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Image classification of PNEUMONIA diseases



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Use case Summary

PNEUMONIA disease



PNEUMONIA is a type of lung infection that is caused by bacteria , fungi or viruses .Pneumonia can caused the swelling of lung tissue and it can cause the lungs to develop fluid or pus in the lungs .There are 2 type of PNUMENIA which is Bacterial Pneumonia and Viral Pneumonia. Bacterial Pneumonia is more severe compare to Viral Pneumonia as Viral Pneumonia tends to recover on its own.



Data Understanding

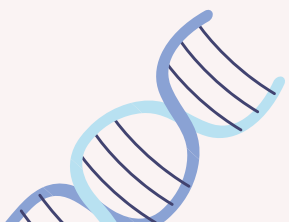
Pneumonia data set

Type Data Set

Pneumonia Image
data set-Xray

Size of data set

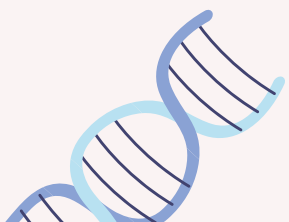
- Training data set-5224
- Testing data set-624



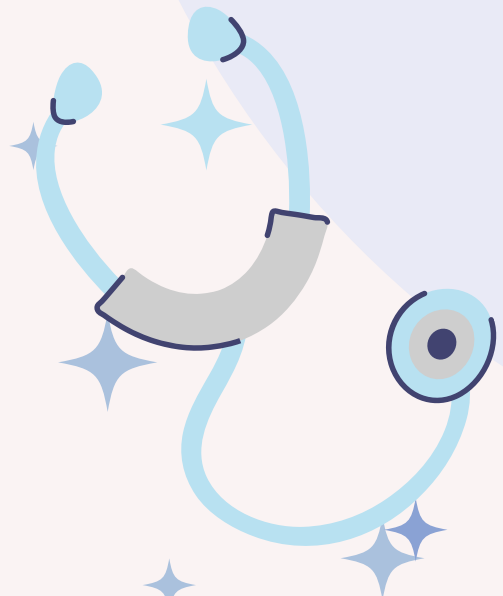
Data Source

Data Source: -

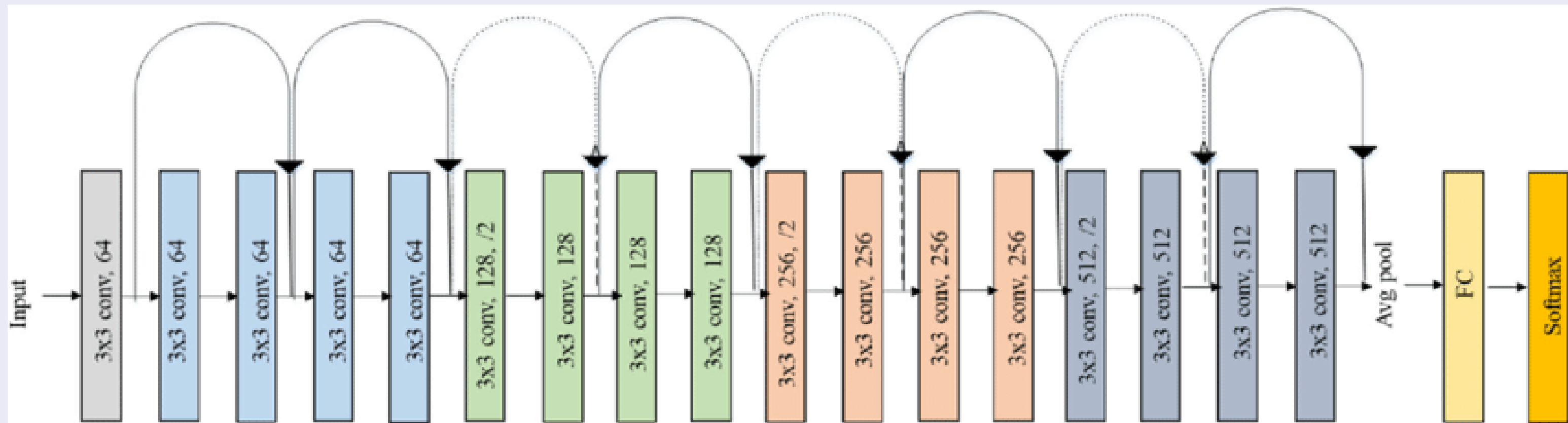
<https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia>



Model Architecture



Model Architecture





Code of the model

Code of the model

Image Transformation

```
#Define the Data Transformation
transform = transforms.Compose([
    transforms.Resize((224, 224)), #Resizing the image for Resnet-18 Algorithm implementation from 513 x 512 to 224x224
    transforms.RandomHorizontalFlip(), #Data Augmentation process where the image are randomly rotating horizontally
    transforms.RandomRotation(20), # data Augmentation process where the image will rotate in a range of +- 20 degrees
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])
])

# Load the data Set
train_dataset = datasets.ImageFolder(root='/content/drive/MyDrive/train_set', transform=transform)
test_dataset = datasets.ImageFolder(root='/content/drive/MyDrive/test_set', transform=transform)


train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)
```



Code of the model

```
[ ] model = models.resnet18(pretrained=True)
    model
```

**Freeze the layer of the
model and unfreeze layer
4.0 and 4.1**



```
#Add fully connected layer to model development
model.fc = nn.Linear(num_features, 2)
model = model.to(device)
model
```

Implement pre-trained model


```
[ ] #Freeze the layers
    for param in model.parameters():
        param.requires_grad = False

[ ] for param in model.layer4.parameters():
    param.requires_grad = True
```


**Fine tune the model by
adding a fully
connected layer**



Code of the model

```
 #define the loss function and Optimizer  
criterion = nn.CrossEntropyLoss()  
optimizer = optim.Adam(model.parameters(), lr=0.001)
```

Cross Entropy loss function and adam optimizer

```
 #Set the random seed  
torch.manual_seed(42)  
torch.cuda.manual_seed(42)
```

Set Random seed to 42



Code of the model

```
##### Train model
train_loss=[]
train_accuary=[]
test_loss=[]
test_accuary=[]

num_epochs = 10  #(set no of epochs)
start_time = time.time() #(for showing time)
# Start loop
for epoch in range(num_epochs): #(loop for every epoch)
    print("Epoch {} running".format(epoch)) #(printing message)
    """ Training Phase """
    model.train()  #(training model)
    running_loss = 0.  #(set loss 0)
    running_corrects = 0
    # load a batch data of images
    for i, (inputs, labels) in enumerate(train_loader):
        inputs = inputs.to(device)
        labels = labels.to(device)
        # forward inputs and get output
        optimizer.zero_grad()
        outputs = model(inputs)
        _, preds = torch.max(outputs, 1)
        loss = criterion(outputs, labels)
```


```
# get loss value and update the network weights
loss.backward()
optimizer.step()
running_loss += loss.item()
running_corrects += torch.sum(preds == labels.data).item()
epoch_loss = running_loss / len(train_dataset)
epoch_acc = running_corrects / len(train_dataset) * 100.
# Append result
train_loss.append(epoch_loss)
train_accuary.append(epoch_acc)
# Print progress
print('[Train #{}] Loss: {:.4f} Acc: {:.4f}% Time: {:.4f}s'.format(epoch+1, epoch_loss, epoch_acc, time.time() -start_time))
```

Train Model

Code of the model

```
#Testing Phase
model.eval()
with torch.no_grad():
    running_loss = 0.
    running_corrects = 0
    for inputs, labels in test_loader:
        inputs = inputs.to(device)
        labels = labels.to(device)
        outputs = model(inputs)
        _, preds = torch.max(outputs, 1)
        loss = criterion(outputs, labels)
        running_loss += loss.item()
        running_corrects += torch.sum(preds == labels.data).item()
    epoch_loss = running_loss / len(test_dataset)
    epoch_acc = running_corrects / len(test_dataset) * 100.
    # Append result
    test_loss.append(epoch_loss)
    test_accuary.append(epoch_acc)
    # Print progress
    print('[Test #{}] Loss: {:.4f} Acc: {:.4f}% Time: {:.4f}s'.format(epoch+1, epoch_loss, epoch_acc, time.time()- start_time))
```

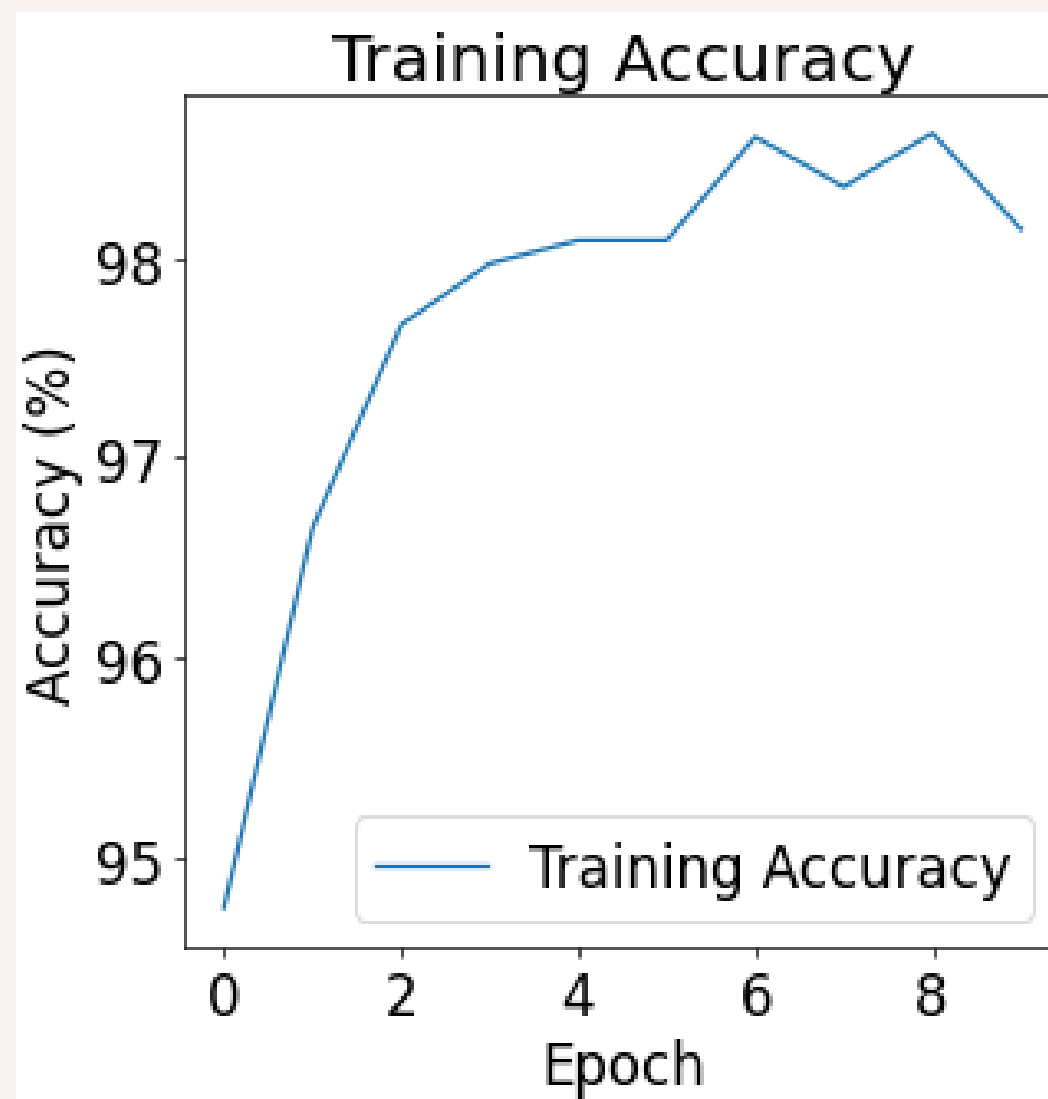
Test Model



Result

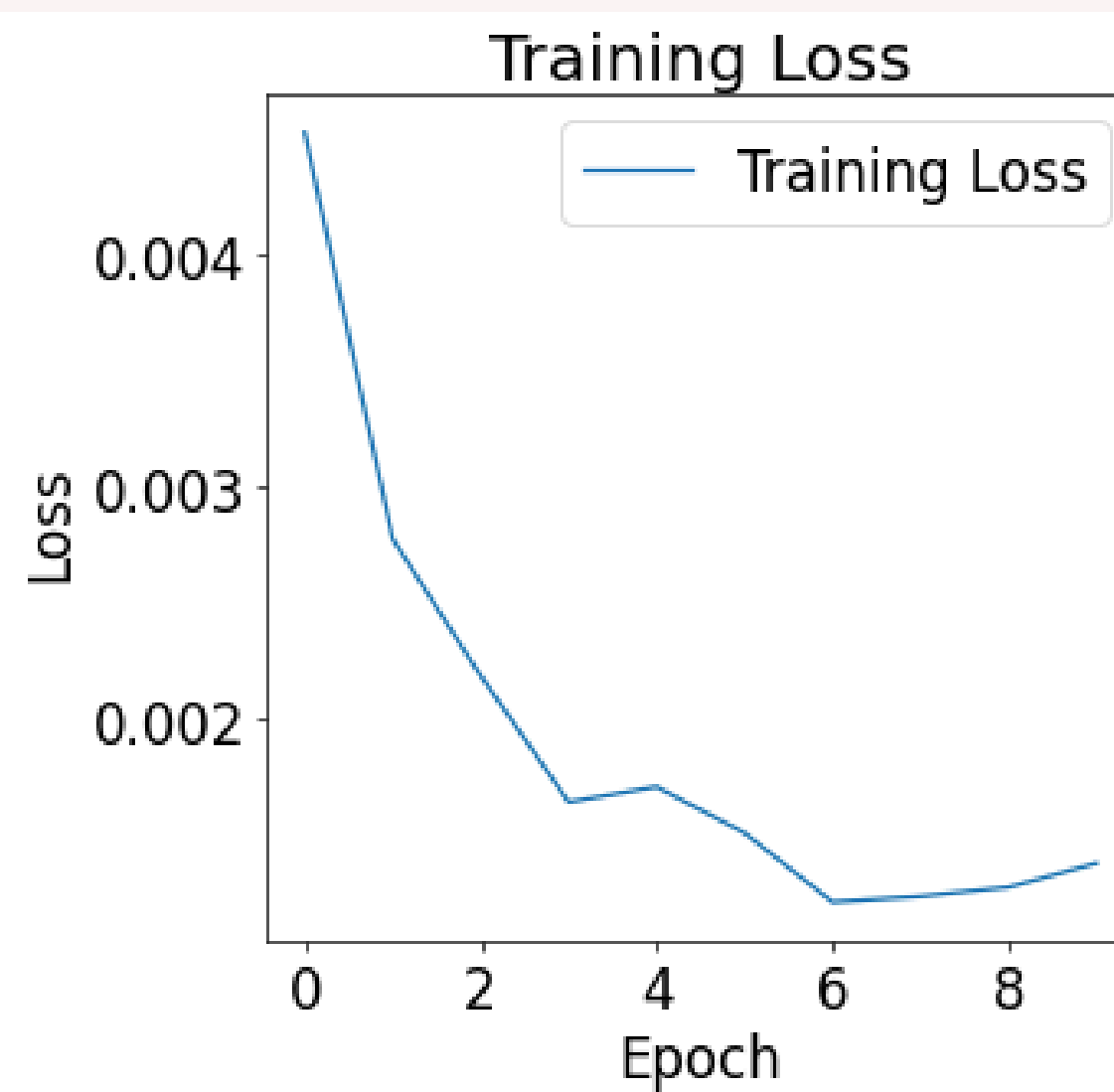
Training Accuracy and Loss

Accuracy



98.1432%

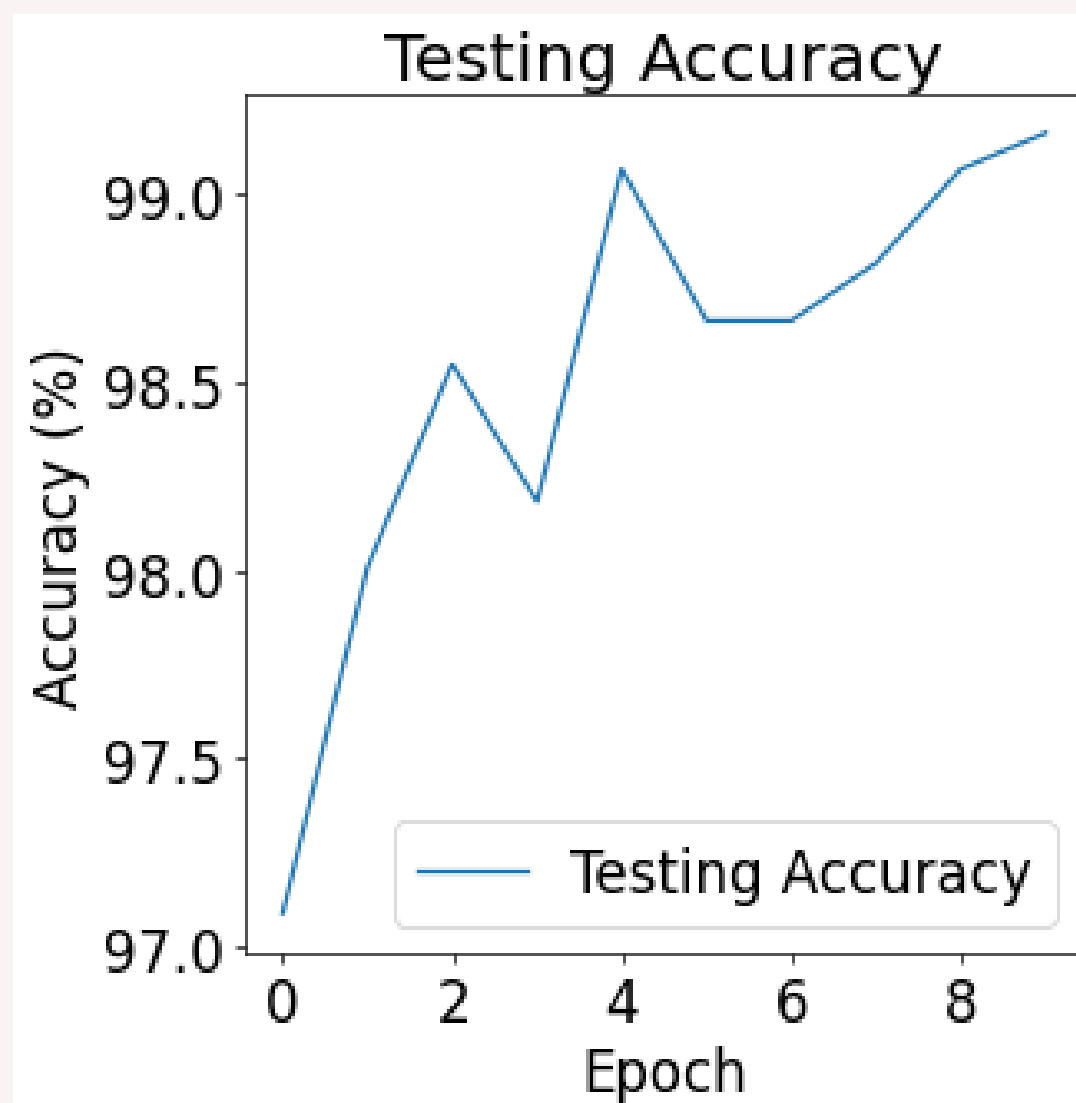
Loss



0.0014

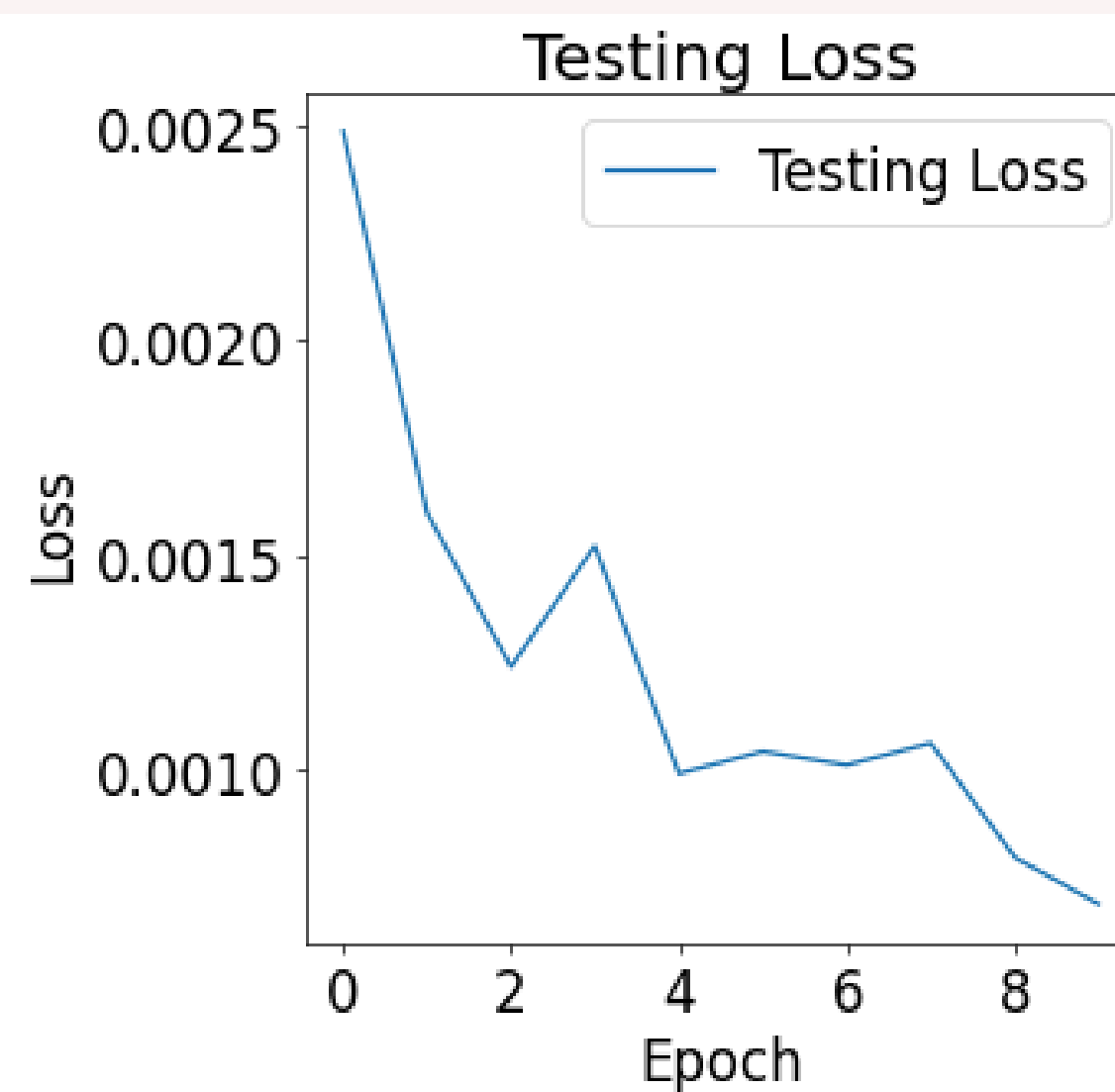
Testing Accuracy and Loss

Accuracy



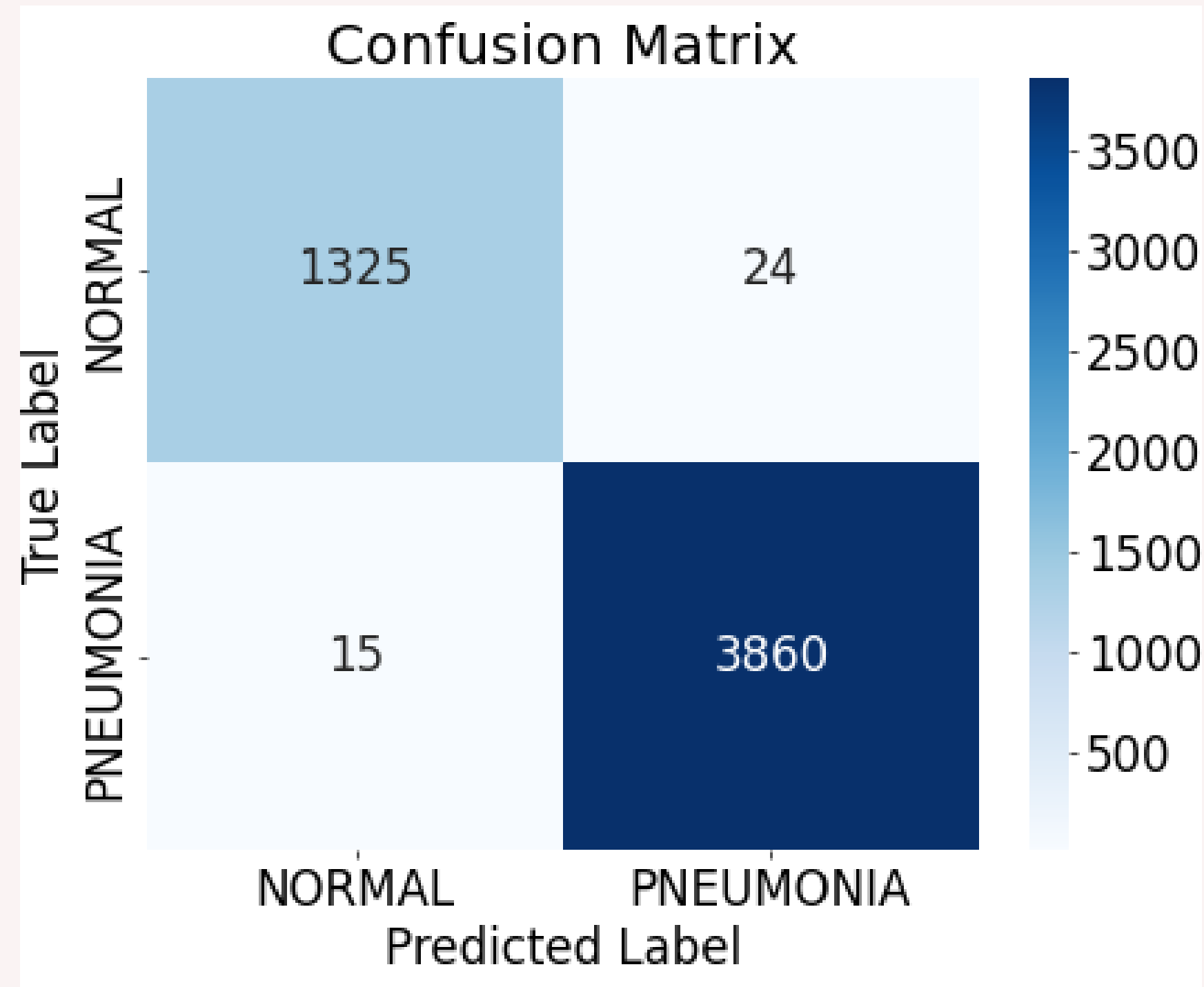
99.1577%

Loss



0.0007

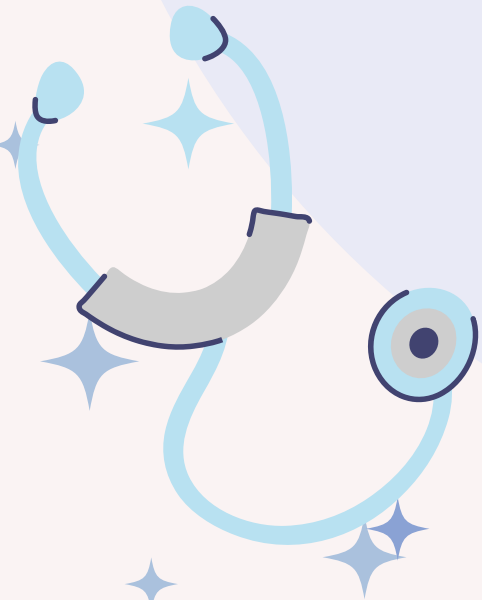
Matrix confusion



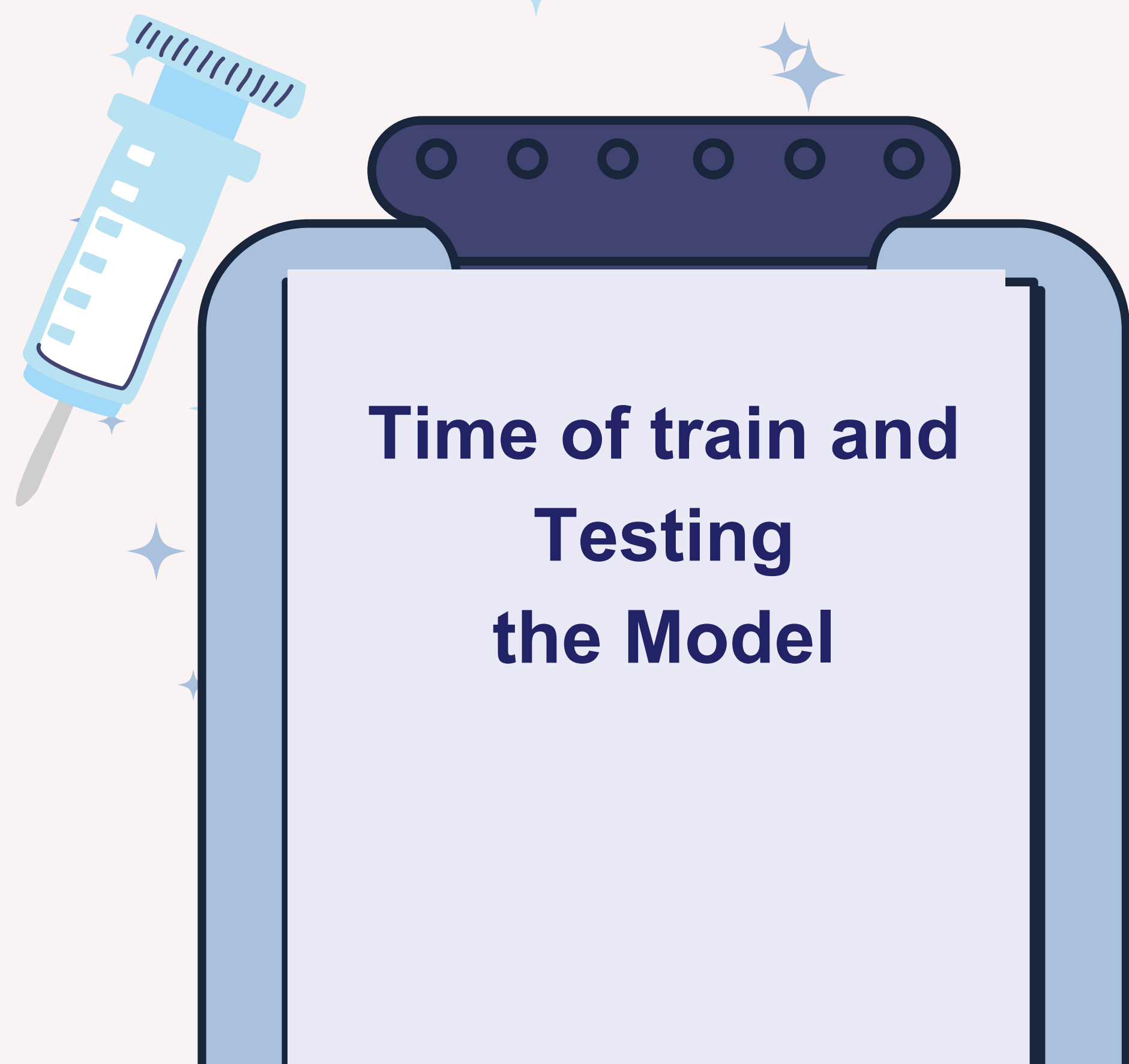


Demo

Challenges



The Current Landscape of Medicine

A light blue syringe with a needle is positioned diagonally on the left side of the slide. Several small, four-pointed light blue stars are scattered around the top left and middle left areas.A light blue clipboard with a dark blue clip at the top holds a white sheet of paper. A light blue syringe is attached to the left side of the clipboard. The text is centered on the paper.

**Time of train and
Testing
the Model**

A light blue clipboard with a dark blue clip at the top holds a white sheet of paper. A light blue DNA double helix is positioned to the left of the clipboard. The text is centered on the paper.

Web Application

A light blue DNA double helix is positioned to the left of the clipboard. Several small, four-pointed light blue stars are scattered around the top right and middle right areas.

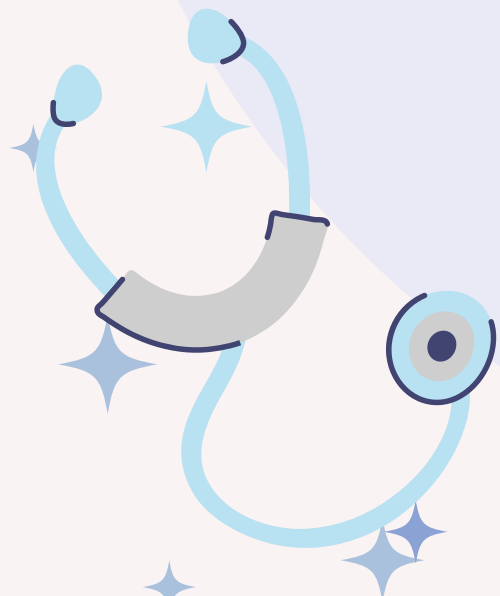
Conclusion

Conclusion

Encouraging discussion and questions

In conclusion the development of the PNEUMONIA Image classification has presented the huge potential of AI to society . It presents the technological advancement through various fields and the potential to grow more.

Reference



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 - Computer Vision Engineer, (3 July 2023), Object Detection Web Application with Python, Streamlit and Detectron2 | Computer vision tutorial. https://youtu.be/n_eMARPqBZI?si=umBTVpPBM5Qlv_Tv.

Thank you

