

## CATHETER AND LINE POSITIONING IN CHEST X-RAYS

# CALP-X

Final Presentation, Team 7

# Team Details

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# Agenda

- Introduction / Abstract
- Problem statement
- Study on the Existing System
- Design methodology
- Modules each individual
- Implementation & Demo
- Conclusion / Future Scope
- Timeline chart
- Learning
- References







## INTRODUCTION & ABSTRACT

- Catheters are life-saving equipment.
- Mal positioning implies serious complications and can even be fatal.
- Early recognition is the key to solve this problem.
- Use medical imaging to train a deep learning model.
- Classify the Catheters into 4 main sub-classes.

# Problem Statement



- Detect the presence and position of catheters and lines on chest x-rays.
- Use deep learning pretrained model to test on 3000 images to categorize different positions of catheters.
- To alert the radiologists in case of mispositioning.

# EXISTING SYSTEM



- At present, no automated system exists for the same.
- Chest radiograph (CXR) plays a crucial role in evaluating the position.
- Other imaging mechanisms like CT scans and MRIs haven't been perfected to be used for the same cause.
- Radiologists are trained to accurately perform the task with minimum error.
- Time lag (latency) between the production of images and the true position of the catheter.
- Catheters may be confused by other similar linear structures like ECG leads and anatomy including ribs.



# Model Design

Research

EDA

Prepare DataLoader

Inference of Test Dataset

Importing Libraries

Image Transformations

Importing Pretrained Model

Result



# Individual Contribution

## Chathurya

Research on type of pre-trained CNNs,  
EDA, SeResnet152D

## Manasa

Research on catheters and existing  
system, EDA, Resnet50

## Vaishnavi

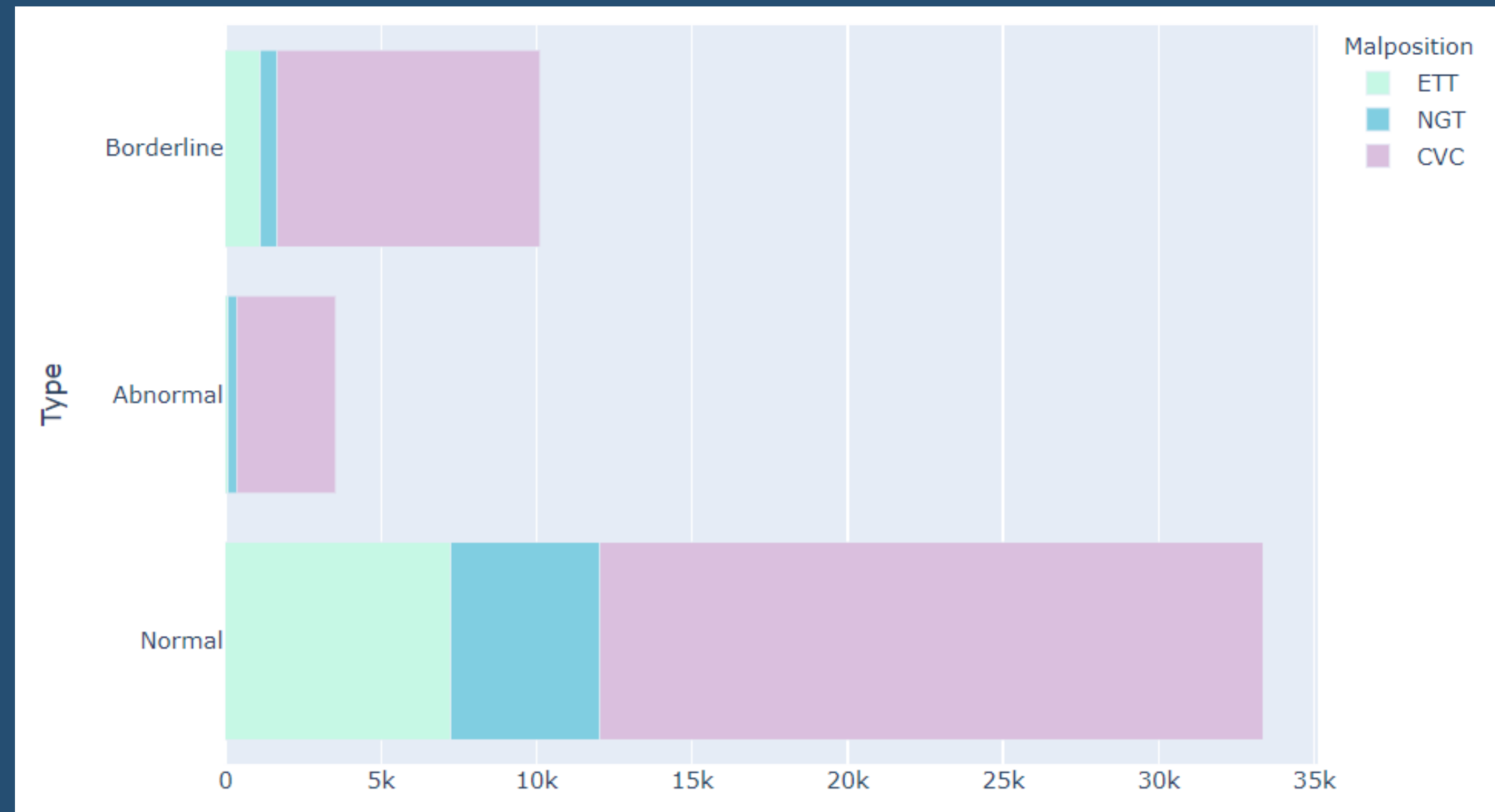
Research on catheters, EDA, Resnet  
200D

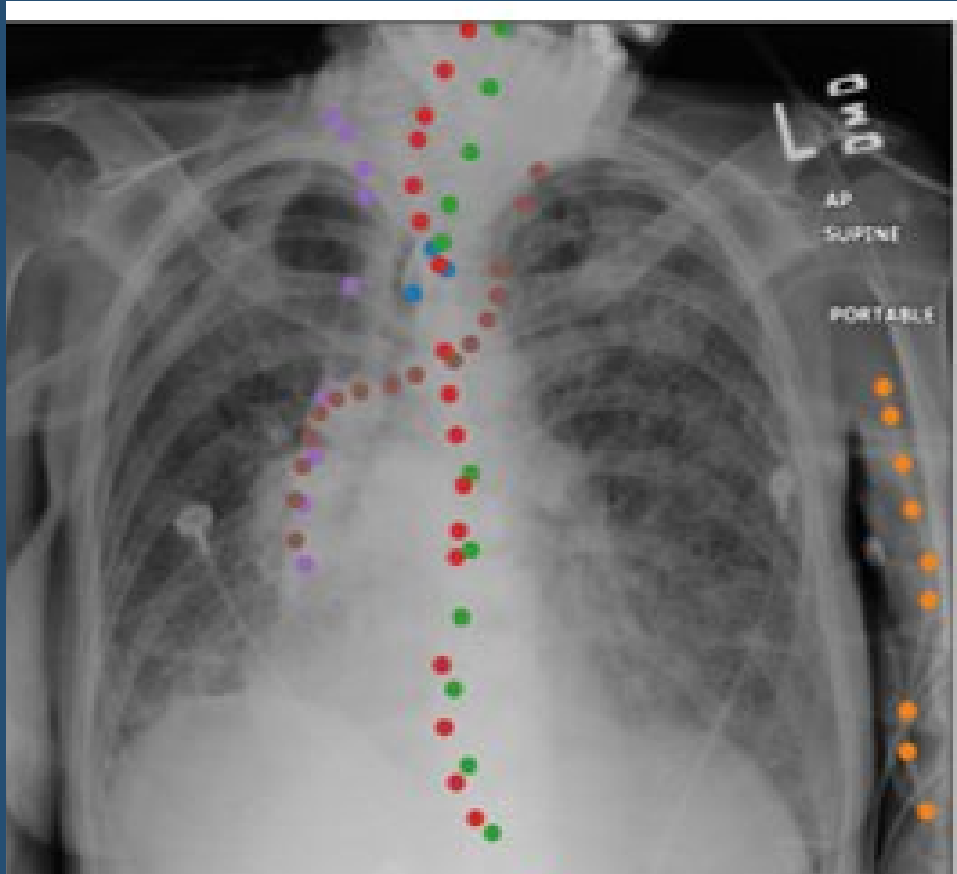
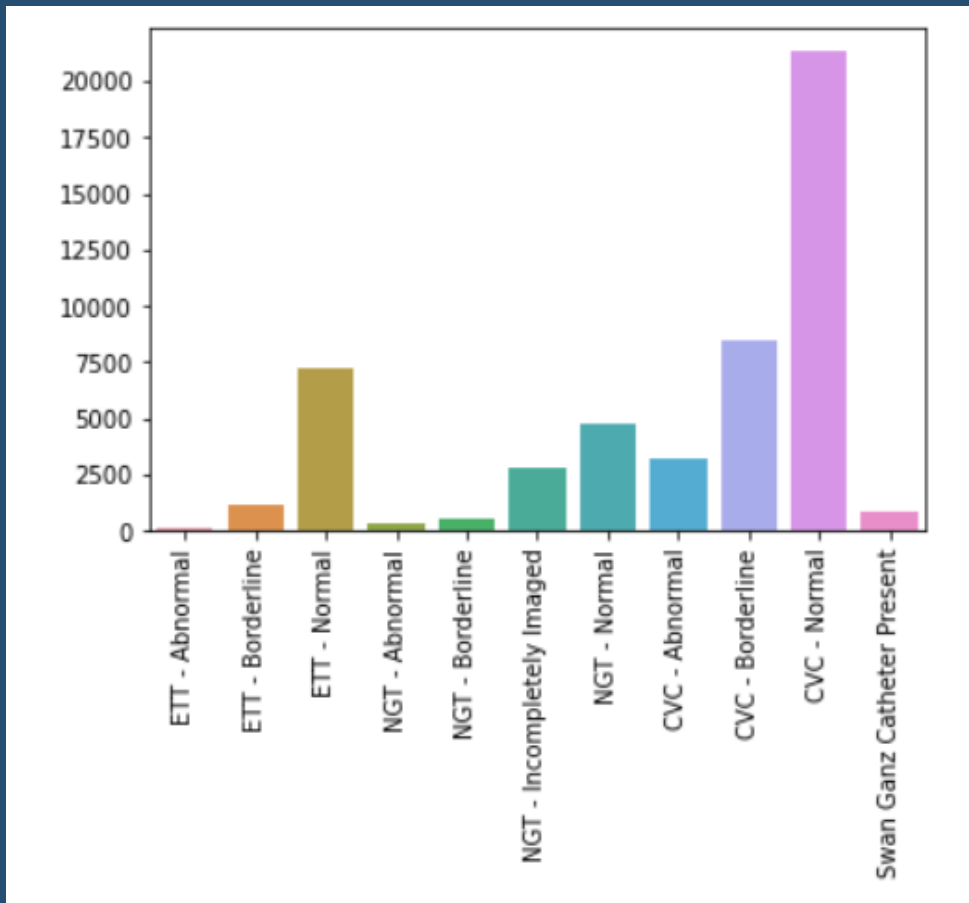
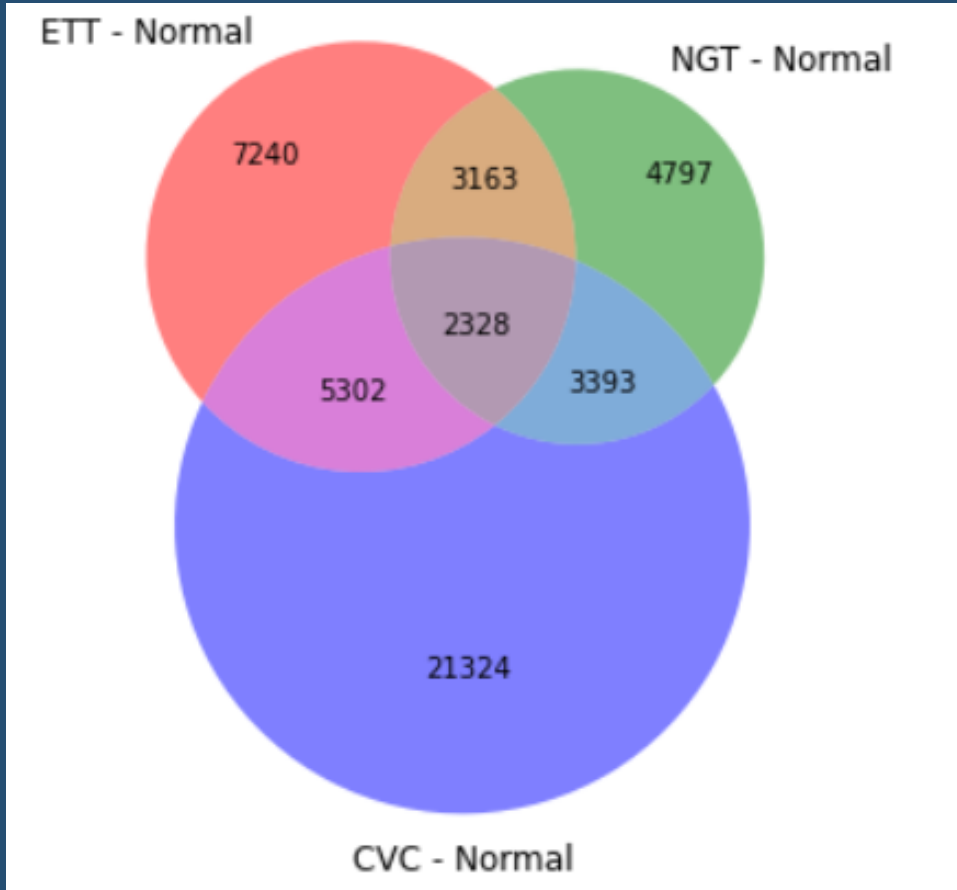
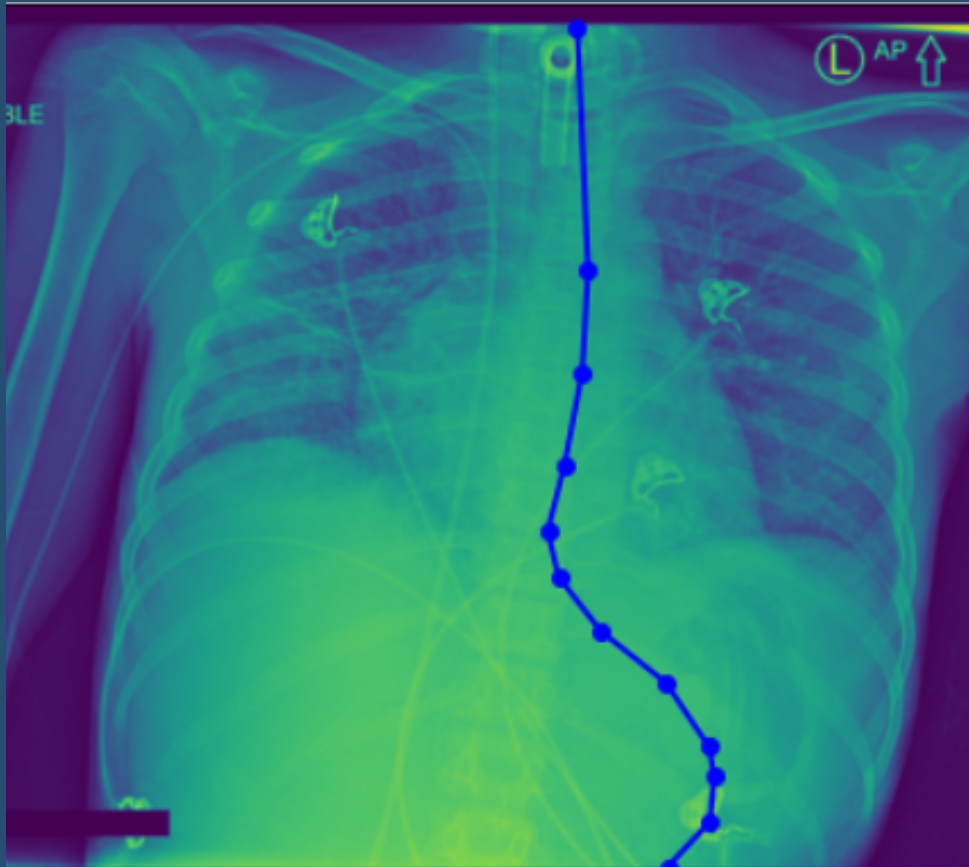
## Moulika

Research on peer review and Streamlit  
app, EDA, Resnet50



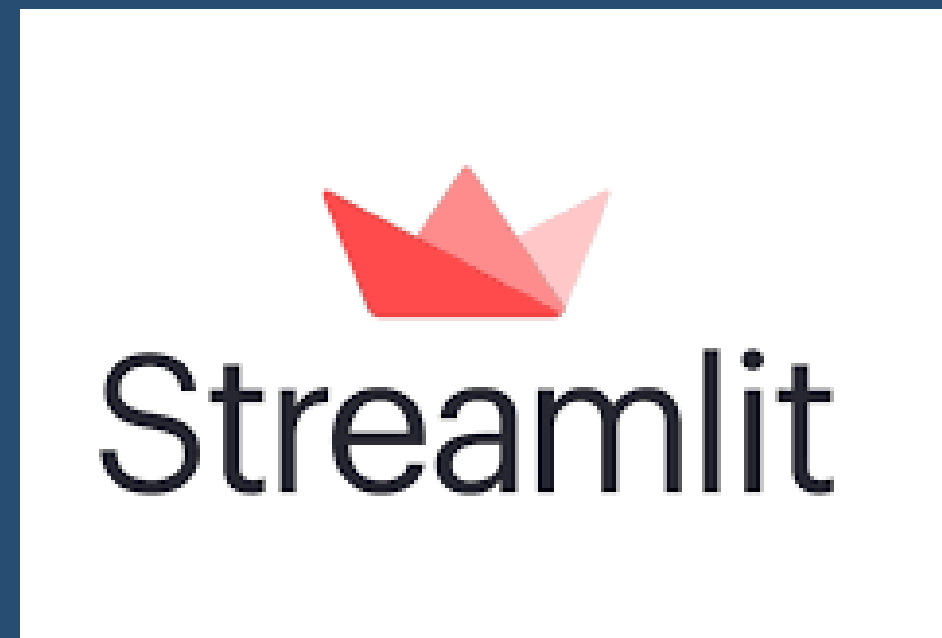
# Exploratory Data Analysis



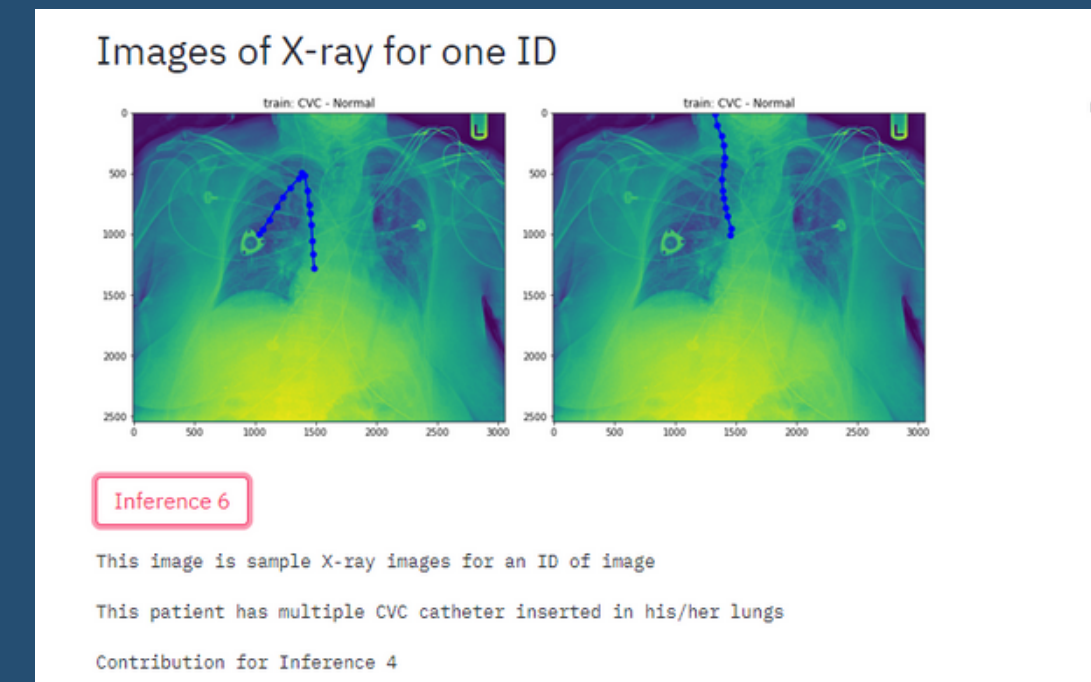




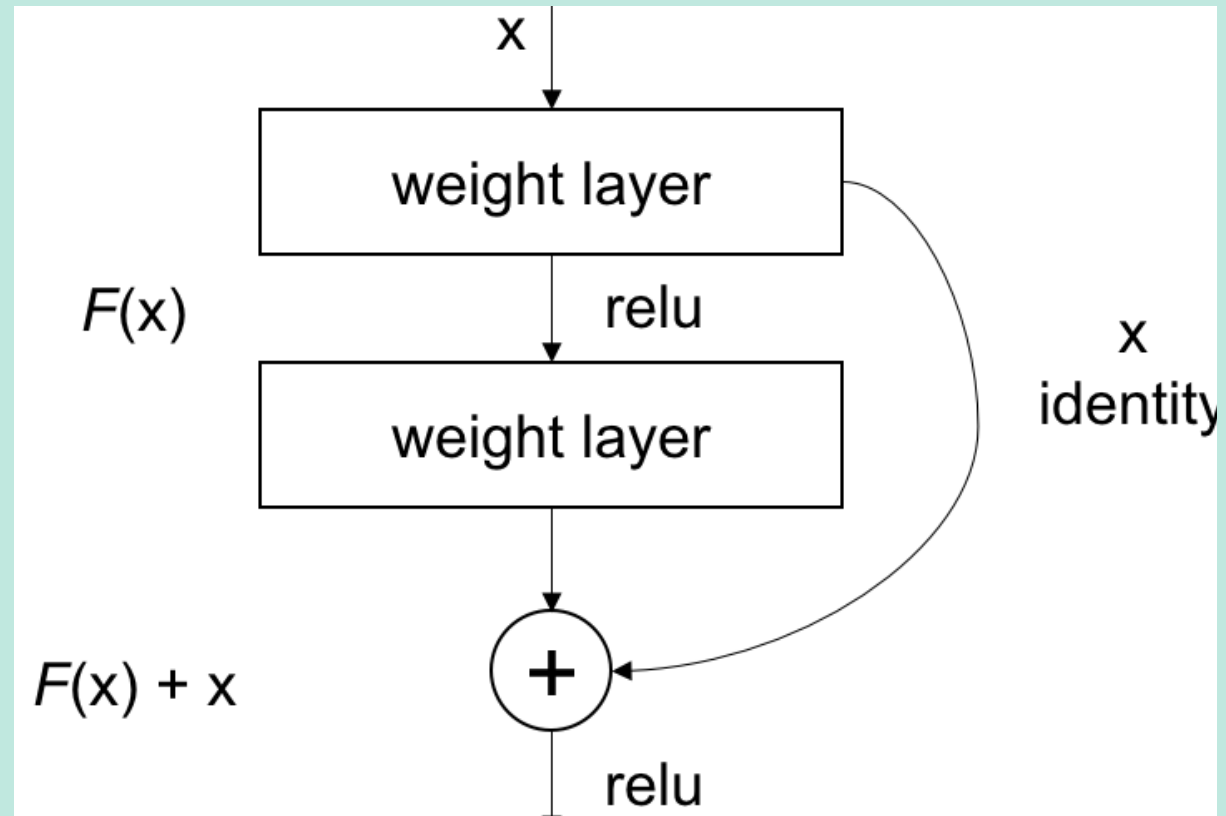
# Streamlit



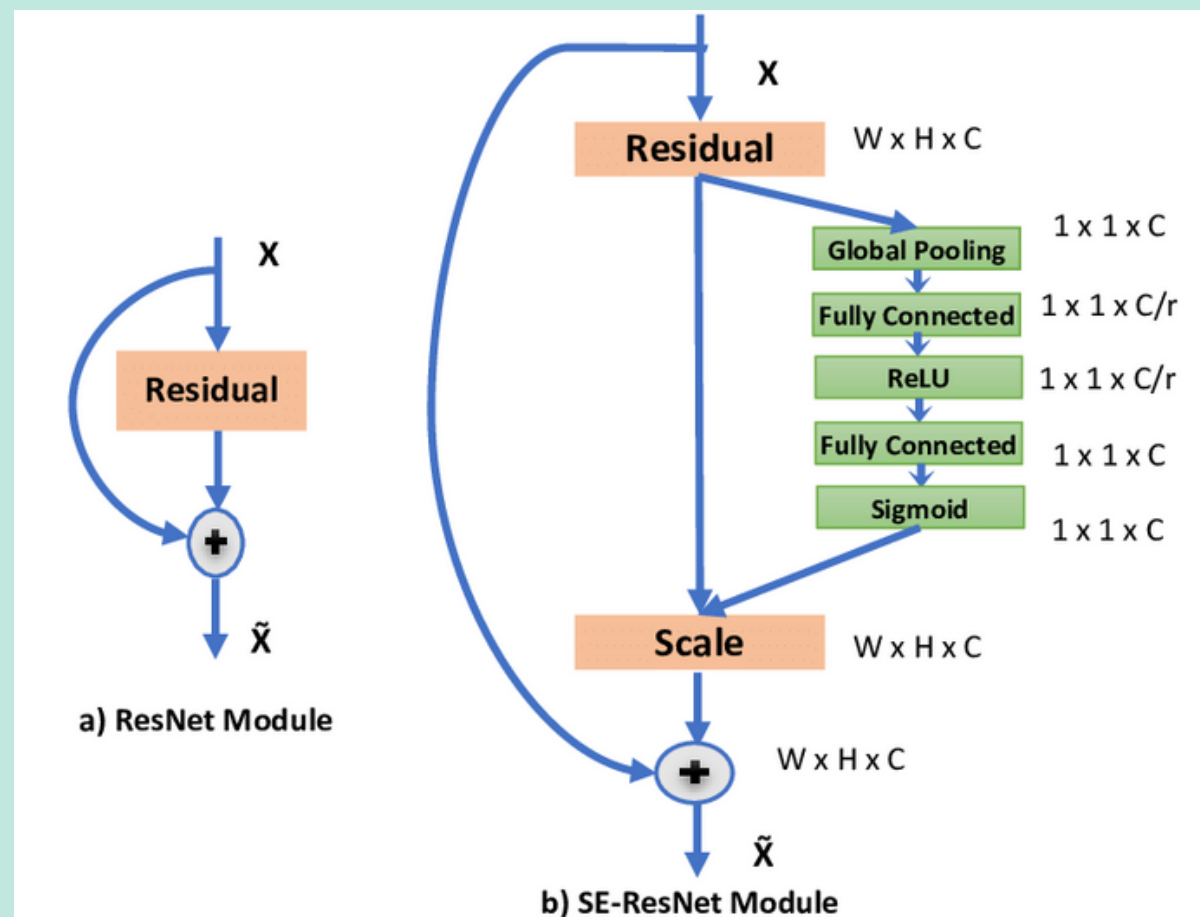
Built an streamlit app



EDA Analysis on Streamlit app



# MODEL



# Functions

## ■ PREPARE TEST DATASET

```
class TestDataset(Dataset):
    def __init__(self, df, transform=None):
        self.df = df
        self.file_names = df['StudyInstanceUID'].values
        self.transform = transform
```

## ■ IMAGE TRANSFORMATIONS

```
def get_transforms():
    return Compose([
        Resize(IMAGE_SIZE, IMAGE_SIZE),
        Normalize(
        ),
        ToTensorV2(),
    ])
```

## ■ MODEL

```
class CustomResNext(nn.Module):
    def __init__(self, model_name='resnext50_32x4d', pretrained=False):
        super().__init__()
        self.model = timm.create_model(model_name, pretrained=pretrained)
        n_features = self.model.fc.in_features
        self.model.fc = nn.Linear(n_features, CFG.target_size)

    def forward(self, x):
        x = self.model(x)
        return x
```

## ■ INFERENCE

```
inference(models, test_loader, device):
    tk0 = tqdm(enumerate(test_loader), total=len(test_loader)) ##progress Bar
    probs = []
    for i, (images) in tk0:
        images = images.to(device)
        avg_preds = []
        for model in models:
            with torch.no_grad():
                y_preds1 = model(images)
                y_preds2 = model(images.flip(-1))
            y_preds = (y_preds1.sigmoid().to('cpu').numpy() + y_preds2.sigmoid().to('cpu').numpy()) / 2
            avg_preds.append(y_preds)
        avg_preds = np.mean(avg_preds, axis=0)
        probs.append(avg_preds)
    probs = np.concatenate(probs)
    return probs
```



# Resnet50

```
class CustomResNext(nn.Module):
    def __init__(self, model_name='resnext50_32x4d', pretrained=False):
        super().__init__()
        self.model = timm.create_model(model_name, pretrained=pretrained)
        n_features = self.model.fc.in_features
        self.model.fc = nn.Linear(n_features, CFG.target_size)

    def forward(self, x):
        x = self.model(x)
        return x
```

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
043.8.498.46923145579096002617...	0.059688	0.577791	0.216742	0.000811	0.010068	0.006182	0.985213	0.031307	0.148838	0.955181	0.998979
043.8.498.84006870182611080091...	0.000051	0.000206	0.000524	0.000288	0.000850	0.000441	0.000092	0.001722	0.008559	0.998135	0.000044
043.8.498.12219033294413119947...	0.000039	0.000121	0.000502	0.000869	0.000471	0.000259	0.000064	0.009284	0.569036	0.653767	0.000054
043.8.498.84994474380235968109...	0.005164	0.026795	0.058099	0.045763	0.026076	0.952735	0.035707	0.158107	0.164486	0.927931	0.011512
043.8.498.35798987793805669662...	0.000292	0.000997	0.001352	0.001461	0.005168	0.000082	0.001627	0.003232	0.045860	0.973941	0.000076



# SeResnet152D

```
class SeResNet152D(nn.Module):
    def __init__(self, model_name='seresnet152d_320'):
        super().__init__()
        self.model = timm.create_model(model_name, pretrained=False)
        n_features = self.model.fc.in_features
        self.model.global_pool = nn.Identity()
        self.model.fc = nn.Identity()
        self.pooling = nn.AdaptiveAvgPool2d(1)
        self.fc = nn.Linear(n_features, 11)

    def forward(self, x):
        bs = x.size(0)
        features = self.model(x)
        pooled_features = self.pooling(features).view(bs, -1)
        output = self.fc(pooled_features)
        return output
```

```
ser_model = SeResNet152D()
ser_model.load_state_dict(torch.load(SER_MODEL_PATH)['model'])
```

Out[18]:

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...	0.002861	0.186532	0.791820	0.000648	0.002636	0.017136	0.980327	0.023258	0.084417	0.947521	9.992568e-01
43.8.498.84006870182611080091...	0.000002	0.000025	0.000052	0.000016	0.000016	0.000006	0.000010	0.021782	0.004071	0.984555	5.294564e-07
43.8.498.12219033294413119947...	0.000023	0.000074	0.000149	0.000226	0.000193	0.000202	0.000278	0.014617	0.471231	0.485876	3.295735e-05
43.8.498.84994474380235968109...	0.005439	0.067142	0.094417	0.077373	0.019847	0.876966	0.039560	0.060899	0.078361	0.737870	2.001944e-03
43.8.498.35798987793805669662...	0.000378	0.001077	0.000824	0.005594	0.001927	0.000676	0.002276	0.007787	0.074417	0.907452	3.312462e-06

# Resnet200D

```
class ResNet200D(nn.Module):
    def __init__(self, model_name='resnet200d_320'):
        super().__init__()
        self.model = timm.create_model(model_name, pretrained=False)
        n_features = self.model.fc.in_features
        self.model.global_pool = nn.Identity()
        self.model.fc = nn.Identity()
        self.pooling = nn.AdaptiveAvgPool2d(1)
        self.fc = nn.Linear(n_features, 11)

    def forward(self, x):
        bs = x.size(0)
        features = self.model(x)
        pooled_features = self.pooling(features).view(bs, -1)
        output = self.fc(pooled_features)
        return output

res_model = ResNet200D()
res_model.load_state_dict(torch.load(RES_MODEL_PATH)['model'])
```

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
043.8.498.46923145579096002617...	0.042606	0.621123	0.217875	0.000425	0.003781	0.011037	0.980665	0.037586	0.140550	0.889836	0.999464
043.8.498.84006870182611080091...	0.000010	0.000032	0.000242	0.000163	0.000110	0.000041	0.000067	0.004692	0.004040	0.998147	0.000002
043.8.498.12219033294413119947...	0.000016	0.000017	0.000109	0.000139	0.000109	0.000012	0.000033	0.005357	0.241475	0.770350	0.000017
043.8.498.84994474380235968109...	0.001823	0.020463	0.044035	0.022296	0.011816	0.919738	0.031636	0.049662	0.051236	0.913974	0.000491
043.8.498.35798987793805669662...	0.000026	0.000189	0.001200	0.001190	0.000670	0.000095	0.002048	0.003164	0.006033	0.991957	0.000002

# Conclusion & Future Scope

**Titanic Survival Prediction**

Titanic Survival Prediction ML App

Pclass  
0

Age  
45

SibSp  
0

ParCh  
1

Fare  
23

Sex\_male  
0

Embarked\_Q  
0

Embarked\_S  
0

Predict the survival

The is 1

The passenger will survive

A successful model has been built

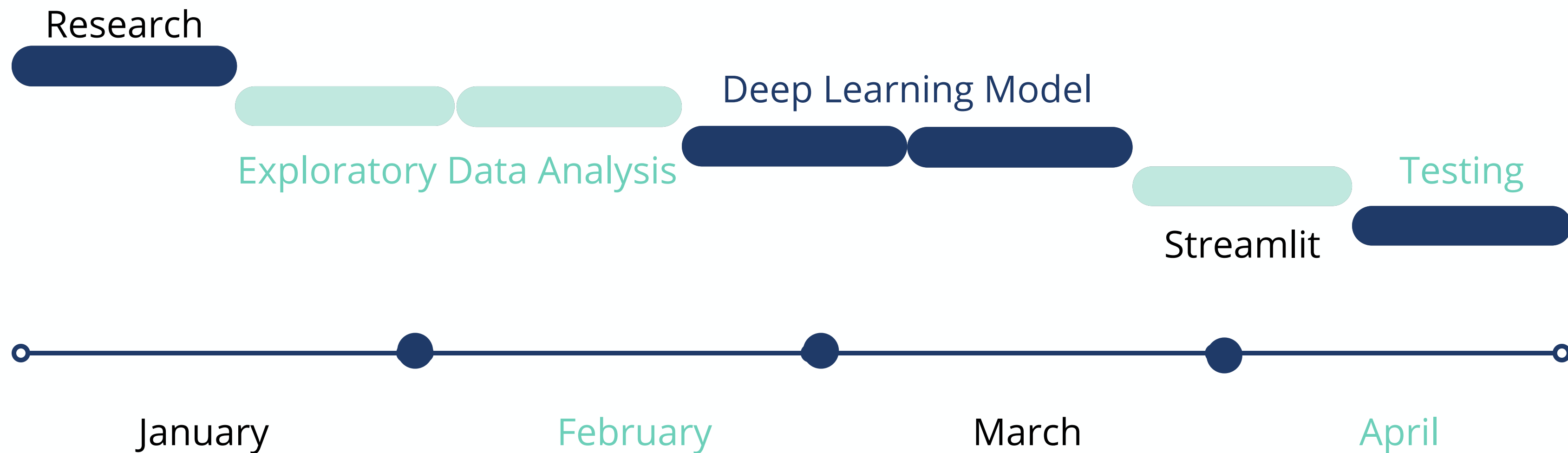
The dataset was run on a pre-trained model

Can use GPU to improve accuracy

GPU- Graphical Processing Unit

Launch an App

We can pickle the trained model and run it on an app using Streamlit.



## TIMELINE CHART





# LEARNING

- Pandas
- Pytorch
- Streamlit
- Pickle
- Matplotlib
- Seaborn
- Different types of pre-trained models of CNN

# REFERENCES

- <https://www.kaggle.com/c/ranzcr-clip-catheter-line-classification/overview>
- <https://docs.google.com/spreadsheets/d/1oWUL60YnAAiGD6-qLYukvk4FmY1qVU3r-58eMterhcE/edit?usp=sharing>
- Please note that the google sheets link above contains the rest of the links.



# THANKYOU