categorizing chest radiographs as critical or non-critical and at recognizing the position of lines and tubes on chest radiographs(Singh et al.; 2019; Dunnmon et al.; 2019). Adding additional layers and developing a dense structure can increase accuracy, which is why we chose to conduct this research using transfer learning. EfficientNet is a pre-trained model which has shown exceptional results on some well-known datasets, such as

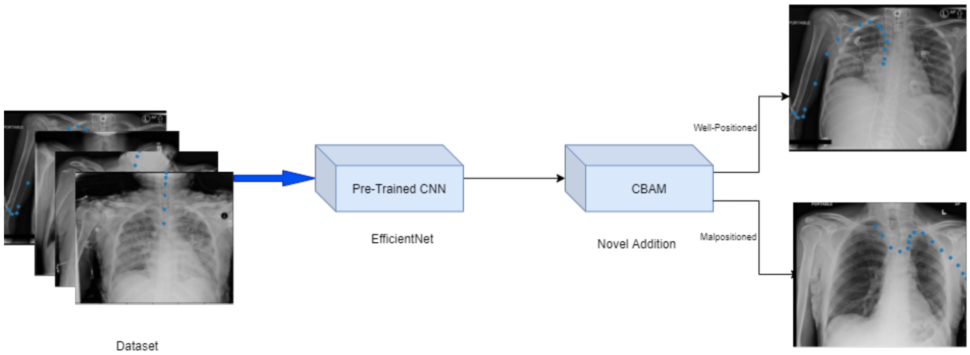
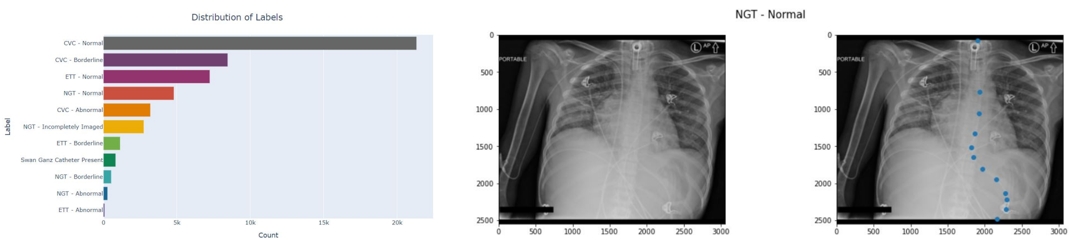


Figure 12: Transfer learning used in research

ImageNet, CIFAR-100, Flowers. The EfficientNet models outperform conventional CNNs in terms of accuracy and efficiency, decreasing parameter size and FLOPS by an order of magnitude[1].Its specialisation may be used to determine the location of tubes and lines on chest radiographs.

EfficientNet-B3 To use the model effectively, we conducted some EDA (Exploratory data analysis) to gain a thorough understanding of the data and then used this understanding to construct the model. To avoid class imbalance, we examined the distribution of different labels in the dataset and plotted the chest radiographs with the annotated data points to gain additional information on the placement of tubes and lines in those X-rays. Additionally, the distribution of each individual label in respect to all other labels is shown to illustrate the dataset distribution. Figure 13 shows the EDA performed before the modeling to get more insights of the dataset. A 'BaseConfig' is designed with batch_size of of 32, n_epochs as 15 (number of epochs), and drop_rate as 0.4. 'Adam' optimizer is used with minimum learning rate of '1e-5'. The loss function used is 'binary_crossentropy' with AUC as the evaluation metrics. Early stopping is also used with the value of patience being 5. Two checkpoints are also added in the class, one is saving the best model and the another is saving the last model to compare with the next model. Now, two different class named 'load_pretrained_model' and 'build_my_model' class is built. While building the model 'GlobalAveragePooling2D' is used and also batch normalization is used with the pre-trained CNN. After building the model, it is validated on the validation batch by generating an array of valid labels whether the predicted labels are correct or not.



(a) Distribution of Labels (b) Chest X-rays with Annotated Data Points

Figure 13: EDA

[1]https://ai.googleblog.com/2019/05/efficientnet-improving-accuracy-and.html

5.2 Novel Approach

Convolutional Neural Networks (EfficientNet) will be used to construct the classification model, as well as the CBAM (Convolutional Block Attention Module) module proposed by Woo et al. (2018). While CNN extracts insightful features by combining cross-channel and spatial data, CBAM prioritizes relevant characteristics along the channel and spatial axes independently for each branch in order to learn "what" and "where" to attend on the channel and spatial axes. It learns which knowledge to emphasize or suppress; as a result, information flows effectively within the network and can improve the accuracy of classifying radiographs with normal and abnormal tube and line positions by having particular information from an input image that causes the network to properly concentrate on tube and line positions, as demonstrated by Woo et al. (2018). Detailed design of this novel approah used is discussed in 4. We modified a portion of the CBAM mechanism and the last section of its spatial module by including the Global Weighted Average Pooling (GWAP) technique.

$$GWAP(x, y, d) = \sum_x \sum_y Attention(x, y, d) Features(x, y, d) / \sum_x \sum_y Attention(x, y, d)$$

A 'data_train_config' class is created in which the learning rate, batch size, number of images in each batch, and base networks for the five different folds are defined. Another class, 'Spatial_Attention' is being built which will take the tensorflow keras layer as the parameter (Woo et al.; 2018). To separate the channel attention module from the spatial attention module, a different class called 'Channel_Attention' is built which takes the parameters as keras layer. After the two layers are built from the two above mentioned classes, GWAP is used. To attain this, a class called 'AttentionWeightedAverage2D' was built which takes parameters as keras layer.

On successful building of the above classes, the 'Chest_Data_Classifier' class is built, which will take an input parameter as a keras model and will build multiple layers calling different classes described above. EffecientNet is used as the pre-trained CNN and the model built by infusing all the defined layers with the pre-trained CNN is saved to load the weights later.

After saving the weights, the model is built using the above classes and built to predict the labels of the test dataset.

Figure 14 shows the model plot which has different layers of the model built using the novel approach.

6 Evaluation

Radiographs with normal and misaligned tubes and lines are not balanced in the utilized dataset. As a result, sensitivity and specificity are employed in these instances. The True Positive rate (percentage of radiographs found with malpositioned catheters and tubes) and True Negative rate (proportion of radiographs detected without malpositioned catheters and tubes) would be calculated. Catheter categorization is a multi-class classification based on radiographic images. An uncertainty matrix, a special kind of contingency table, may be used to determine the correctness of each class. Numerous evaluative measures may be calculated using the confusion matrix. Also, accuracies and losses across multiple folds would be verified in order to see the performance of the novel

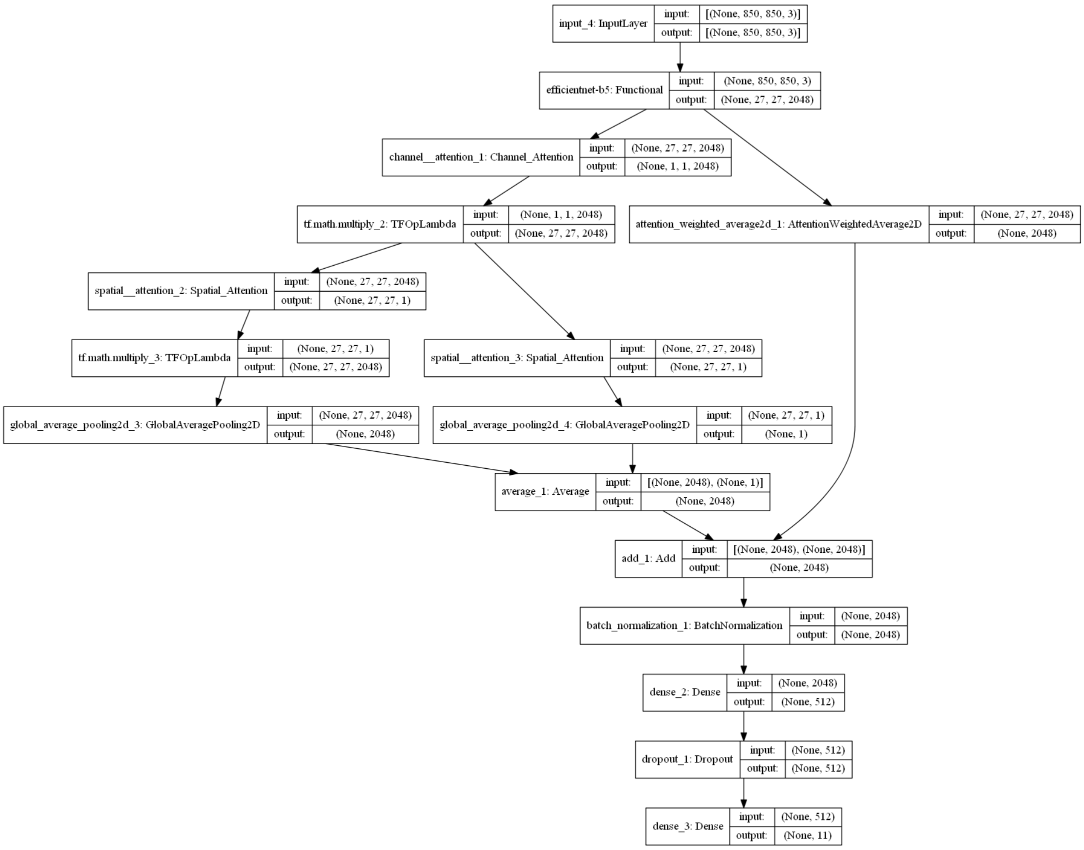


Figure 14: Model plot of the Novel approach

model created. Also, a spreadsheet containing the image's instance ID and the probability of the image falling into one of the categories (ETT Normal, ETT Borderline, ETT Abnomal, NGT Normal, NGT Borderline, NGT Abnormal, CVC Normal, CVC Borderline, CVC Abnormal, SWAN GANZ Catheter present, NGT incorrectly imaged) will be seen and validated for all the labels present.

6.1 Baseline Approach : EfficientNet CNN

The EfficientNet model was trained and validated using images. The model was trained using 30.1 thousand training images with a batch size of 32. Each epoch step had 846 images. The model was trained with pre-trained weights and 15 epochs. As seen in Figure 15, the results of EfficientNet on the dataset for classifying chest radiographs with appropriately positioned tubes and lines resulted in high accuracy with minimal loss. The model attained a test accuracy of 0.91 and a validation accuracy of 0.89. The loss curve in the figure was close to zero, and the accuracy of validation increased as the number of epochs increased. We utilized the early stopping callback in the code with patience 5, which means that once the model gets the required output and the loss does not change further, the model would terminate. This optimization technique speeds up the model. The results indicate that EfficientNet, when trained using a transfer learning technique, is capable of detecting the position of tubes and lines on chest radiographs with a high degree of accuracy and a negligible loss value.

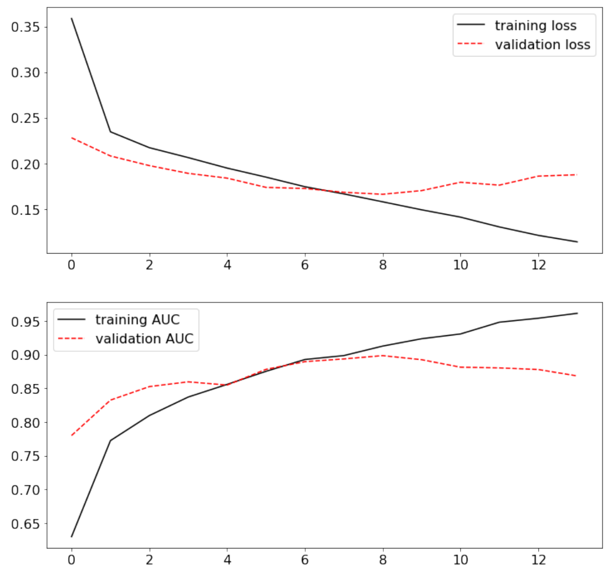
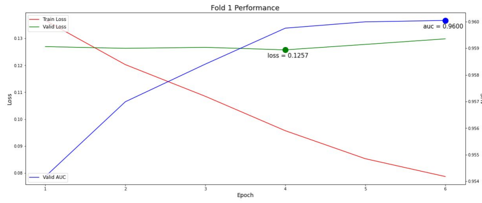


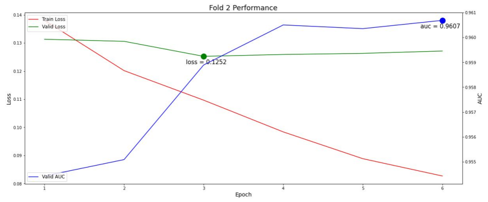
Figure 15: Loss and Accuracy of Training and Validation data

6.2 Novel Approach : EfficientNet CNN with CBAM and GWAP

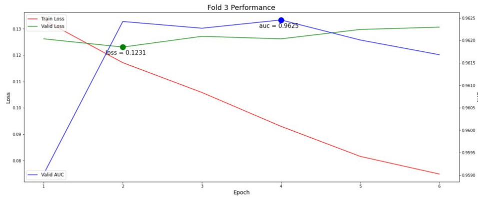
The Convolutional block attention module combined with a pre-trained network is extremely effective at learning from radiographs and assigning the probability of that chest radiograph falling into one of the categories. The accuracy and loss plots are shown for five folds in each of six epochs in Figure 16. The primary criterion for evaluation is the accuracy and loss of information over many folds. The accuracy parameter determines the accuracy of that specific fold and train set for a certain batch size, whereas the loss parameter determines the loss using binary cross-entropy loss. As seen in Figure 16a, the CBAM model obtained a validation accuracy of 0.96 and a very low loss of 0.1257 in the first fold. The model learns from the instance with a second-fold accuracy of 0.96, making it extremely effective and quick. At early epochs in each of the folds, the loss diminishes and approaches zero. It can be seen that in Figure 16b that the validation accuracy and loss has improved by a very small amount and has become 0.9607 and 0.1252 respectively. As usual the training loss is approaching towards zero. After the second fold, in the third fold the validation accuracy and loss has become 0.9625 and 0.1231 respectively as seen in Figure 16c. Both the loss and accuracy is improving across every fold. In the fourth fold as is seen in Figure 16d, the accuracy and loss has become 0.9627 and 0.1228. Now, in the last fold i.e. fifth fold the accuracy and loss values are 0.9630 and 0.1235 as seen in Figure 16e which is the highest amongst all the folds. This demonstrates that the developed model is extremely successful, and that separating the mixed characteristics into distinct channel and spatial features improves the model's accuracy in recognizing the catheters and lines on the chest radiograph. Table 2 shows the results for 5-fold cross-validation explained above in the tabular format. Cross-validation was performed to evaluate the novel model's performance using previously unknown data. That is, to test the model's general performance when used to make predictions on data that was not used during the model's training.



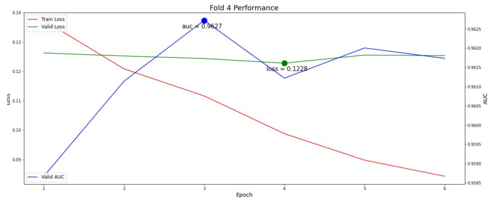
(a) Fold 1



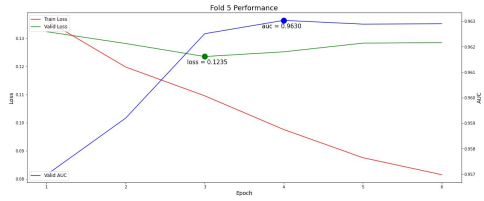
(b) Fold 2



(c) Fold 3



(d) Fold 4



(e) Fold 5

Figure 16: Loss and AUC for different Folds

n_fold	Validation Loss	Validation Accuracy
1	0.1257	0.9600
2	0.1252	0.9607
3	0.1231	0.9625
4	0.1228	0.9627
5	0.1235	0.9630

Table 2: 5-fold cross validation

6.3 Discussion

The purpose of this research is to assess the performance of a newly suggested strategy that incorporates an attention-based CBAM technique. This approach was prompted by observed studies in the field of computer vision mentioned in related work. This technique was tested on several image datasets (ImageNet-1K, MS COCO, and VOC 2007), and it was discovered that adding this lightweight module significantly enhanced network speed, which we selected as the state-of-the-art for this research (Woo et al.; 2018). We compared transfer learning models with CBAM for the purpose of resolving the problem of detecting the position of tubes and lines on chest radiographs (Singh et al.; 2019; Dunnmon et al.; 2019).

As indicated in the preceding subsections 6.1 and 6.2, we compared the models' accuracies. EfficientNet's accuracy on the chest radiograph dataset is 0.89 for validation and 0.91 for testing, as previously mentioned. The novel technique CBAM based on the attention mechanism achieved the maximum achievable accuracy, 0.9630, for validation and test data sets. CBAM is more exact than transfer learning models in detecting tubes and lines on chest radiographs. According to the state-of-the-art at the time of this research, the accuracy attained was about 0.9 percent for various benchmark datasets, demonstrating the uniqueness of this research effort in detecting the position of tubes and lines on chest radiographs using the CBAM approach. Figure 17 shows the final CSV created after running the baseline model against test dataset. Figure 18 depicts a snapshot of the final spreadsheet, which contains the estimated proportion of images that fall into each group. The highlighted point illustrates the precise output that the CBAM model produces for each radiograph. All other probabilities are negligible and may be easily overlooked. All of the data indicate that CBAM is quite effective at detecting the location of tubes and lines on chest radiographs.

StudyInstanceUID	ETT - Abnormal	ETT - Borderline	ETT - Normal	NGT - Abnormal	NGT - Borderline	NGT - Incompletely Imaged	NGT - Normal	CVC - Abnormal	CVC - Borderline	CVC - Normal	Swan Ganz Catheter Present
1.3680043.8.498.24641136930096467169...	0.000040	0.000086	0.000028	0.000163	0.000263	5.792791e-05	0.000194	0.004411	0.440072	0.686257	0.000056
1.3680043.8.498.12690617441924311870...	0.000054	0.000032	0.000011	0.000050	0.000048	3.019369e-05	0.000067	0.070709	0.218832	0.814413	0.000137
1.3680043.8.498.12475334287210977140...	0.000001	0.000003	0.000002	0.000009	0.000005	3.140399e-07	0.000004	0.004553	0.006865	0.983964	0.000013
1.3680043.8.498.55782720675326550262...	0.000352	0.002103	0.000833	0.001191	0.000931	7.462741e-03	0.002320	0.013834	0.077376	0.920613	0.000217
1.3680043.8.498.31365479801404007311...	0.023695	0.567942	0.556721	0.019073	0.121555	1.584163e-01	0.348152	0.063127	0.386769	0.342052	0.000546

Figure 17: Final Predictions of the Test data having probability of being the particular label

StudyInstanceUID	ETT - Abnormal	ETT - Borderline	ETT - Normal	NGT - Abnormal	NGT - Borderline	NGT - Incompletely Imaged	NGT - Normal	CVC - Abnormal	CVC - Borderline	CVC - Normal	Swan Ganz Catheter Present
43.8.498.46923145579096002617...	2.208163e-05	2.539416e-02	9.708167e-01	1.479139e-05	7.429431e-04	3.008313e-03	9.940944e-01	0.006447	0.059842	0.968643	9.999943e-01
43.8.498.84006870182611080091...	1.069400e-09	3.707888e-08	3.857427e-07	4.198821e-07	8.645618e-08	6.542579e-09	8.789124e-08	0.049204	0.024251	0.956644	3.082640e-06
43.8.498.12219033294413119947...	1.110414e-10	2.721529e-08	2.237614e-08	2.845800e-07	2.130279e-06	1.291258e-08	9.623458e-08	0.002942	0.253688	0.812886	3.176127e-07
43.8.498.84994474380235968109...	5.419382e-04	1.187538e-04	2.124890e-05	9.107623e-03	7.470000e-04	9.905593e-01	2.024026e-03	0.048668	0.316277	0.732969	3.136972e-04
43.8.498.35798987793805669662...	2.853687e-09	3.941081e-07	2.147806e-06	3.483655e-07	1.494529e-06	2.056559e-09	1.747906e-05	0.002341	0.026494	0.986989	3.982171e-07

Figure 18: Spreadsheet showing the results achieved by CBAM

7 Conclusion and Future Work

This research presented a method of combining CNNs and CBAMs to determine how effectively deep learning algorithms can detect misplaced tubes and lines on chest radiographs. CBAM is a novel technique presented by Woo et al. (2018) that highlights characteristics along the channel and spatial axes independently in order to choose "what" and "where" to attend. As a consequence, the network learns which characteristics should be stressed and which should be suppressed, therefore increasing the network's information flow efficiency. The suggested technique significantly improves the detection accuracy of misplaced tubes and lines compared to prior studies. The model's accuracy is excellent and consistent when compared to other transfer learning approaches.

The strength of the proposed unique CBAM approach is that it learns by segmenting the features and concentrating on the most essential portions of the image, which results in increased accuracy. The model's drawback is that it requires an exceptionally long amount of time to train due to the size of the dataset. The research in this area can eliminate the need for radiologists to view radiographs and determine the location of tubes and lines manually, which is extremely error-prone when hospitals are already overcrowded, and even when a large number of patients require intubation due to the COVID-19 explosion. As accuracy and sensitivity are critical in the medical domain, this research can be expanded or used as a foundation for achieving 100 percent accuracy in determining the location of tubes and lines on chest radiographs in the future by utilizing larger datasets, as larger datasets improve the results and provide a more accurate model.

References

Ambrosini, P., Ruijters, D., Niessen, W. J., Moelker, A. and van Walsum, T. (2017). Fully automatic and real-time catheter segmentation in x-ray fluoroscopy, *International conference on medical image computing and computer-assisted intervention*, Springer, pp. 577–585.

Bello, I., Zoph, B., Vaswani, A., Shlens, J. and Le, Q. V. (2019). Attention augmented convolutional networks, *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 3286–3295.

Çallı, E., Sogancioglu, E., van Ginneken, B., van Leeuwen, K. G. and Murphy, K. (2021). Deep learning for chest x-ray analysis: A survey, *Medical Image Analysis* p. 102125.

Dunnmon, J. A., Yi, D., Langlotz, C. P., Ré, C., Rubin, D. L. and Lungren, M. P. (2019). Assessment of convolutional neural networks for automated classification of chest radiographs, *Radiology* **290**(2): 537–544.

Fu, J., Liu, J., Tian, H., Li, Y., Bao, Y., Fang, Z. and Lu, H. (2019). Dual attention network for scene segmentation, *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 3146–3154.

Higgs, A., McGrath, B., Goddard, C., Rangasami, J., Suntharalingam, G., Gale, R., Cook, T., Society, D. A. et al. (2018). Guidelines for the management of tracheal intubation in critically ill adults, *British journal of anaesthesia* **120**(2): 323–352.

Hu, J., Shen, L. and Sun, G. (2018). Squeeze-and-excitation networks, *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 7132–7141.

Jain, S. N. (2011). A pictorial essay: Radiology of lines and tubes in the intensive care unit, *The Indian journal of radiology & imaging* **21**(3): 182.

Kao, E.-F., Jaw, T.-S., Li, C.-W., Chou, M.-C. and Liu, G.-C. (2015). Automated detection of endotracheal tubes in paediatric chest radiographs, *Computer methods and programs in biomedicine* **118**(1): 1–10.

Khan, A., Sohail, A., Zahoora, U. and Qureshi, A. S. (2020). A survey of the recent architectures of deep convolutional neural networks, *Artificial Intelligence Review* **53**(8): 5455–5516.

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

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**(4): 393–402.

Li, X., Hu, X. and Yang, J. (2019). Spatial group-wise enhance: Improving semantic feature learning in convolutional networks, *arXiv preprint arXiv:1905.09646* .

Liu, J.-e. and An, F.-P. (2020). Image classification algorithm based on deep learning-kernel function, *Scientific programming* **2020**.

Park, J., Woo, S., Lee, J.-Y. and Kweon, I. S. (2018). Bam: Bottleneck attention module, *arXiv preprint arXiv:1807.06514* .

Sakthivel, M. K., Bosemani, T., Bacchus, L. and Pamuklar, E. (2020). Malpositioned lines and tubes on chest radiograph–a concise pictorial review, *Journal of Clinical Imaging Science* **10**.

Singh, V., Danda, V., Gorniak, R., Flanders, A. and Lakhani, P. (2019). Assessment of critical feeding tube malpositions on radiographs using deep learning, *Journal of digital imaging* **32**(4): 651–655.

Wang, F., Jiang, M., Qian, C., Yang, S., Li, C., Zhang, H., Wang, X. and Tang, X. (2017). Residual attention network for image classification, *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3156–3164.

Woo, S., Park, J., Lee, J.-Y. and Kweon, I. S. (2018). Cbam: Convolutional block attention module, *Proceedings of the European conference on computer vision (ECCV)*, pp. 3–19.

Yi, X., Adams, S. J., Henderson, R. D. and Babyn, P. (2020). Computer-aided assessment of catheters and tubes on radiographs: How good is artificial intelligence for assessment?, *Radiology: Artificial Intelligence* **2**(1): e190082.

Yu, D., Zhang, K., Huang, L., Zhao, B., Zhang, X., Guo, X., Li, M., Gu, Z., Fu, G., Hu, M. et al. (2020). Detection of peripherally inserted central catheter (picc) in chest x-ray images: A multi-task deep learning model, *Computer Methods and Programs in Biomedicine* **197**: 105674.

Zhao, Z.-Q., Zheng, P., Xu, S.-t. and Wu, X. (2019). Object detection with deep learning: A review, *IEEE transactions on neural networks and learning systems* **30**(11): 3212–3232.