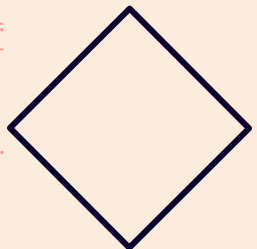
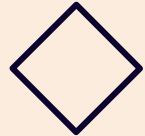
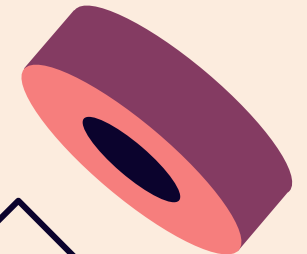
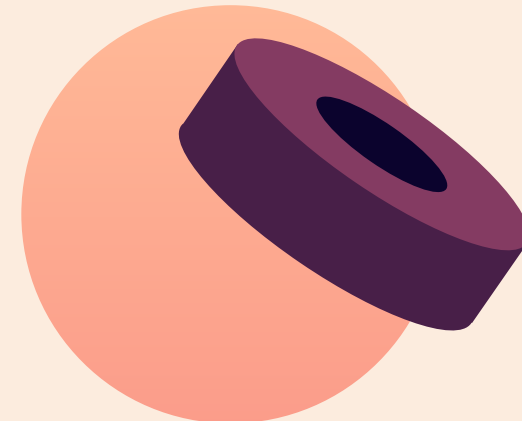
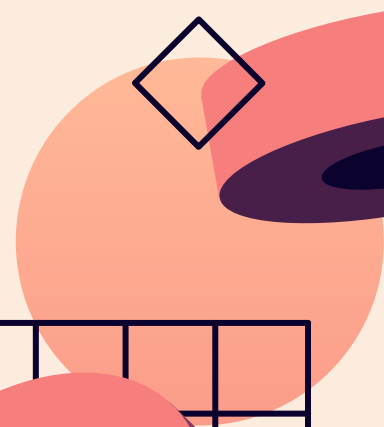
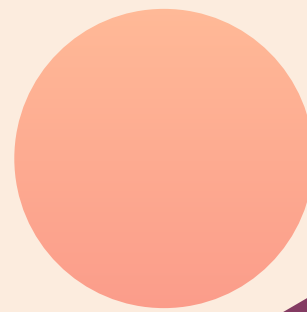
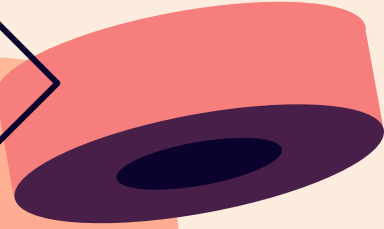
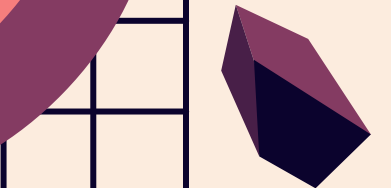
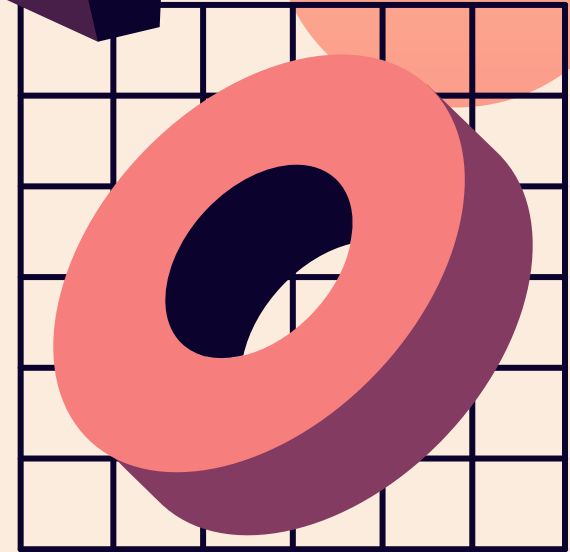
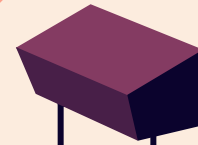


# Catheter Placement

Group 2.



# This is our team.



Byron Shim



Yohan  
Nanayakkara



Jaehong Kang



Charles Connell



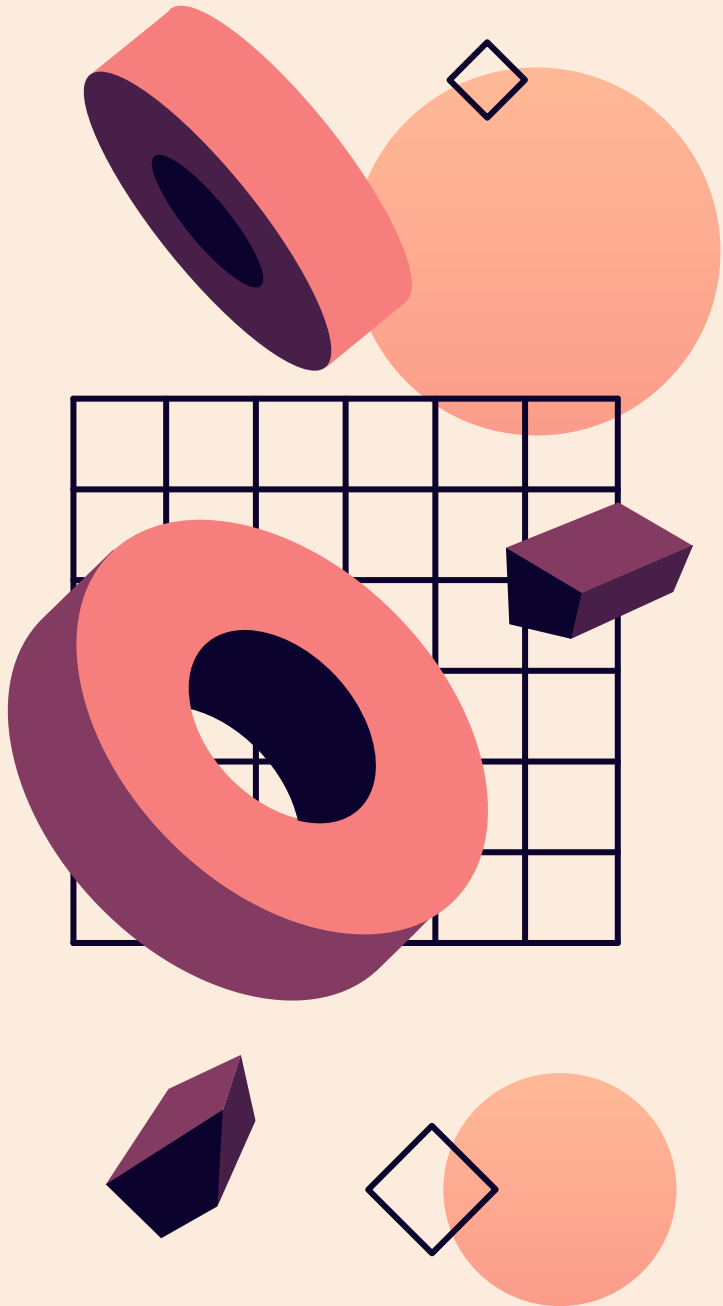
Aden Siau



Stefano Nicholas  
Rusli



Avish Narayan



# Table of contents.

**01**

**Introduction**

**02**

**What is a catheter?**

**03**

**Exploratory Data Analysis**

**04**

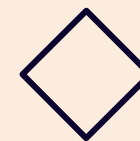
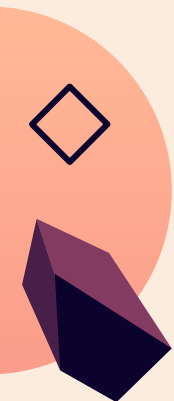
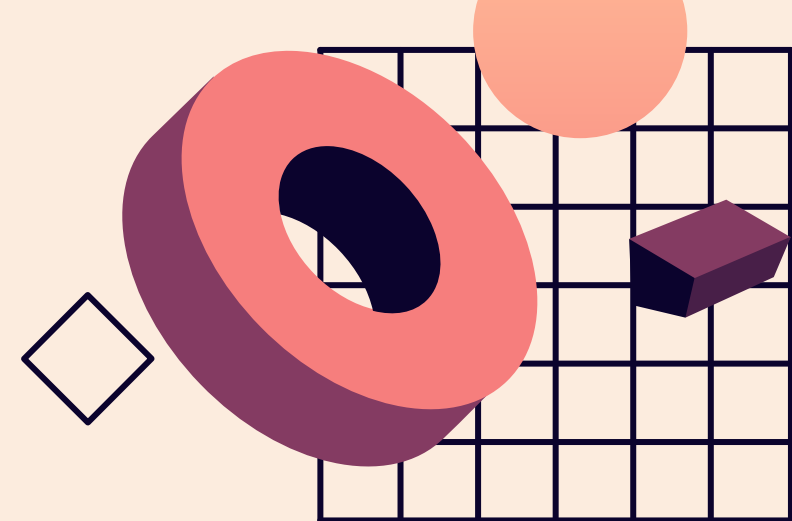
**Modelling**

**05**

**Conclusion**

01

# Introduction





# Context

- Medical devices using in medical procedures to perform functions such as removing fluids or delivering medication
- Placed in veins connecting to stomach or heart
- Medical complications can arise due to malpositioned lines/tubes in patients
- Early detection can be extremely beneficial



# Benefits and implications

## Benefits

- Mitigate risk of human error
- Early detection of complications
- Faster decision making

## implications

- Increased reliance of ai use for diagnostics
- Ethical and legal considerations



# Benefits to Everyday Person

Specific to catheters:

- Classifying the catheter type
- Determining if position is correct

In general:

- Can be applied to other X-rays such as broken bones
- Automating detection can reduce wait times
- Process will be faster and cheaper



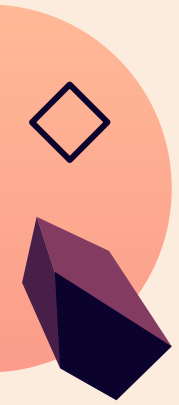
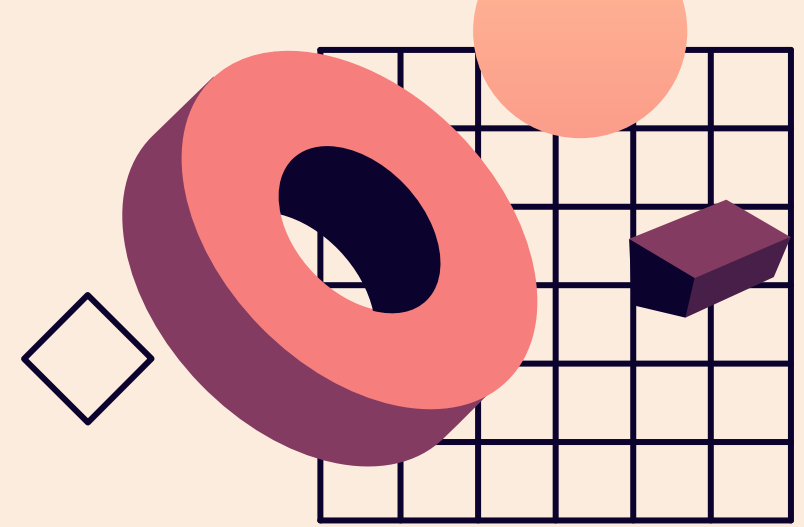
# Project goals

- Create a range of binary classification models that detects each catheter type
- Create a multi-label classification model that can determine the positioning of a certain type of catheter
- This will allow incorrectly positioned catheters to be identified faster, speeding up processes and ensuring procedures are done correctly.



02

# What is a Catheter?





# Catheter Classifications

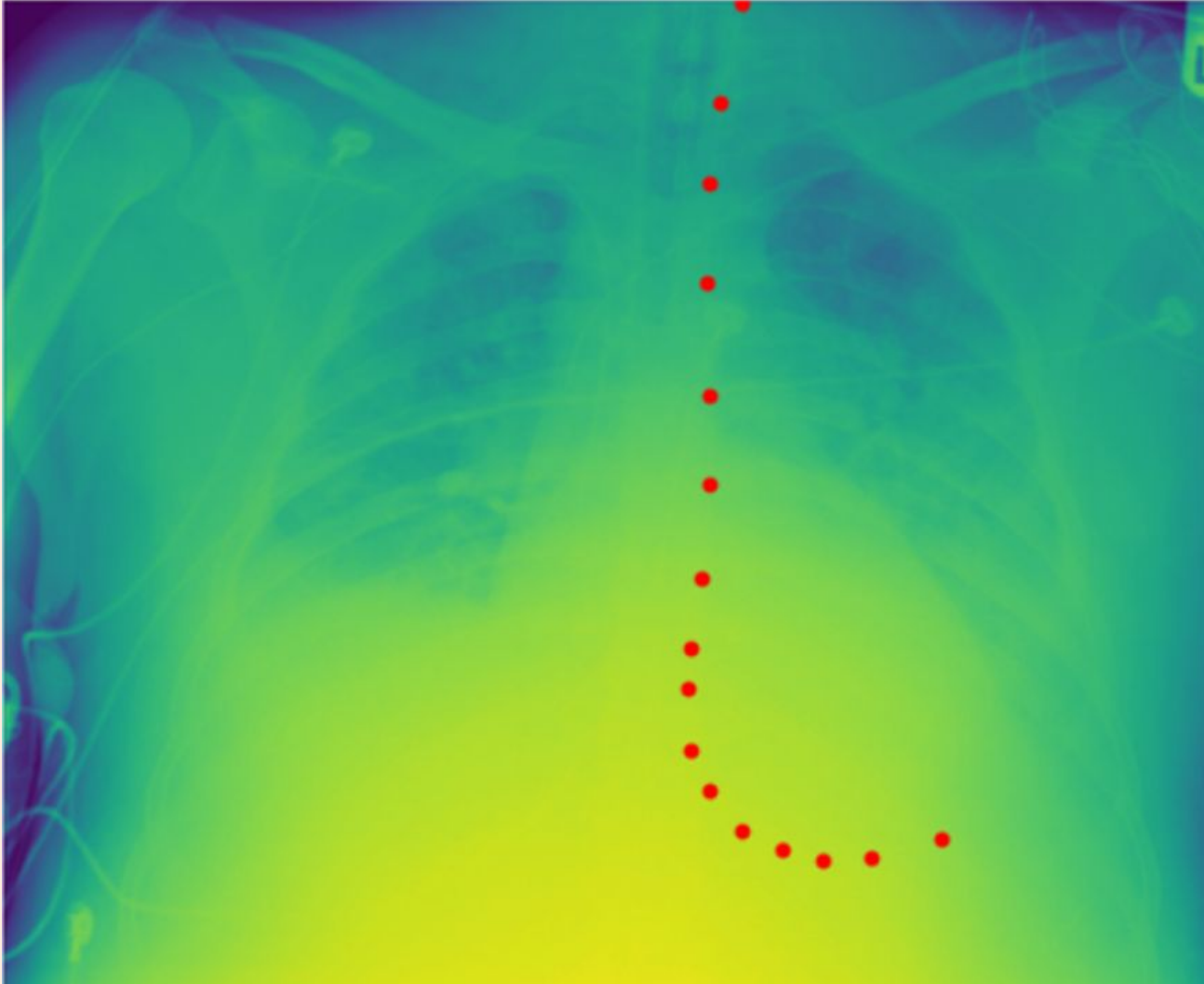
Types of catheters:

- NGT
- ETT
- CVC

Classifications:

- Normal
- Abnormal
- Borderline
- Incompletely Imaged

# NGT – Nasogastric Tube (Normal)



Place of insertion:

- Nostril
- Mouth

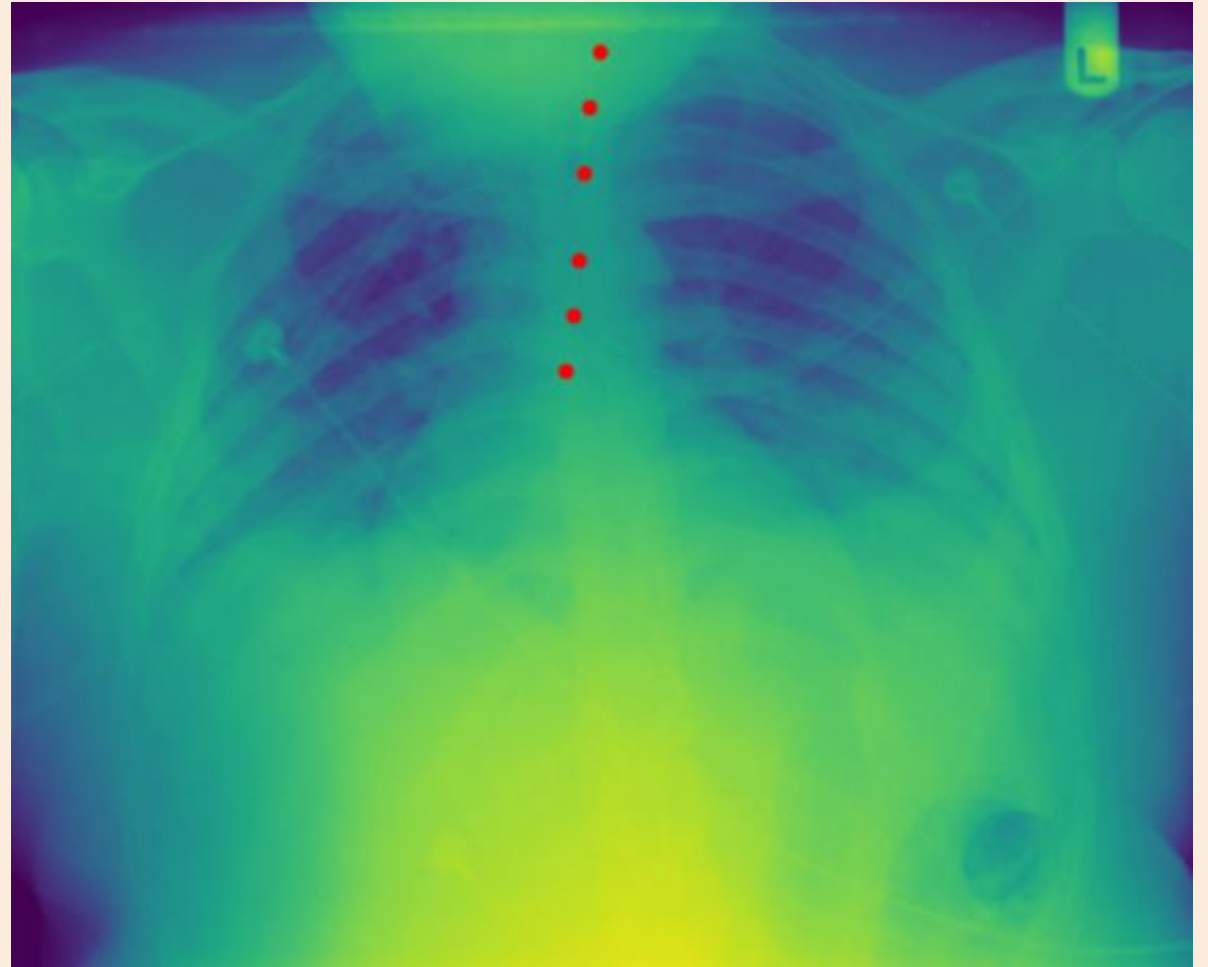
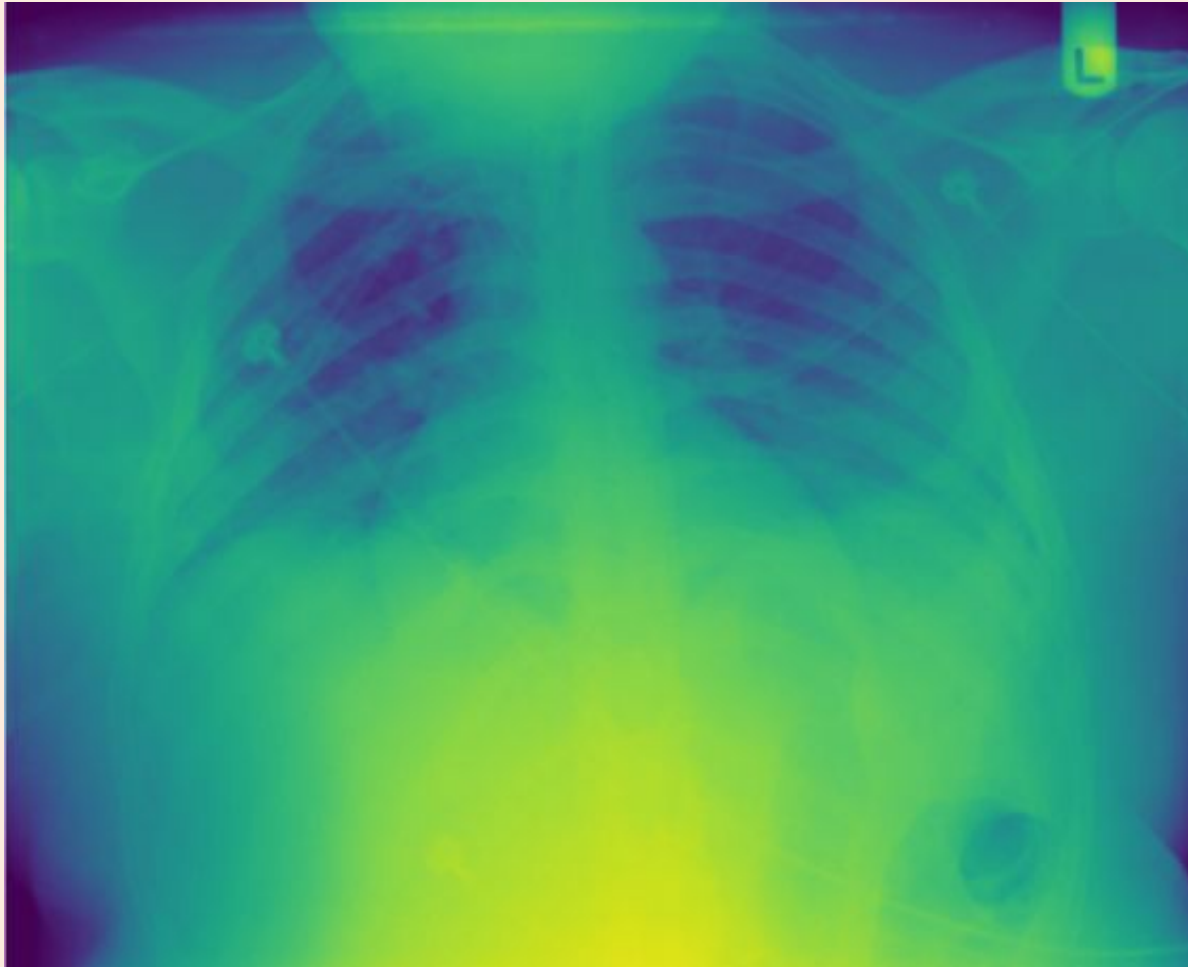
Where it sits:

- Down the esophagus, in the stomach

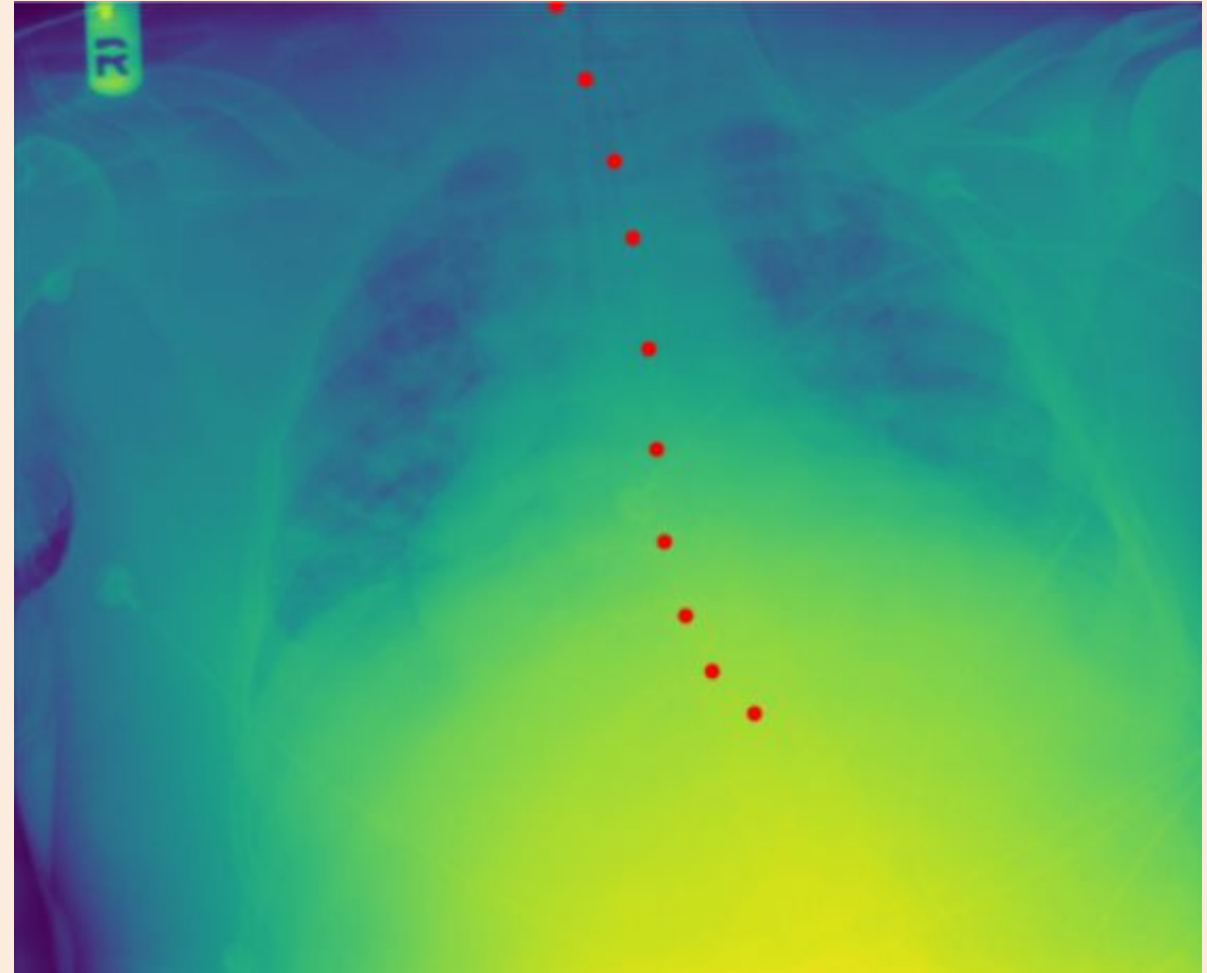
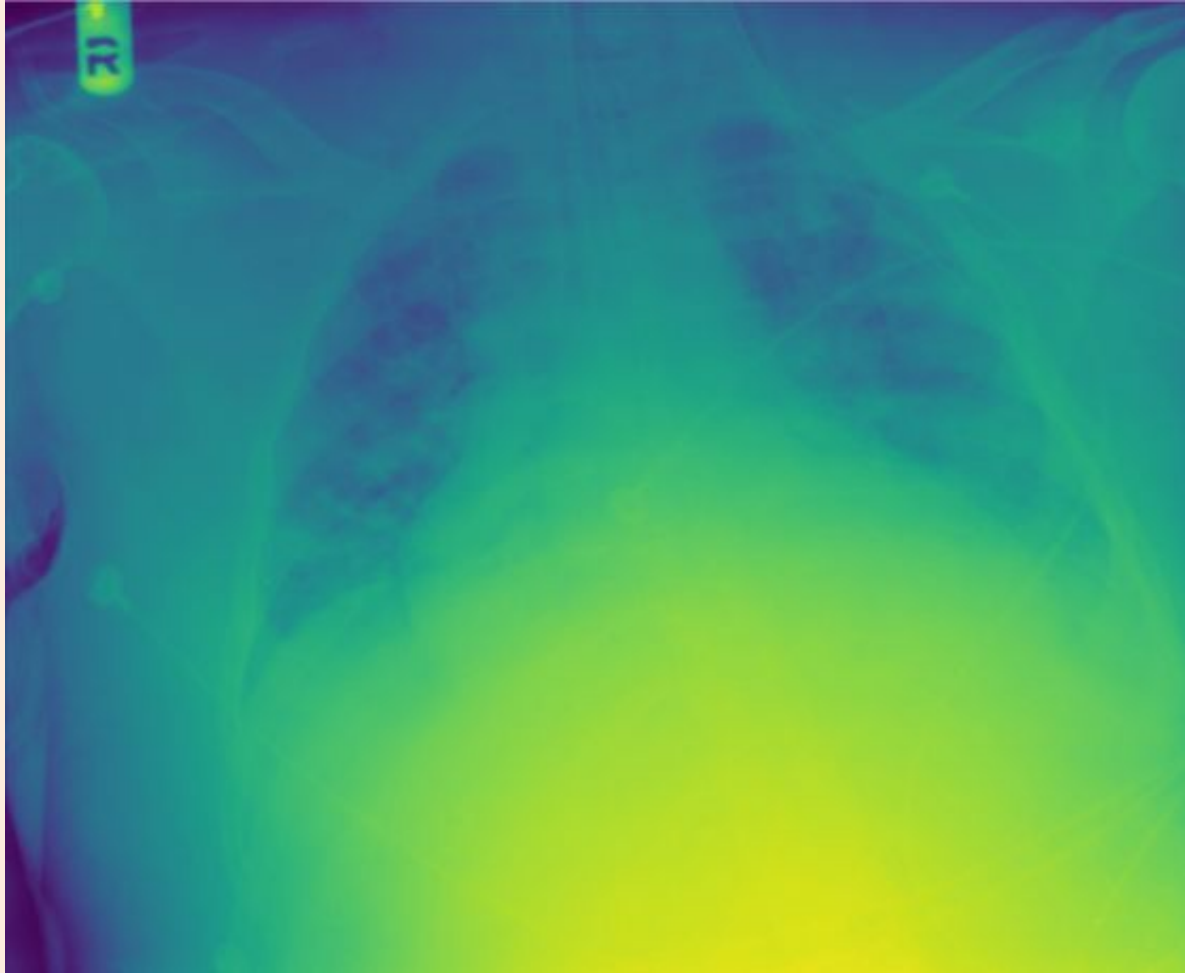
What it does:

- Delivers food or medicine
- Draw substances out, e.g. poisons

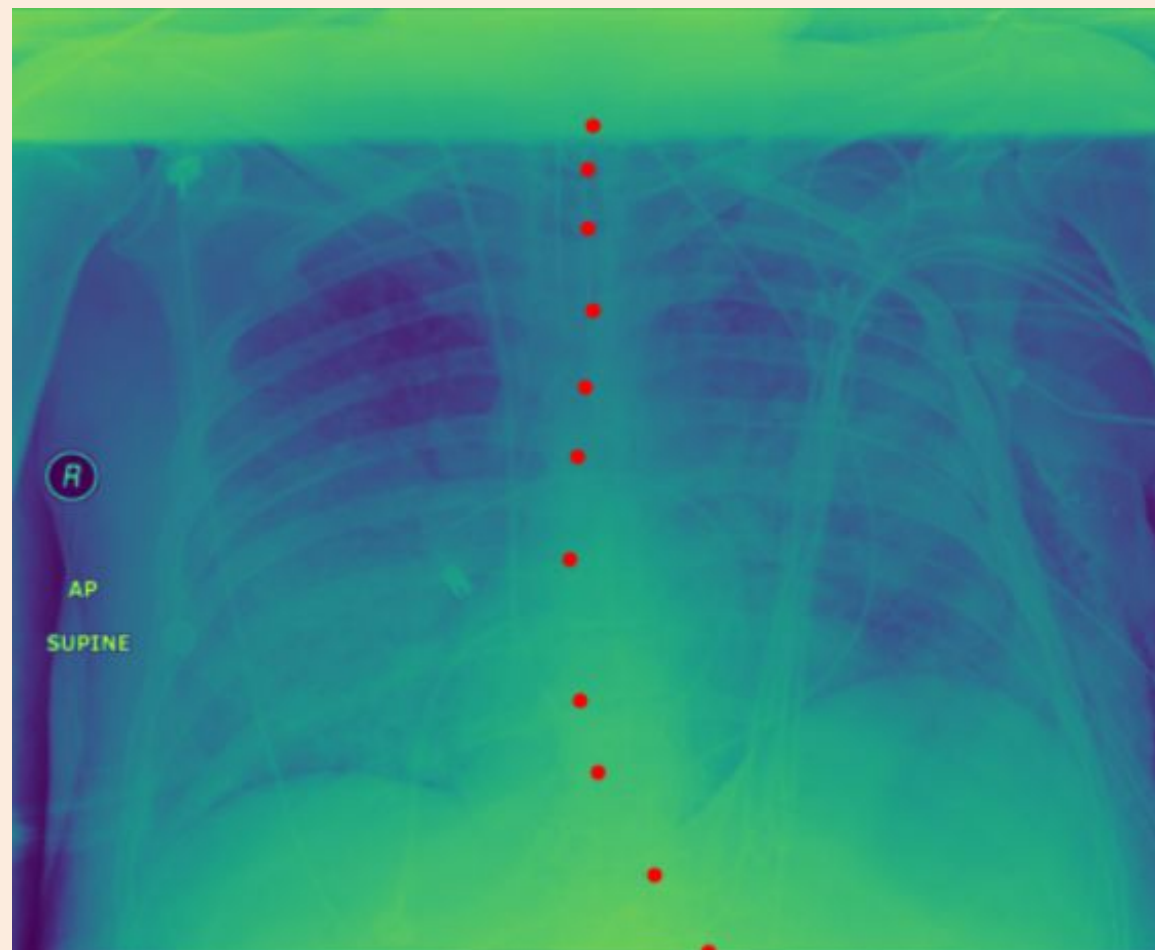
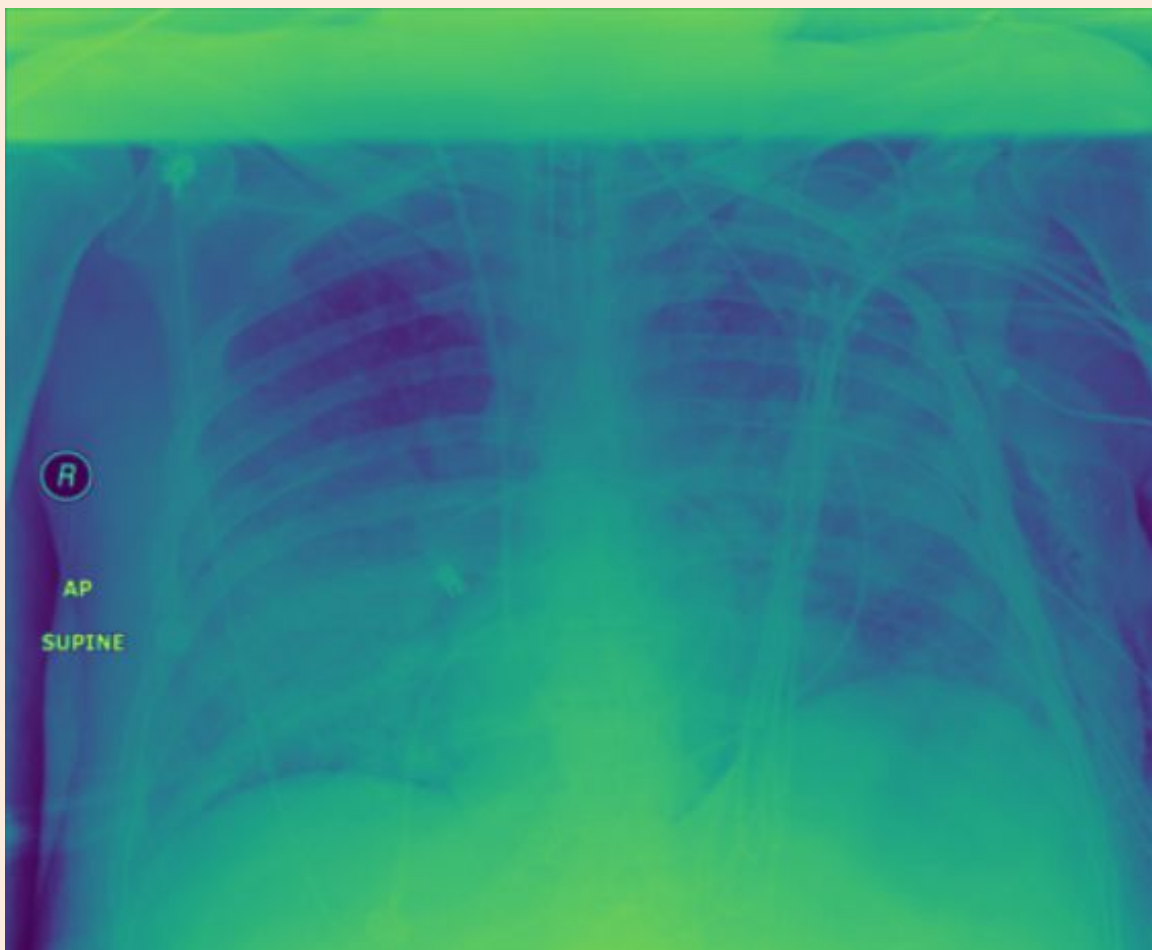
# NGT Abnormal



# NGT Borderline



# NGT Incompletely Imaged





# ETT – Endotracheal Tube (Normal)



Place of insertion:

- Mouth (common in emergencies) or nose

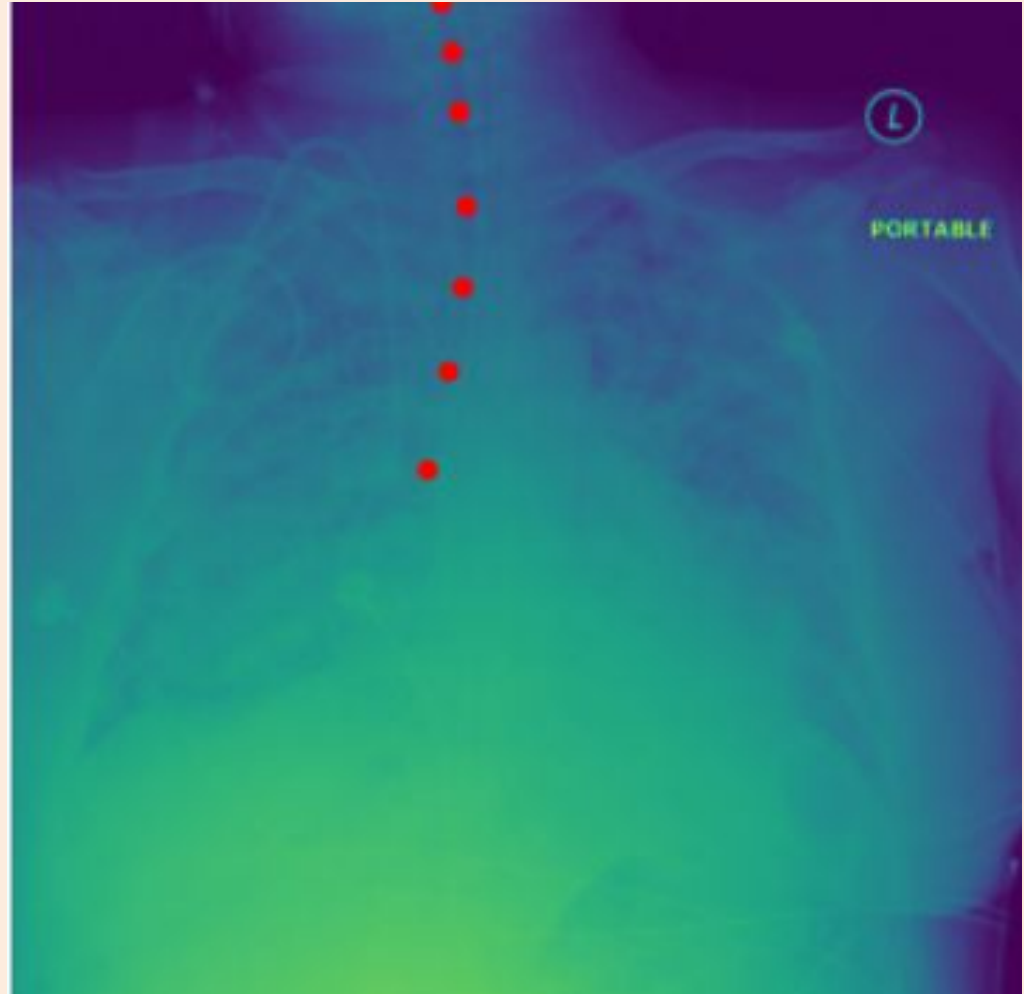
Where it sits:

- In the windpipe
- Just below the collarbones

What it does:

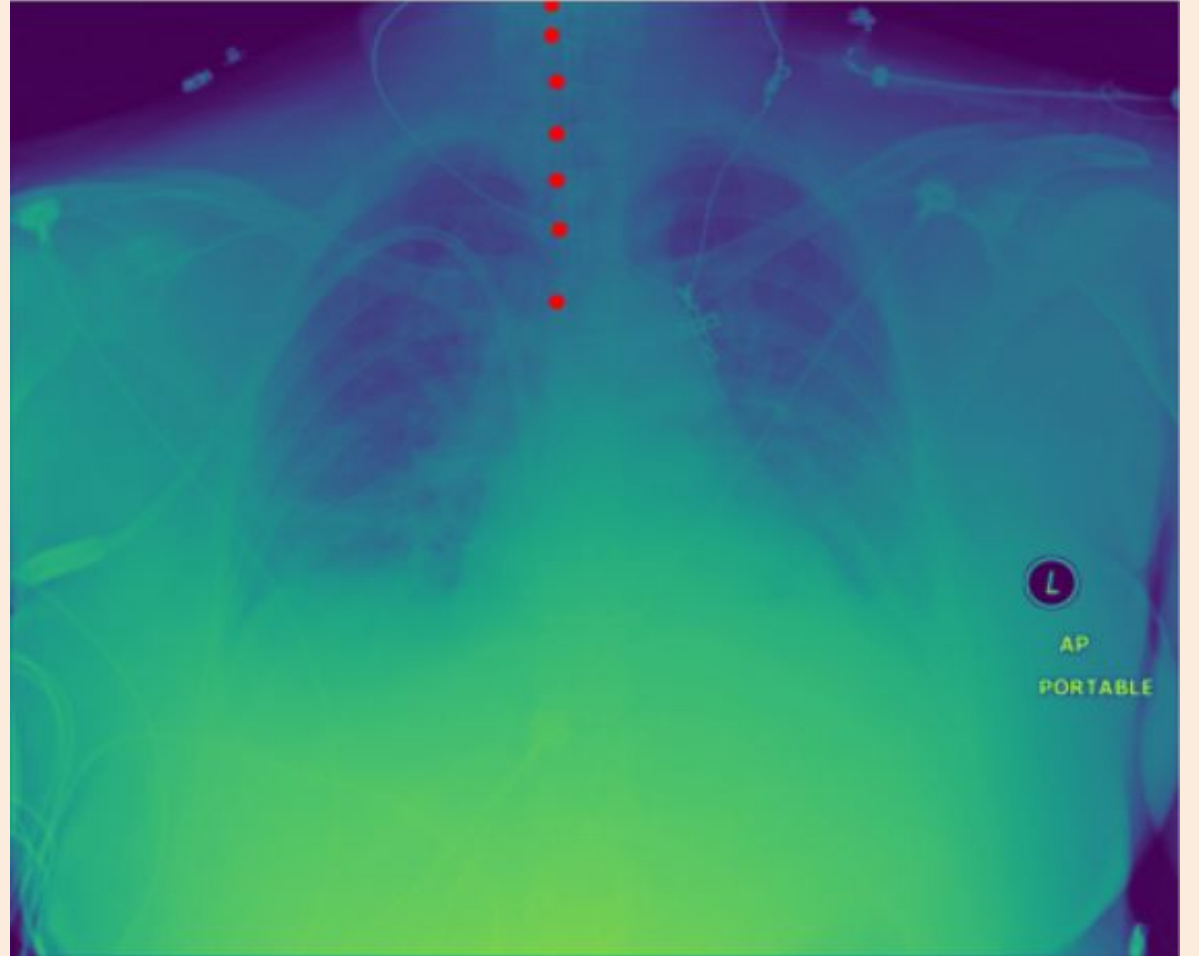
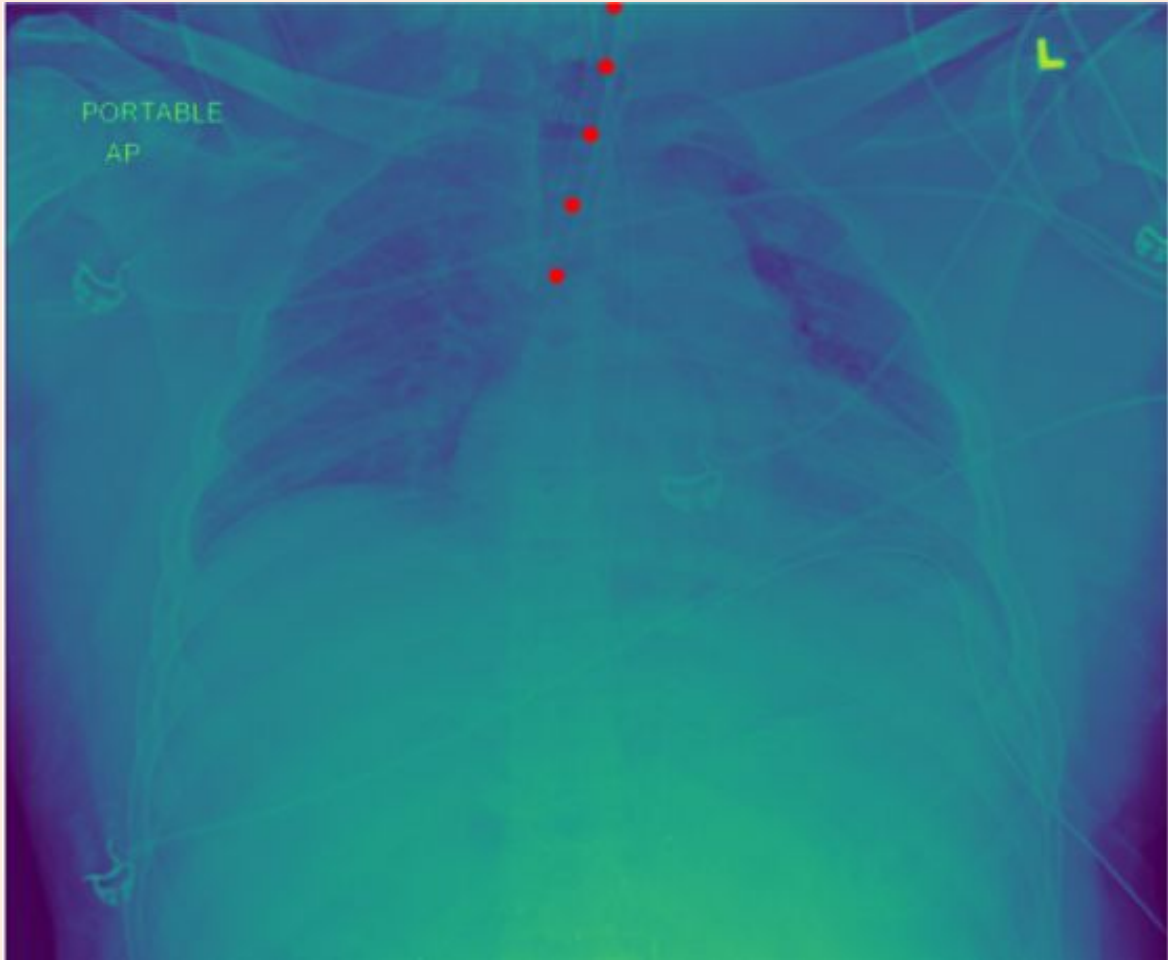
- Keeps the airway open
- Provides uncontaminated oxygen, medicine or anesthesia

# ETT Abnormal





# ETT Borderline



# CVC – Central Venous Catheter



Place of insertion:

- PICC (Peripherally inserted central catheter) inserted in arm
- Subclavian vein or neck

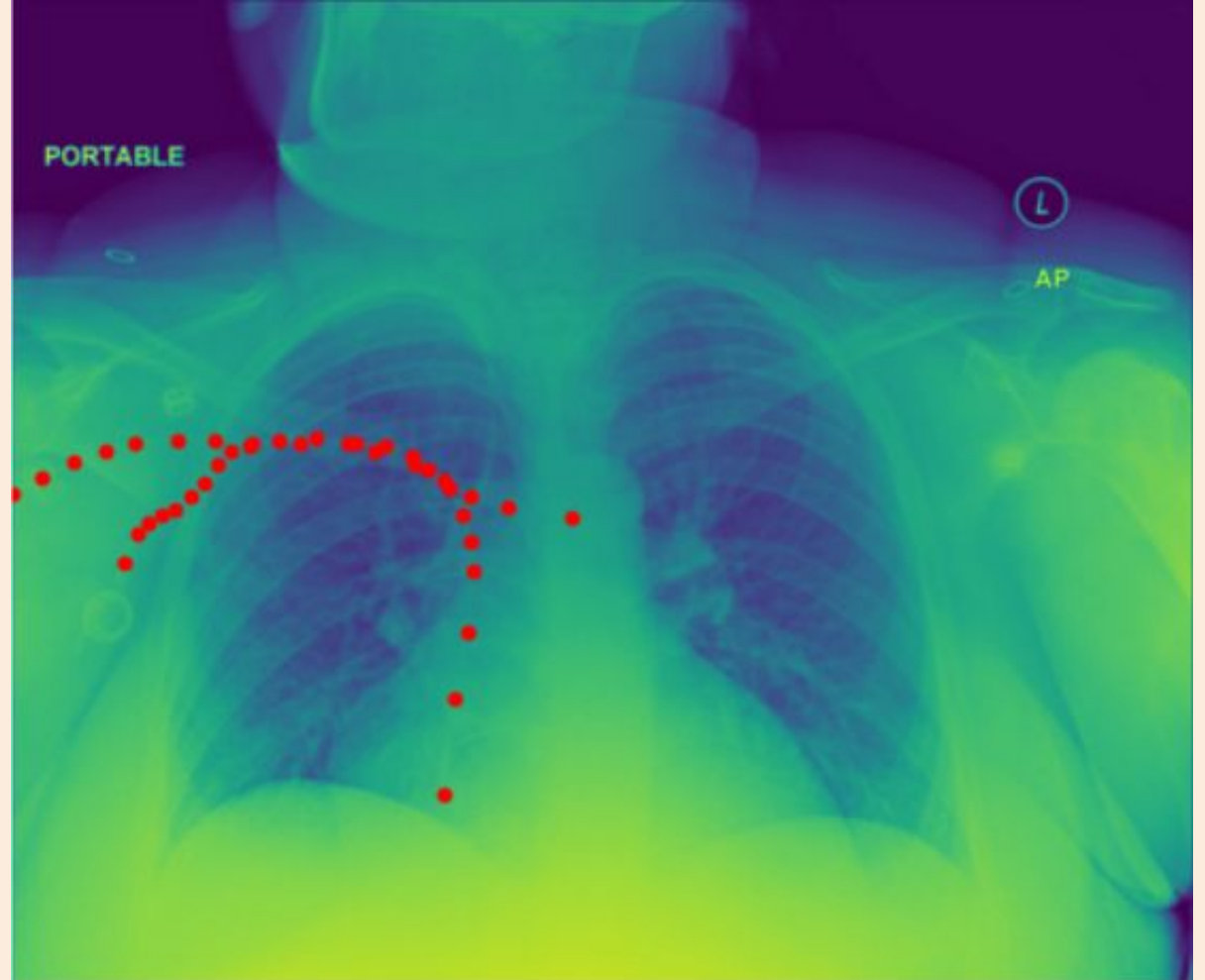
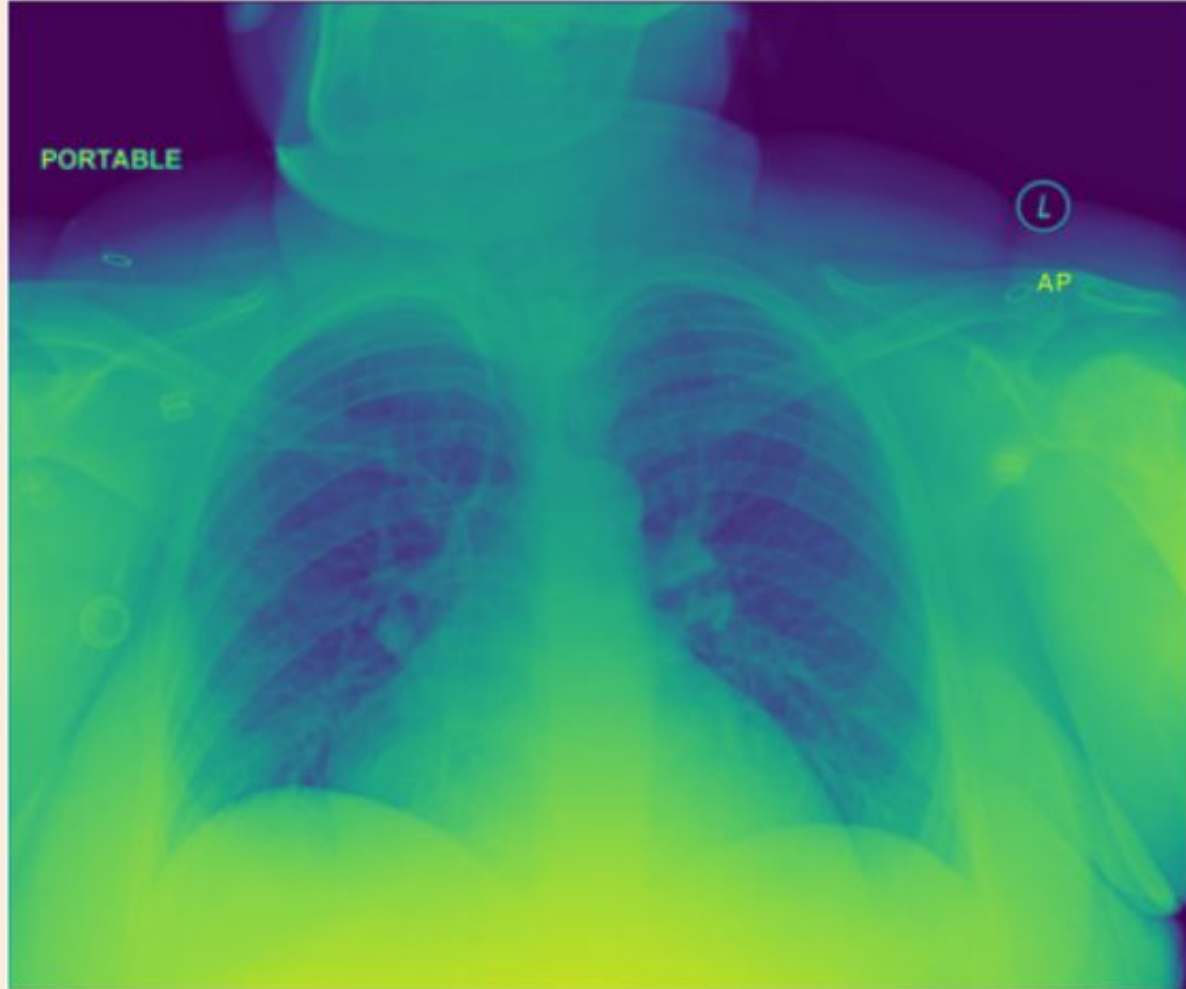
Where it sits:

- Ideally the vena cava (large vein just before the right atrium)
- This is so intravenous fluids can be pumped through the body as quickly as possible

What it does:

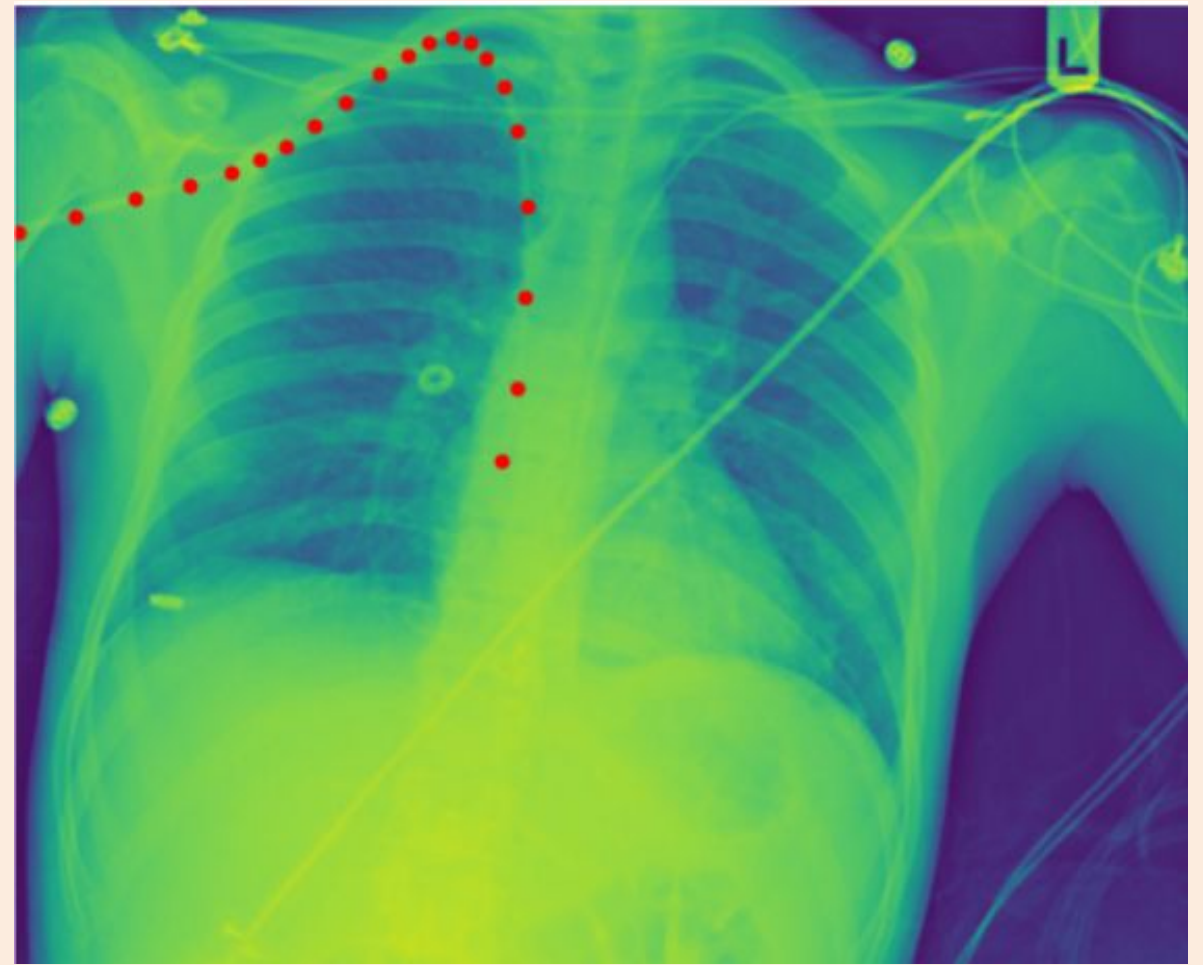
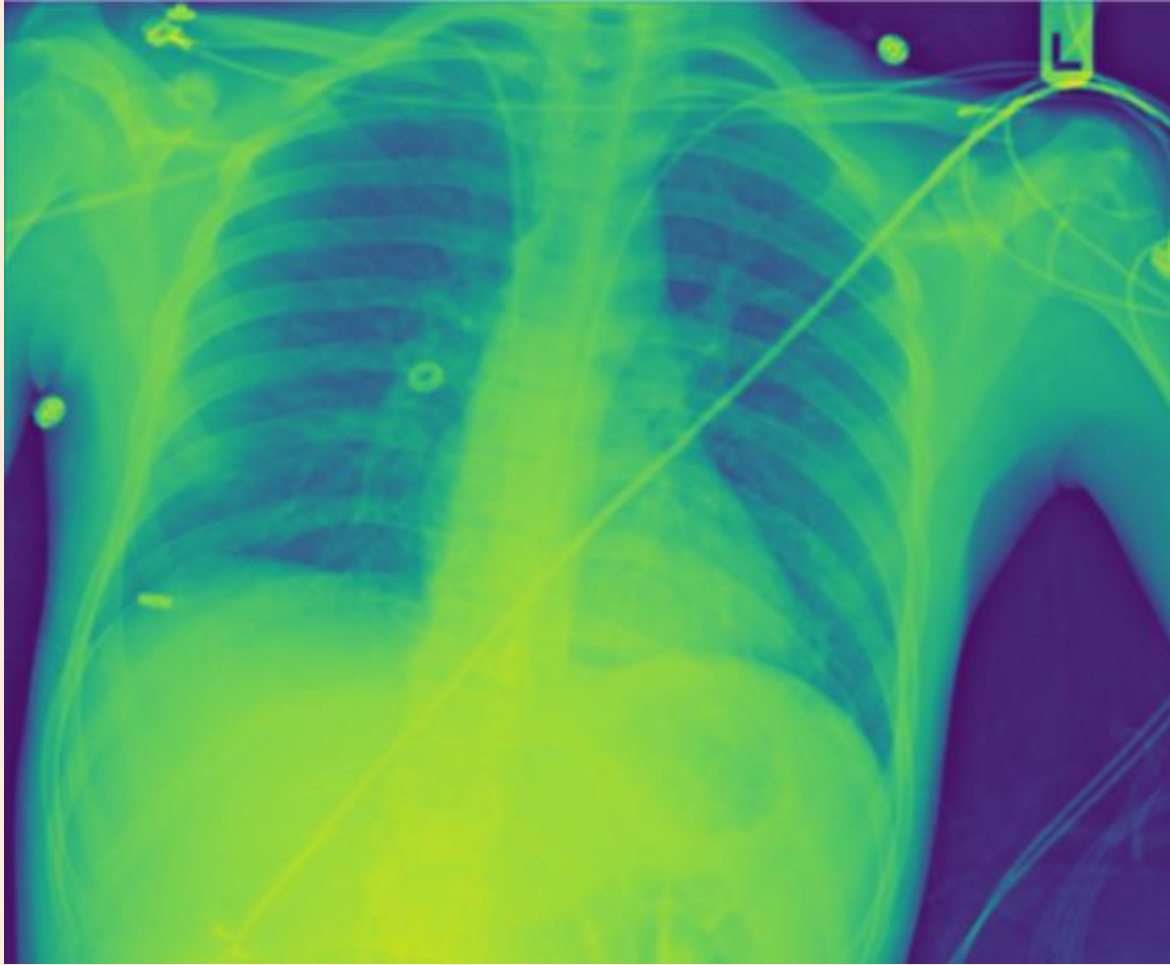
- Mainly administers medication

# CVC Abnormal





# CVC Borderline



# Swan Ganz – Type of CVC

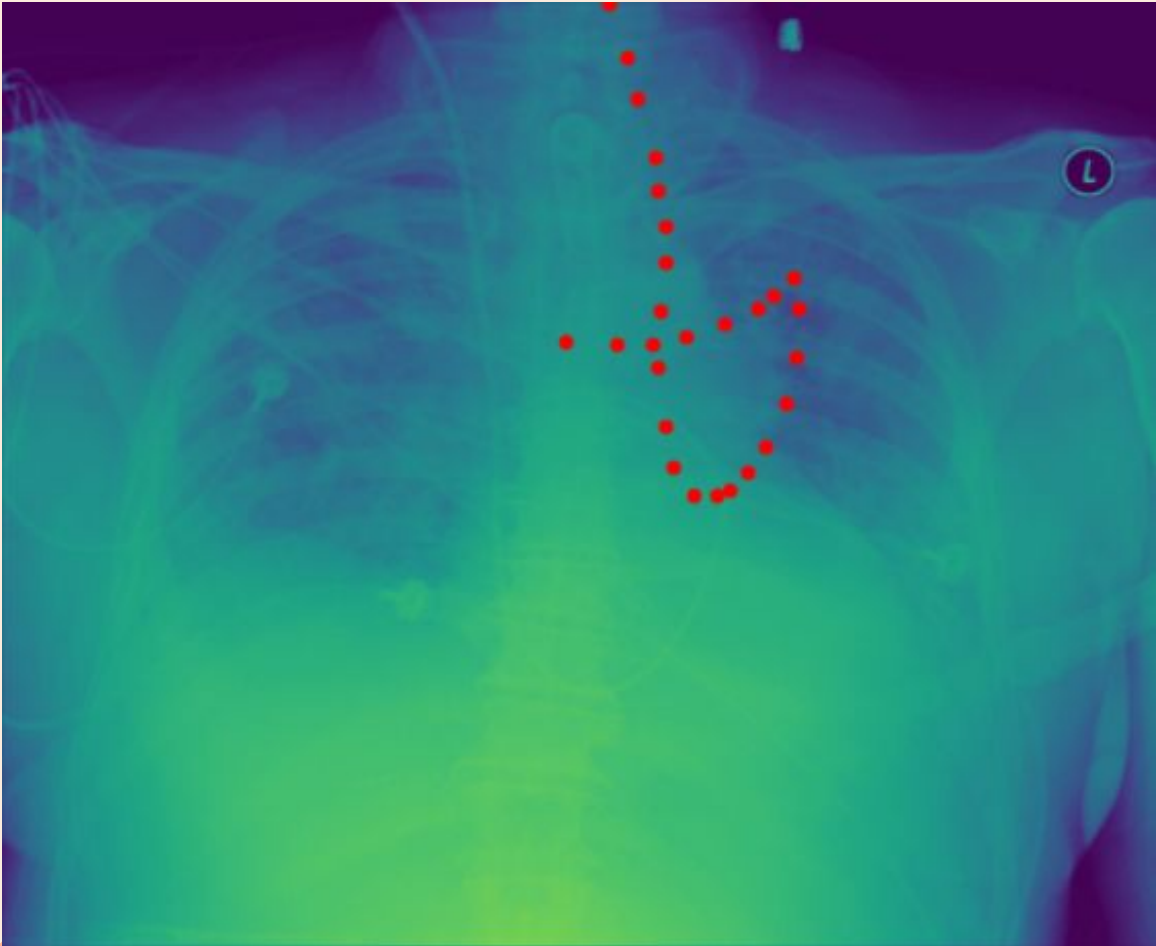
Does more than a normal cvc, it can measure:

- Cardiac Output
- Left atrial pressure
- Pulmonary artery pressure

Where it sits:

- Pulmonary artery – between right ventricle and lungs

Provides information about heart strength and health



# Data We Received

## Images:

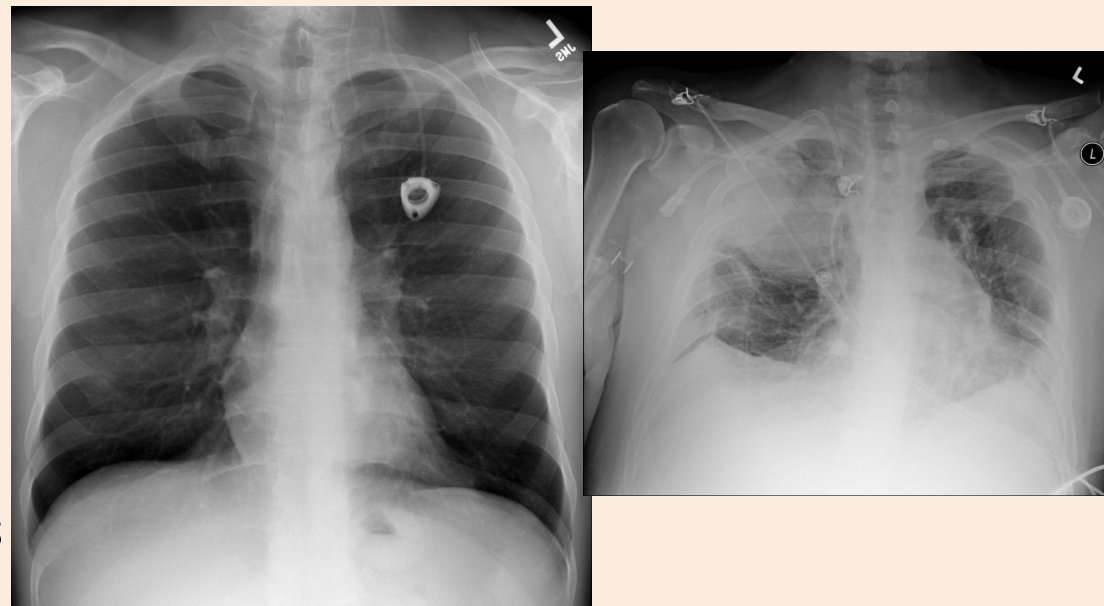
- Folder with 30083 images
- Each image is a medical scan that contains a number of catheters

## Train CSV:

- CSV that indicates what catheter types are present in a particular image

## Annotations:

- Each row provides the coordinates of a catheter present in an image
- 18000 annotations
- 9095 unique images





# Data

The data received was already clean:

- No duplicates
- No missing values

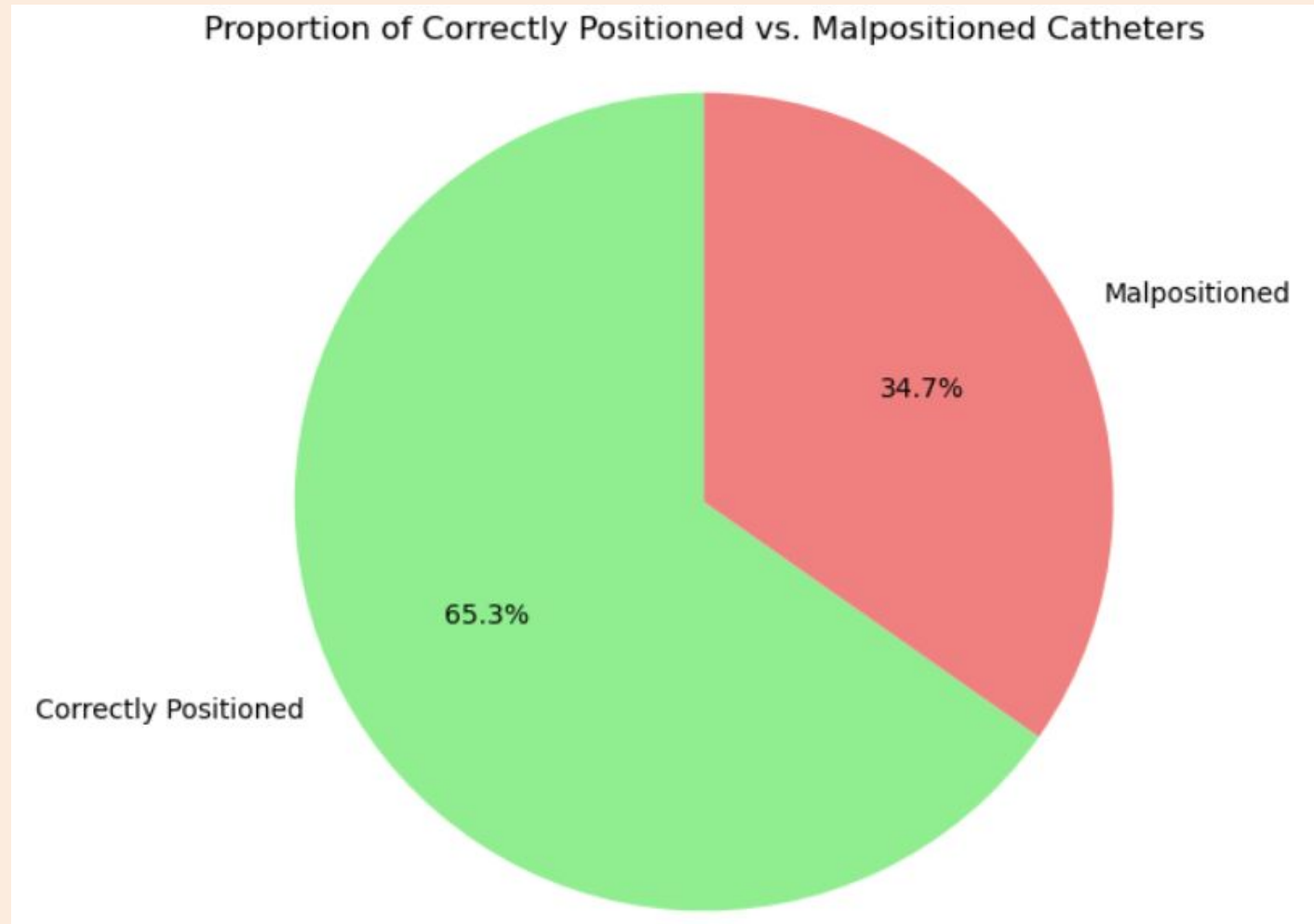
```
Duplicates present: 0
```

03

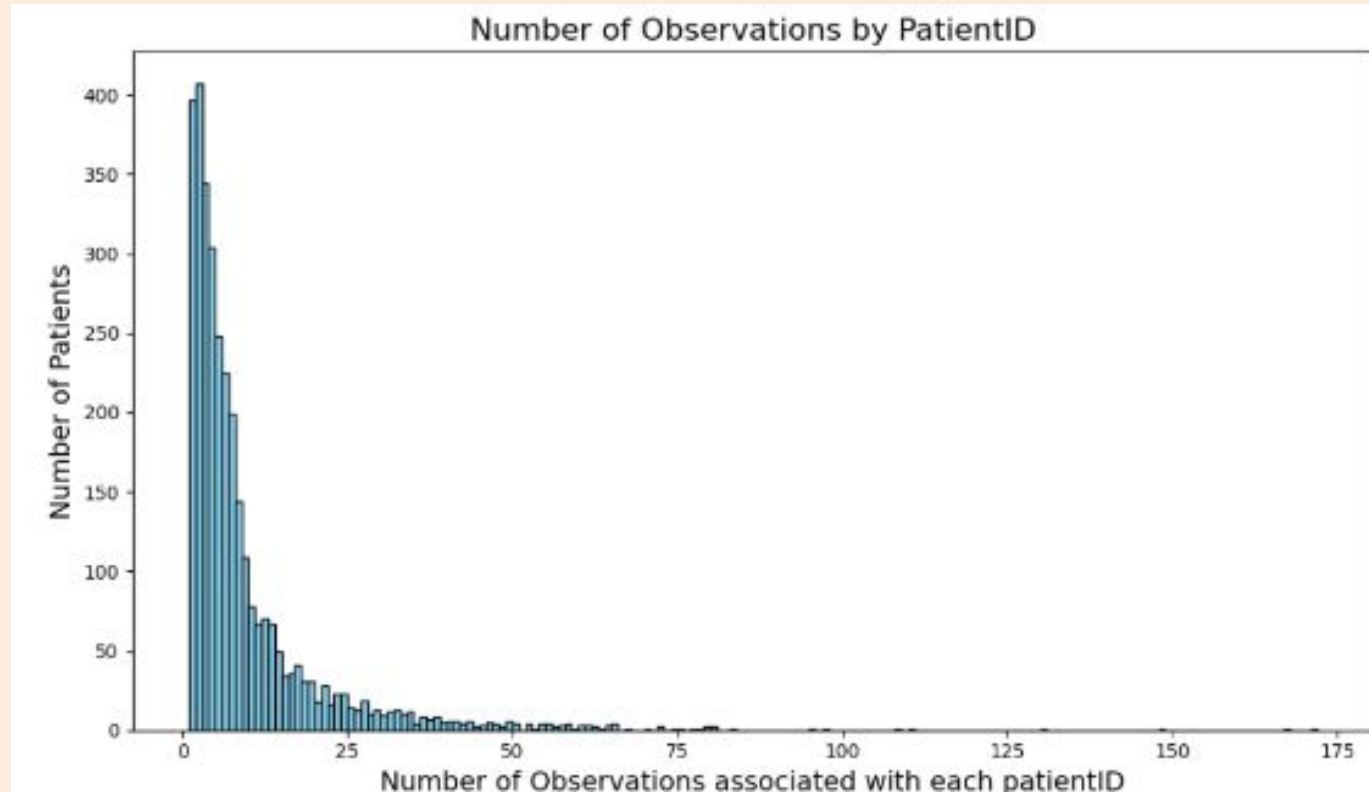
# Exploratory Data Analysis



# Positioned vs Malpositioned



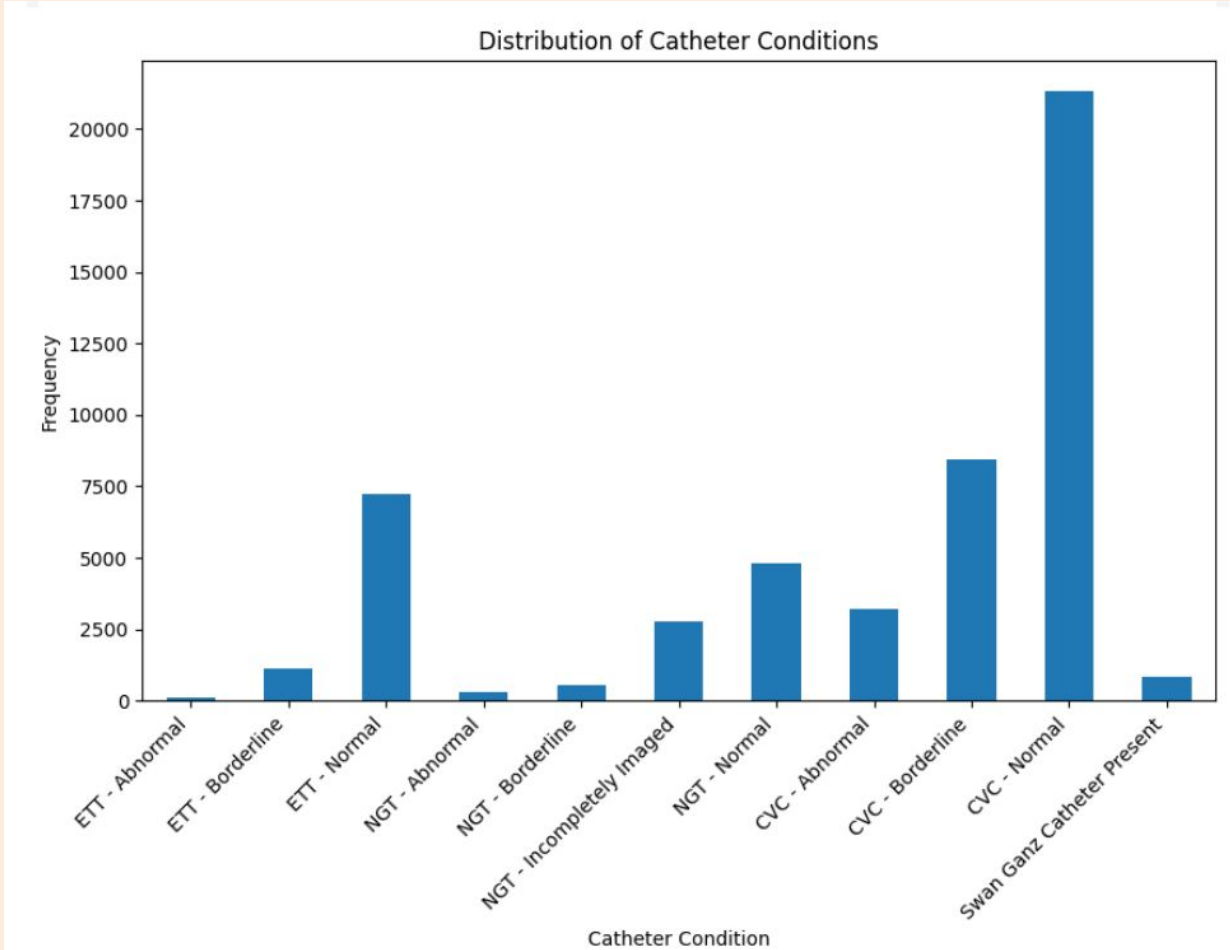
# Number of Observations



Total number of unique patients: 3255

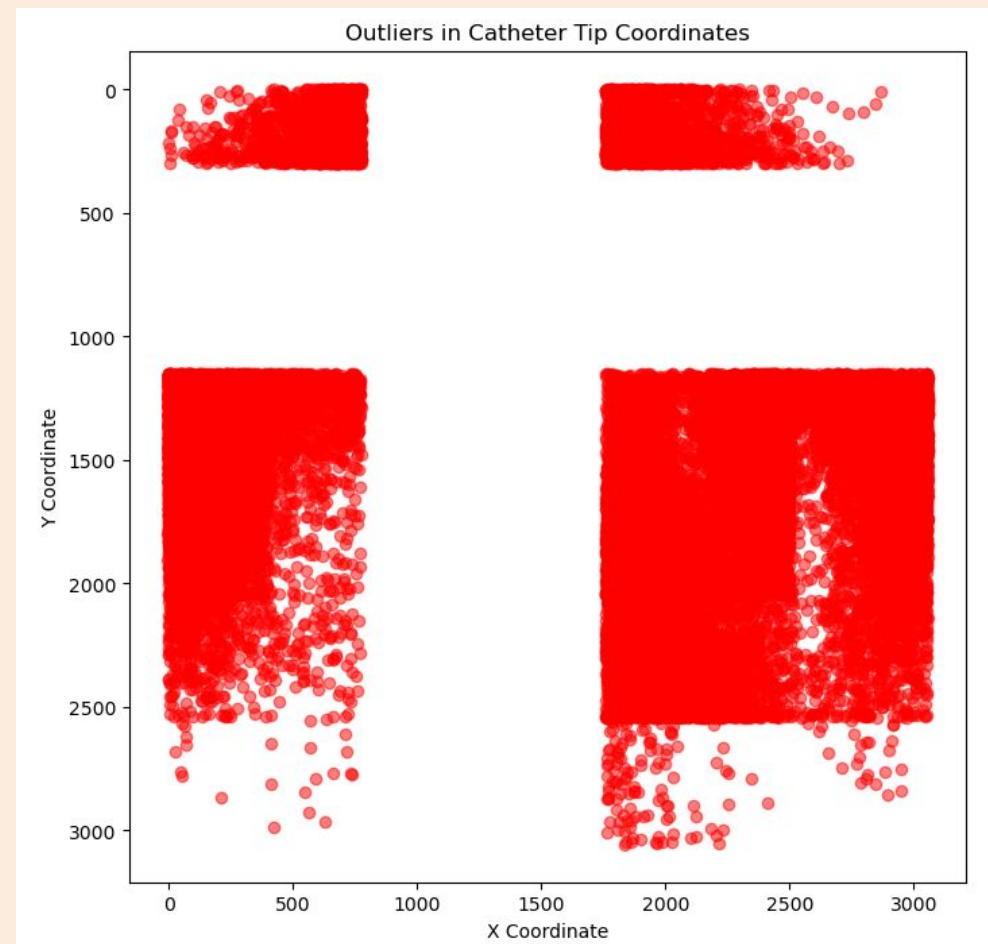
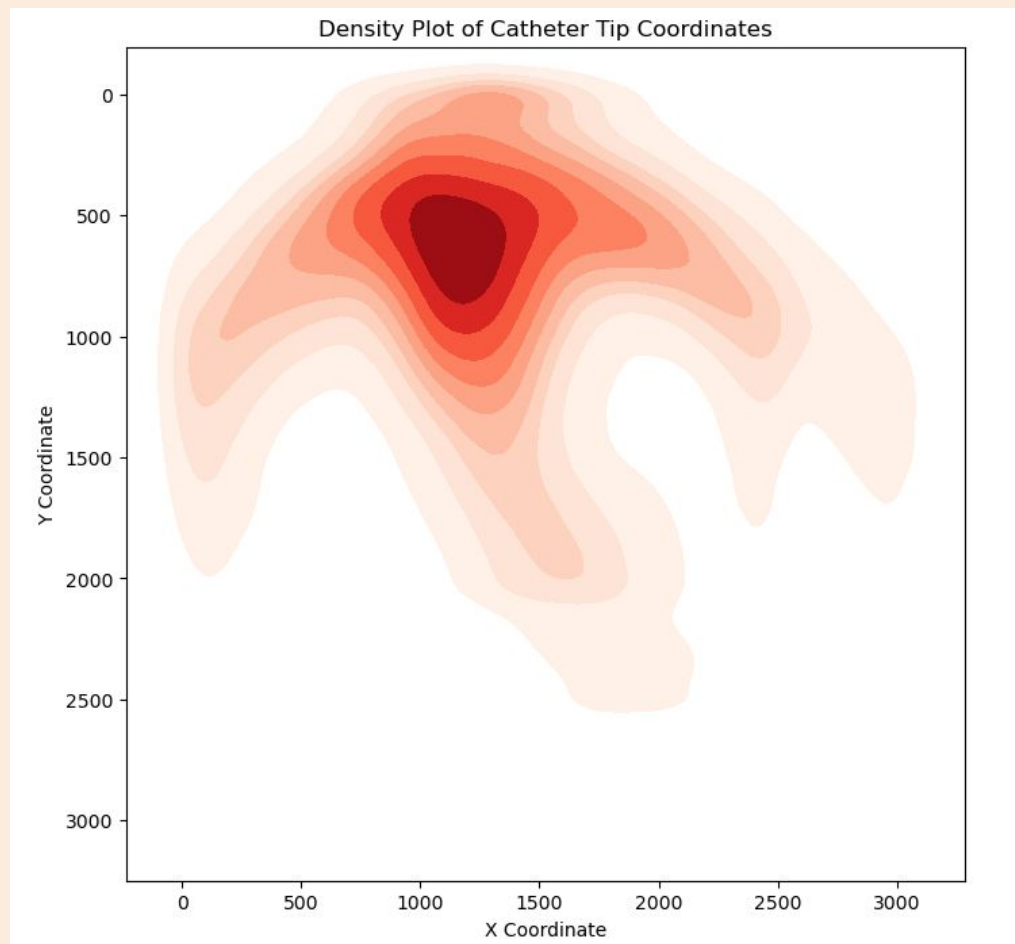
Number of patients with more than one observation: 2858

# Distribution of Catheters



	0
ETT - Abnormal	79
ETT - Borderline	1138
ETT - Normal	7240
NGT - Abnormal	279
NGT - Borderline	529
NGT - Incompletely Imaged	2748
NGT - Normal	4797
CVC - Abnormal	3195
CVC - Borderline	8460
CVC - Normal	21324
Swan Ganz Catheter Present	830

# Concentration and Outliers





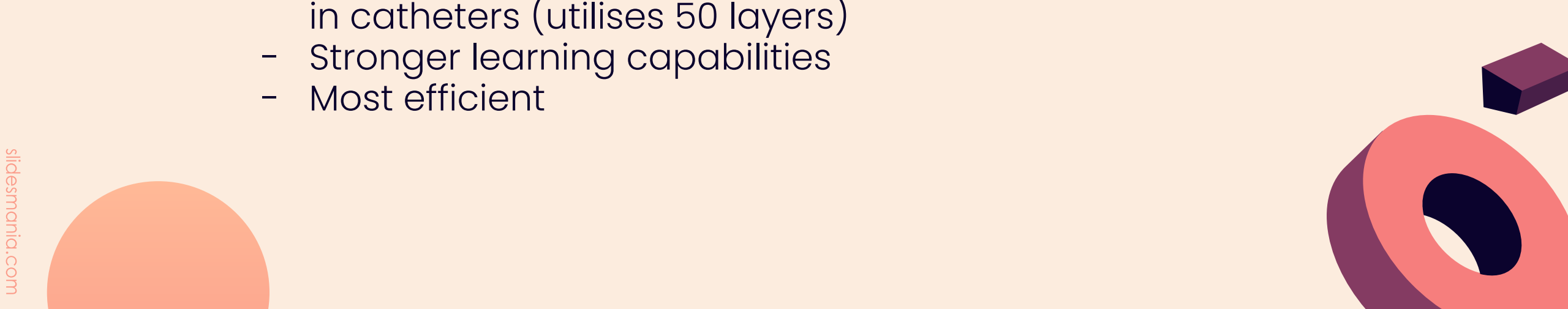
04

# Preprocessing and Data Manipulation + Modelling



# Deep Neural Network architecture

For modelling we decided to predominantly use the pre-built model in **ResNet50**:

- Other CNN models performed worse or the same
  - ResNet is more suitable:
    - In medical image classification, small details can be crucial for distinguishing between different types of abnormalities in catheters (utilises 50 layers)
    - Stronger learning capabilities
    - Most efficient
- 

# ResNet50 Architecture

- Custom layers on top include a **global average pooling layer**, a **dense layer** with 128 units, **dropout layer** to prevent overfitting, and a **dense output layer**.
- Overall using 50 layers from ResNet and 4 custom layers

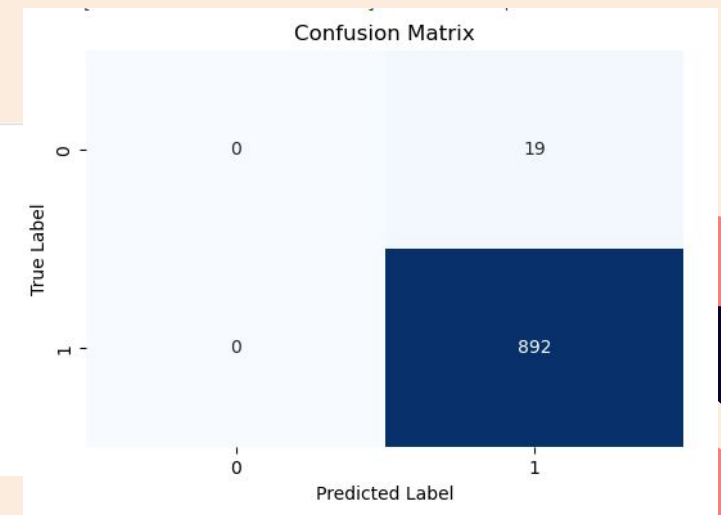
Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 7, 7, 2048)	23587712
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 128)	262272
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 10)	1290
Total params: 23,851,274		
Trainable params: 263,562		
Non-trainable params: 23,587,712		

# Binary Classification: CVC

As CVC catheters were the most prevalent, we first looked at categorising catheters as CVC or non-CVC

- Trained on the whole data set (30083 images)
- Obtained extremely high accuracies
- Confusion matrix is from a smaller subset however reflects what is occurring

```
Epoch 1/10  
114/114 [=====] - 1151s 10s/step - loss: 0.1143 - accuracy: 0.9827 - val_loss: 0.1004 - val_accuracy: 0.9791  
Epoch 2/10  
114/114 [=====] - 774s 7s/step - loss: 0.0947 - accuracy: 0.9830 - val_loss: 0.1040 - val_accuracy: 0.9791  
Epoch 3/10  
114/114 [=====] - 573s 5s/step - loss: 0.0907 - accuracy: 0.9830 - val_loss: 0.1002 - val_accuracy: 0.9791  
Epoch 4/10  
114/114 [=====] - 571s 5s/step - loss: 0.0889 - accuracy: 0.9830 - val_loss: 0.1019 - val_accuracy: 0.9791  
Epoch 5/10  
114/114 [=====] - 1072s 9s/step - loss: 0.0899 - accuracy: 0.9830 - val_loss: 0.1062 - val_accuracy: 0.9791  
Epoch 6/10  
114/114 [=====] - 1125s 10s/step - loss: 0.0898 - accuracy: 0.9830 - val_loss: 0.1061 - val_accuracy: 0.9791
```





# Binary Classification 2: CVC

Due to the imbalance between CVC and non-CVC the model was biased and inaccurate

- Applying weights to the model
- Upsampling non-CVC catheters

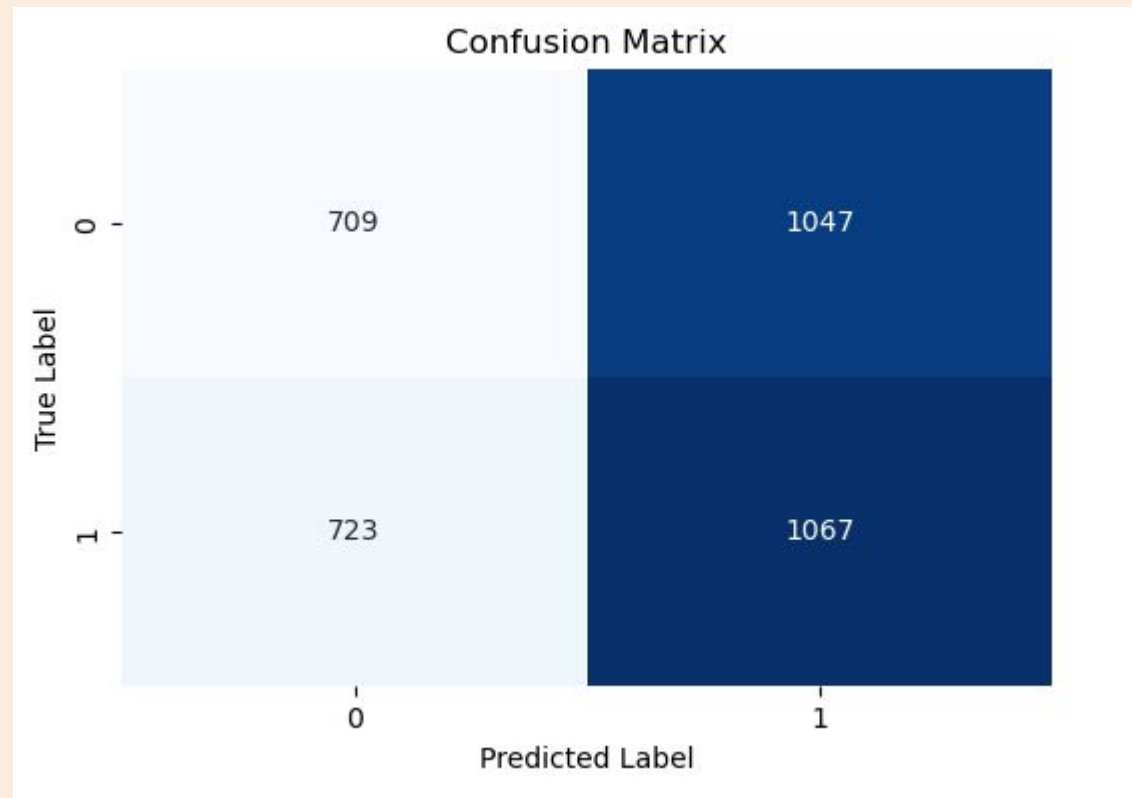
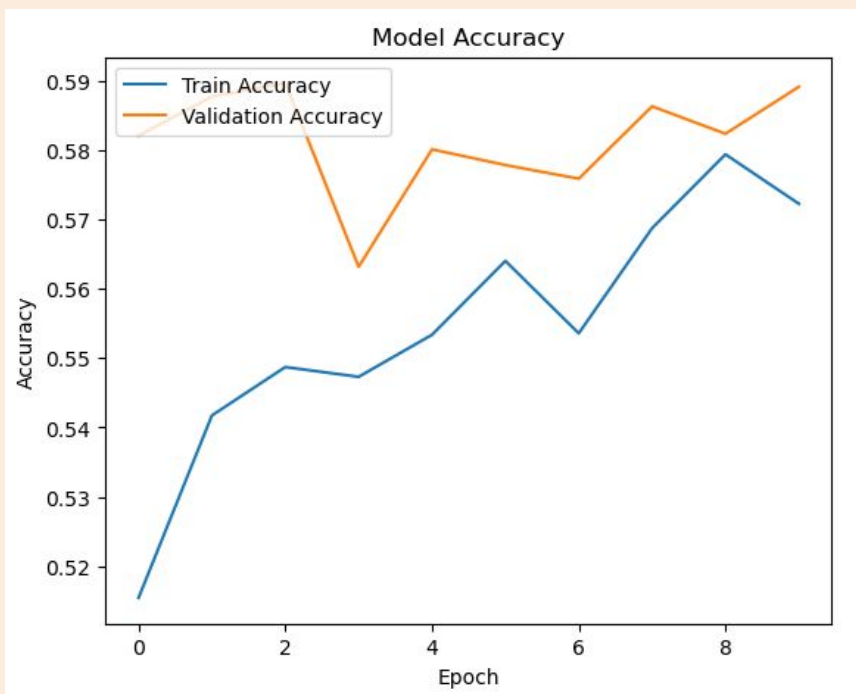
Second attempt:

- Filtered data to only images with annotations
- 20% validation split

Original		Upsampled	
CVC_numeric		CVC_numeric	
1	29333	1	14666
0	750	0	14666

Original		Upsampled	
CVC_numeric		CVC_numeric	
1	8866	0	8866
0	229	1	8866

# Binary Classification: CVC results



```
111/111 [=====] - 442s 4s/step - loss: 0.6705 - accuracy: 0.5964  
Validation Loss: 0.6705045700073242  
Validation Accuracy: 0.596446692943573
```

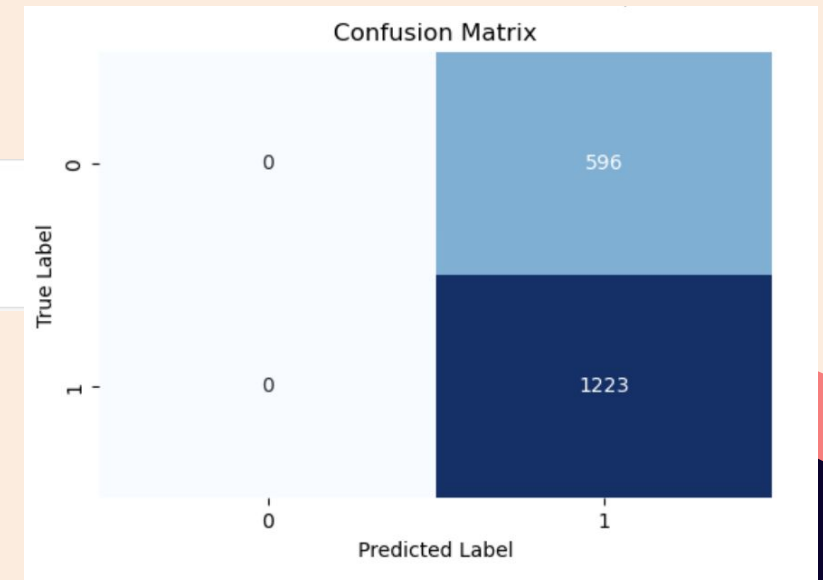
# Binary Classification: ETT

We also looked at classifying ETT catheters as ETT or non-ETT

- ETT catheters were less prevalent
- Ratio between ETT and non-ETT seemed more balanced than CVC (expected a higher accuracy)

```
ETT_numeric
0      6101
1      2994
..      .
```

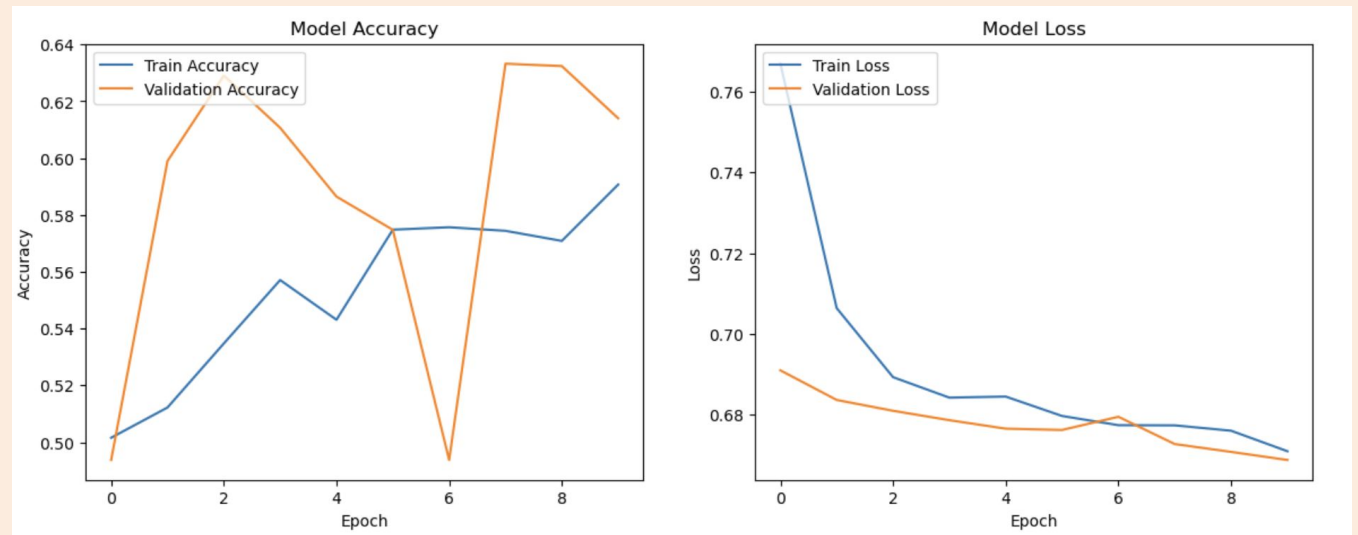
```
57/57 [=====] - 226s 4s/step - loss: 0.6089 - accuracy: 0.6723
Validation Loss: 0.6089034080505371
Validation Accuracy: 0.6723474264144897
```



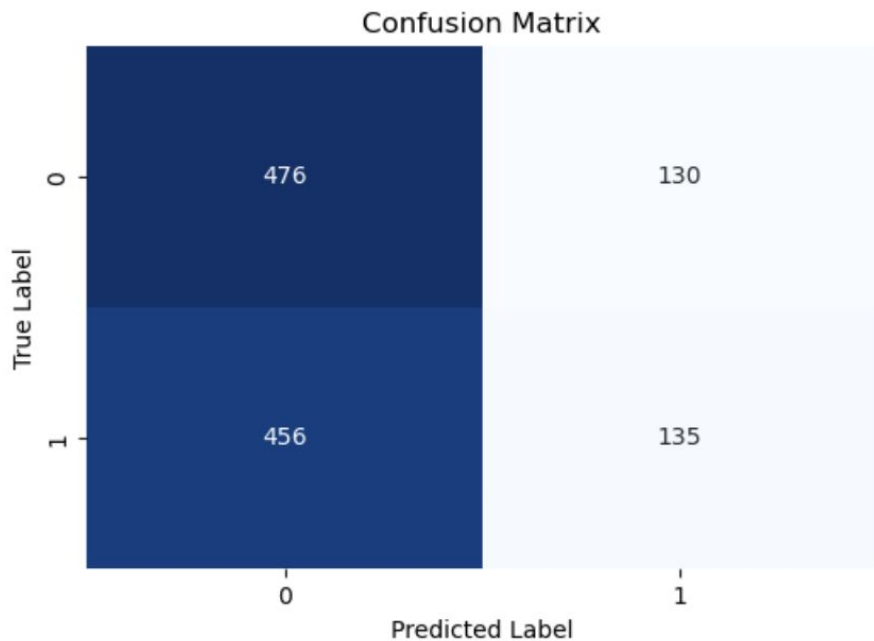
# Binary Classification: ETT 2

Down-sampled  
ETT\_numeric

0	2994
1	2994



38/38 [=====] - 146s 4s/step - loss: 0.6691 - accuracy: 0.6182  
Validation Loss: 0.6691277027130127  
Validation Accuracy: 0.6182122230529785



# Binary Classification: NGT

Built a model to classify images as 'NGT' or 'non-NGT'

- The distribution of NGT to non-NGT images was much more even compared to CVC and ETT

NGT_numeric	
0	5918
1	3177

```
57/57 [=====] - 193s 3s/step - loss: 0.6139 - accuracy: 0.6537  
File Browser n Loss: 0.613928496837616  
Validation Accuracy: 0.6536558270454407
```

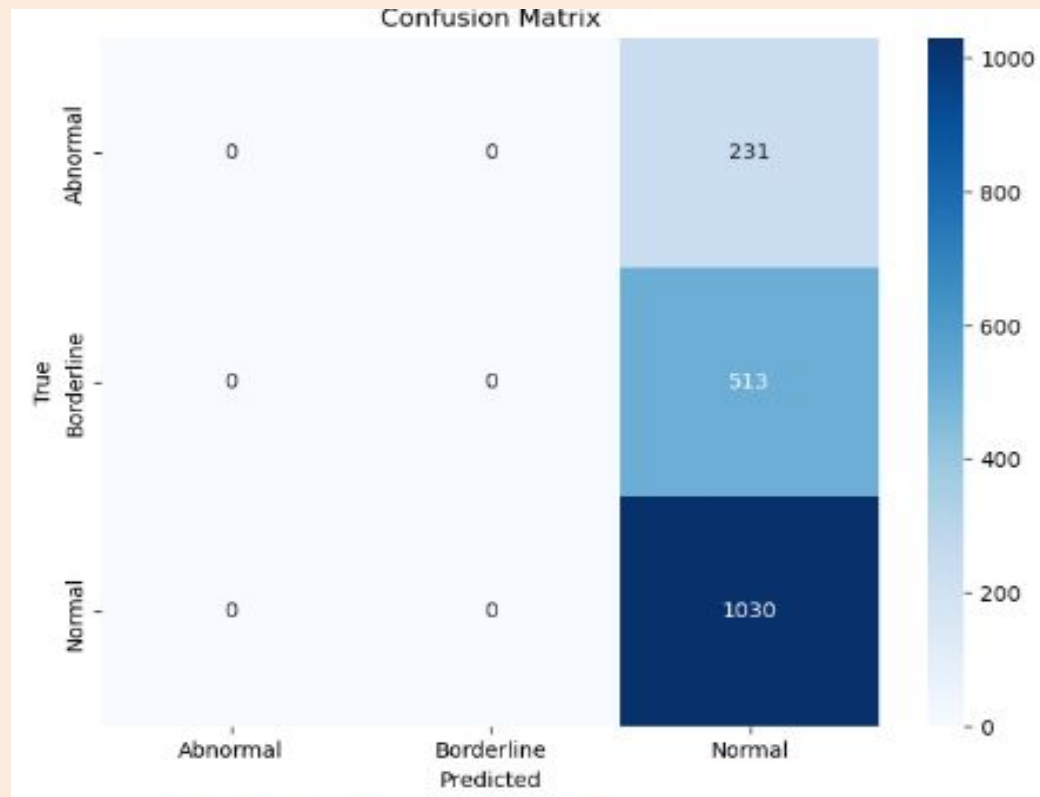
# Categorical: Multi-label CVC Catheter Classification Setup

- Due to software limitations, we only worked with X-ray images with only one catheter present
- Created categorical columns classifying the catheters
- Removed multiple catheter instances for software efficiency
- Upsampled abnormal and borderline data for balancing
- Only focussed on annotated data

```
CVC_type
normal      5147
borderline  1619
abnormal     751
Name: count, dtype: int64
```

```
CVC_type
normal      5147
borderline  5147
abnormal     5147
Name: count, dtype: int64
```

# Categorical: Multi-label CVC Catheter Classification Initial results



Validation Loss: 0.9419806003570557  
Validation Accuracy: 0.5806087851524353

	precision	recall	f1-score	support
abnormal	0.00	0.00	0.00	231
borderline	0.00	0.00	0.00	513
normal	0.58	1.00	0.73	1030
accuracy			0.58	1774
macro avg	0.19	0.33	0.24	1774
weighted avg	0.34	0.58	0.43	1774

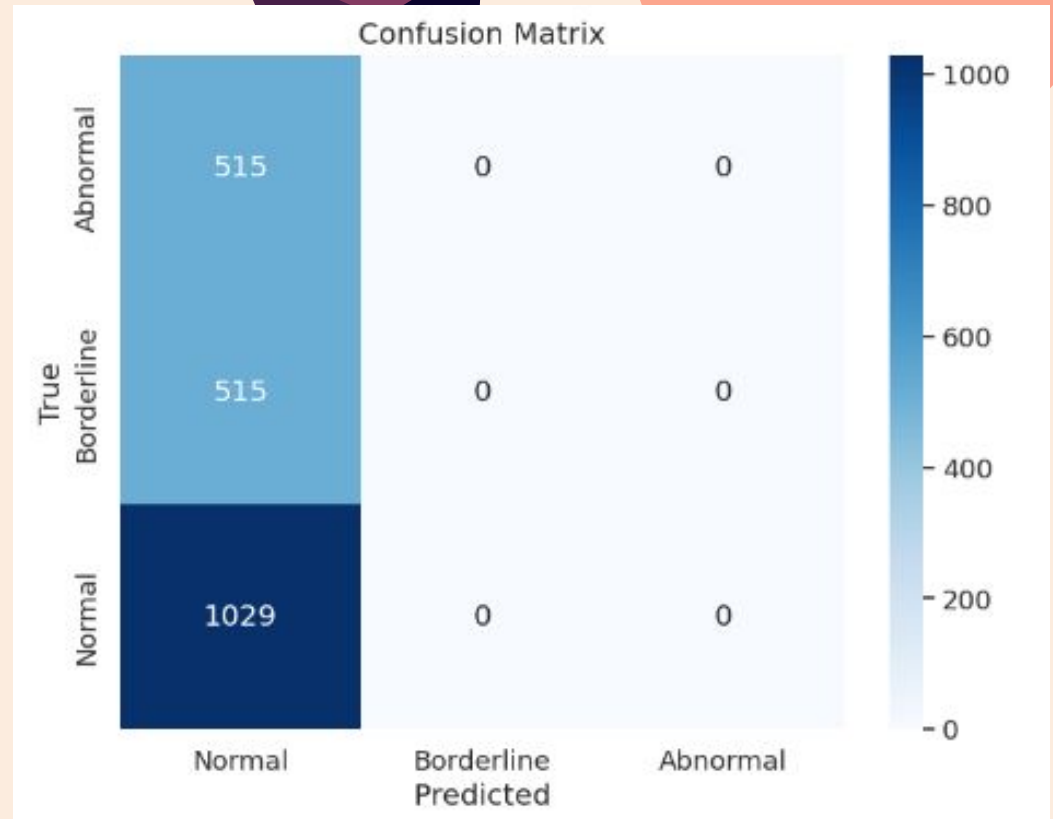
# Categorical: Multi-label CVC Catheter Classification

## Balanced Results

	precision	recall	f1-score	support
abnormal	0.25	1.00	0.40	515
borderline	0.00	0.00	0.00	515
normal	0.00	0.00	0.00	1029
accuracy			0.25	2059
macro avg	0.08	0.33	0.13	2059
weighted avg	0.06	0.25	0.10	2059

Validation Loss: 0.6365716457366943

Validation Accuracy: 0.6666667461395264





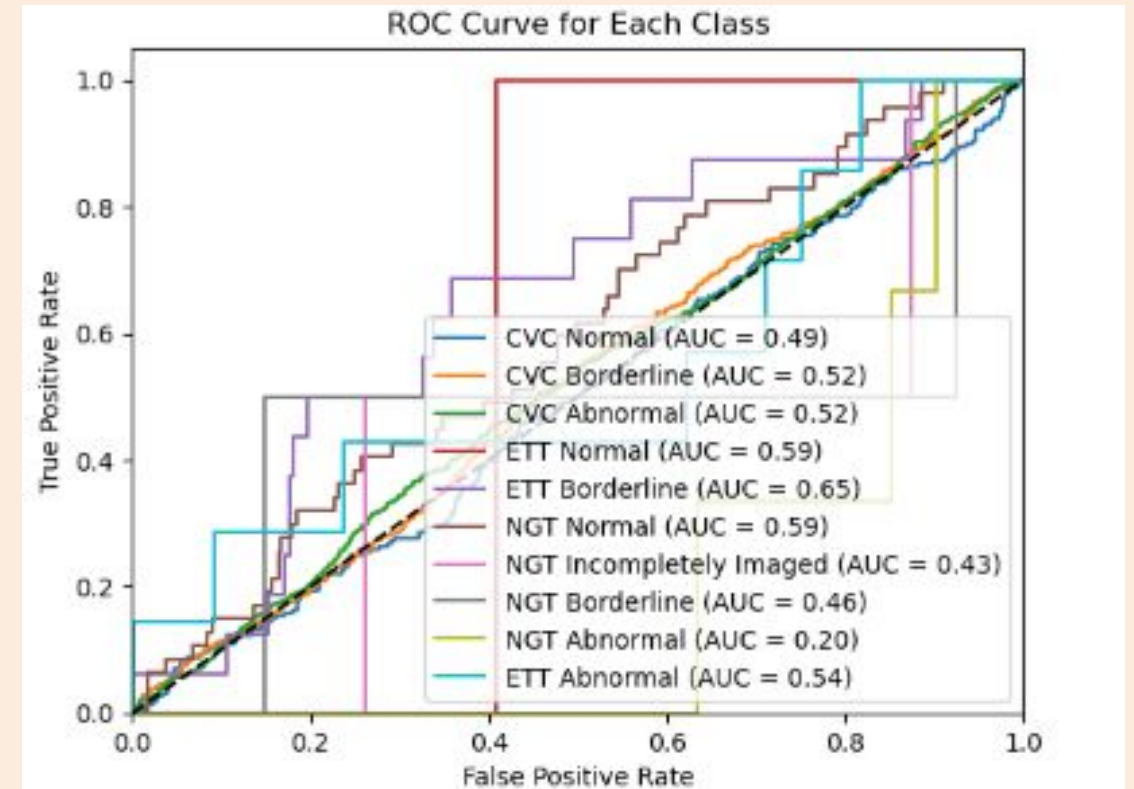
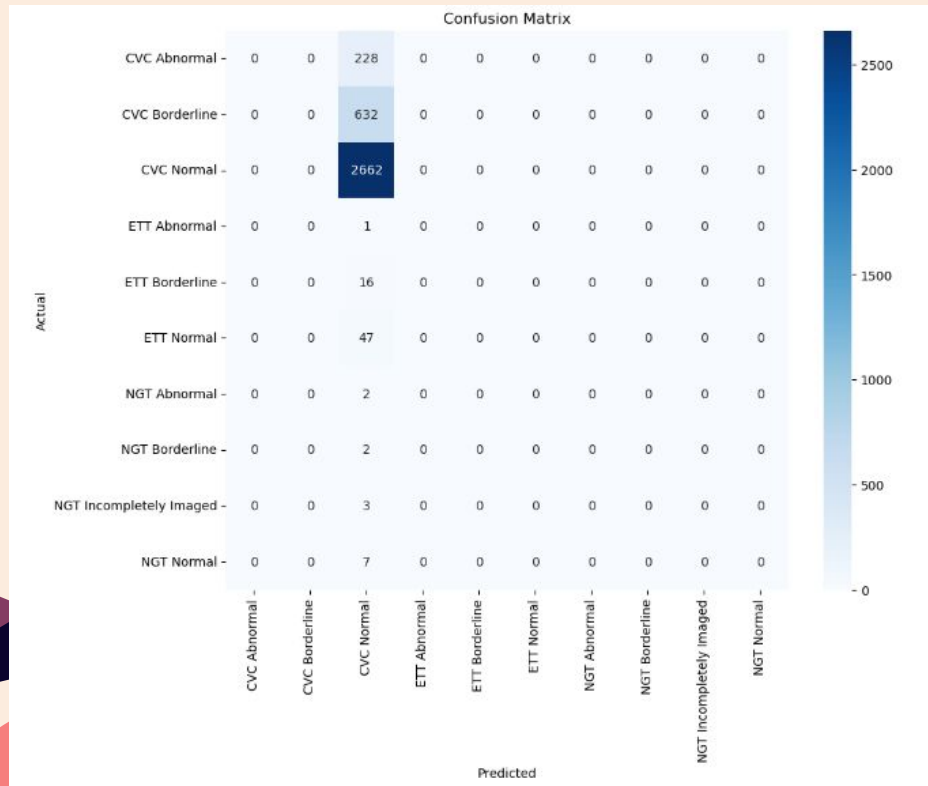
## Categorical: Multi-label Catheter Classification setup

- 17999 studies
- Due to software limitations, we only worked with X-ray images with only one catheter present
- With significant undersampling, we added class weights
- Created categorical columns classifying the catheters

```
CVC - Normal      13312
ETT - Normal      8532
CVC - Borderline  6453
NGT - Normal      6087
NGT - Incompletely Imaged 3480
CVC - Abnormal    2421
ETT - Borderline  1432
NGT - Borderline   659
Swan Ganz Catheter Present 555
NGT - Abnormal    336
ETT - Abnormal     92
dtype: int64
```

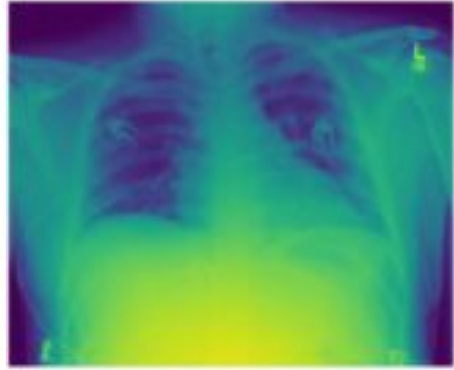
```
CVC - Normal      3689
CVC - Borderline  1145
CVC - Abnormal     569
NGT - Normal       37
NGT - Incompletely Imaged 17
ETT - Normal       10
NGT - Abnormal      8
NGT - Borderline    7
ETT - Borderline     3
ETT - Abnormal      1
Swan Ganz Catheter Present 0
dtype: int64
```

# Multi-label Catheter Classification Results

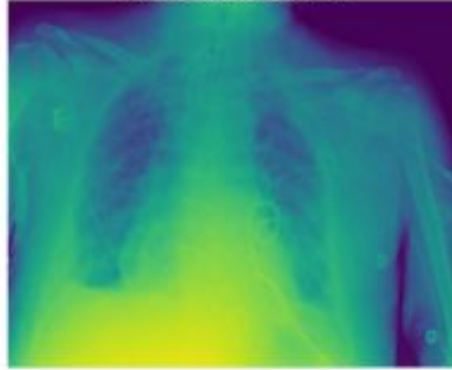


Validation Loss: 0.8148368000984192  
Validation Accuracy: 0.7393973469734192

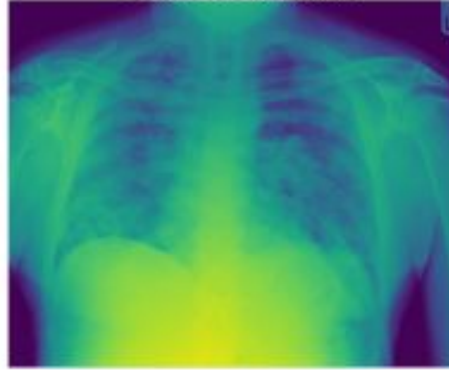
True: CVC Borderline  
Pred: CVC Normal



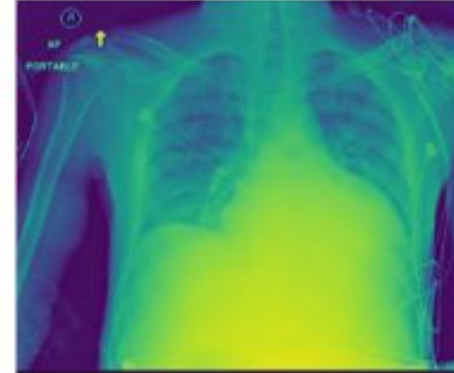
True: CVC Borderline  
Pred: CVC Normal



True: CVC Borderline  
Pred: CVC Normal



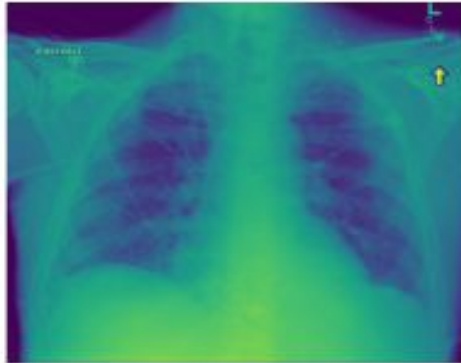
True: CVC Borderline  
Pred: CVC Normal



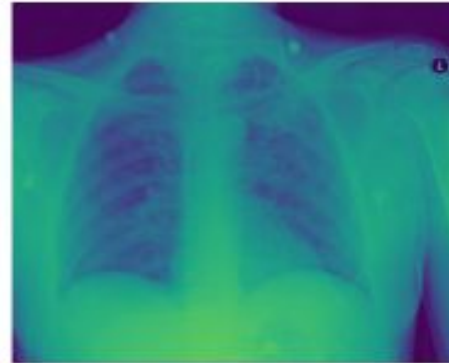
True & Pred: CVC Normal



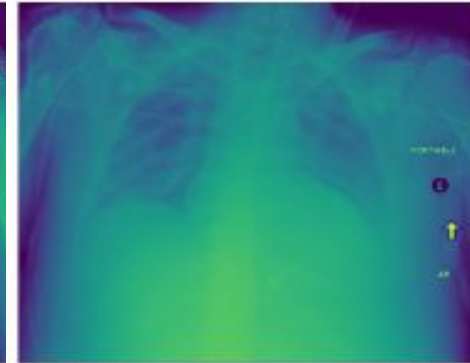
True & Pred: CVC Normal



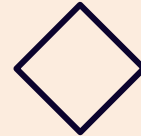
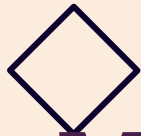
True & Pred: CVC Normal



True & Pred: CVC Normal



## Categorical: Multi-label Catheter Classification True vs Predicted



# Model Interpretation – LIME

Highlights – the parts that most influence the models prediction. Shows that the model is focusing on the correct anatomical features related to the catheter type.

Green – positive influence.

Red – negative influence

LIME (Local Interpretable Model-agnostic Explanations) explains individual predictions by identifying parts of the input (like regions in an image) that most influence the model's decision.

Original Image



Model Explanation with LIME

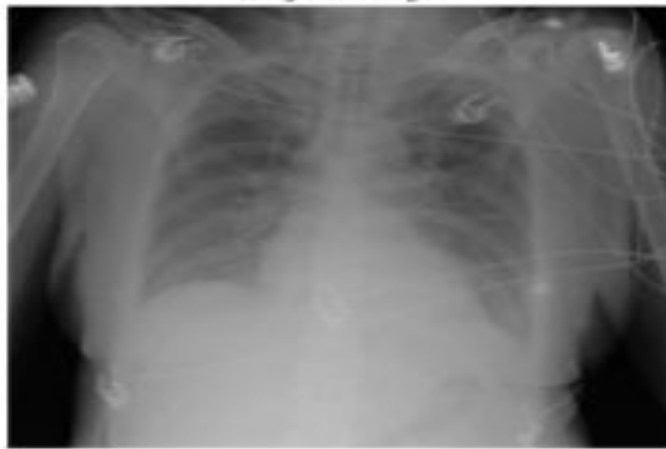
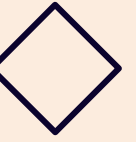
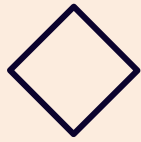


Original Image

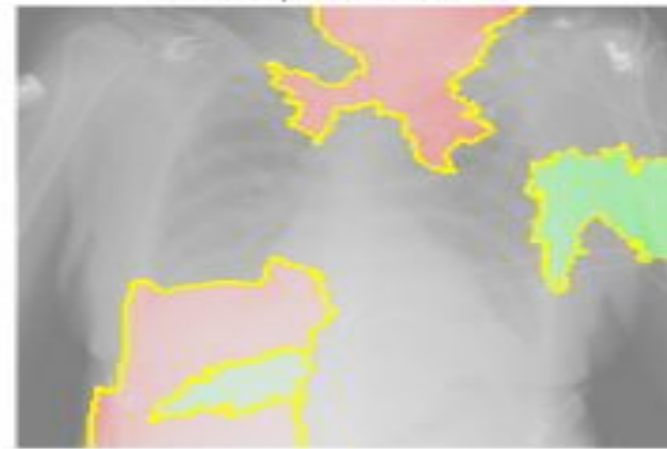


Model Explanation with LIME





Original Image



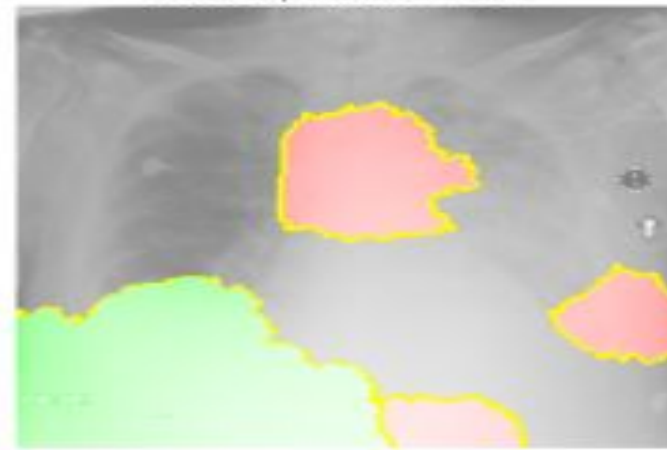
Model Explanation with LIME



Original Image



Model Explanation with LIME

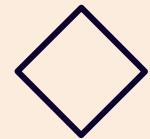
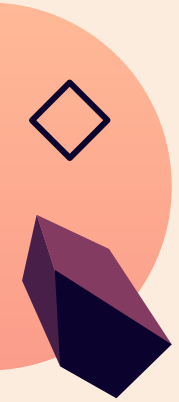
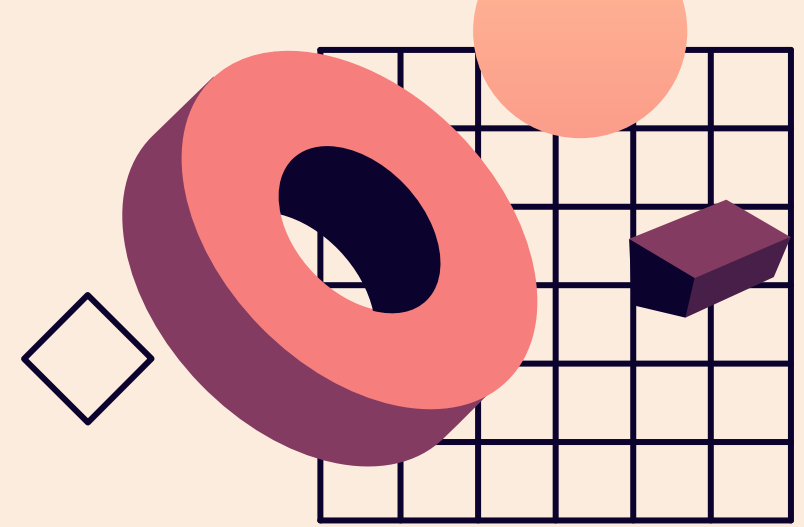







05

# Conclusion





# Results

- Models must be refined before being implemented into hospitals and clinics
  - Fixed one issue of unbalanced data, however poor accuracies could be due to:
    - Data quality
    - Poor choice of model
    - Overfitting
- 



# Summary

- Over 30,000 images of chest x-rays
- Research on the types of catheters.
- $\frac{1}{3}$  of the catheters were malpositioned
- CVC is most common type of catheter
- We used ResNet50 and the Multi-label Catheter Classification performed best with 73.93%





# References

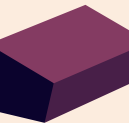
Kolikof, J. (July, 2023). *Central Venous Catheter*. National Library of Medicine.  
<https://www.ncbi.nlm.nih.gov/books/NBK557798/>

Signon, F. (Oct, 2022). *Nasogastric Tube*. National Library of Medicine.  
<https://www.ncbi.nlm.nih.gov/books/NBK556063/>

Ahmed, R. (July, 2023). *Endotracheal Tube*. National Library of Medicine.  
<https://www.ncbi.nlm.nih.gov/books/NBK539747/>

Hosny, A. (Aug, 2018). *Artificial intelligence in radiology*. National Library of Medicine.  
<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6268174/>

Shim, J. (2024). 'How to identify a catheter'. Interview by Byron Shim, 20 August.





**Thank you!**

**Do you have any questions?**

