Pediatric Pneumonia Detection with CNNs

Automating Medical Diagnoses

Machine Learning II Final Project
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Group 4

Introduction

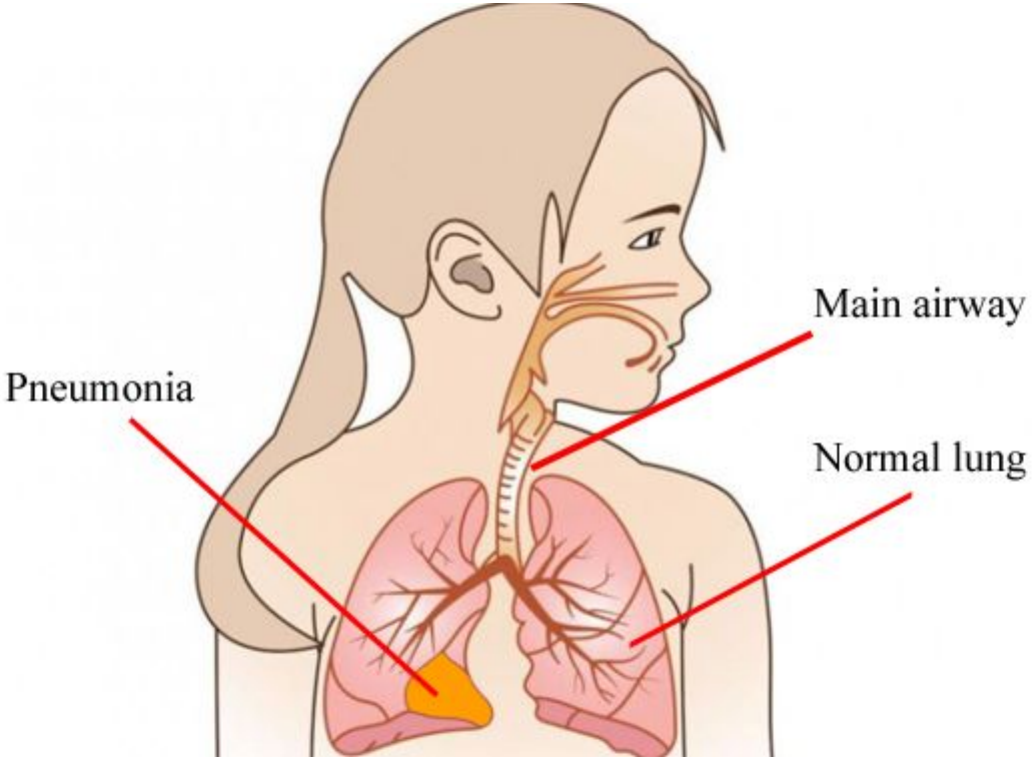
Automating Medical Diagnoses
For Pediatric Pneumonia

Pediatric Pneumonia

- What is it ?
  Infection in the lungs; air sacs fill with fluid

- What causes it?
  Viruses, Bacteria etc

- Why choose this ?
  Estimated to be leading cause of childhood mortality worldwide



Treatment Plans

Viral Pneumonia

- Bedrest+Fluids
- Pain Medication
- Antiviral (Most cases resolve on their own however)

Normal

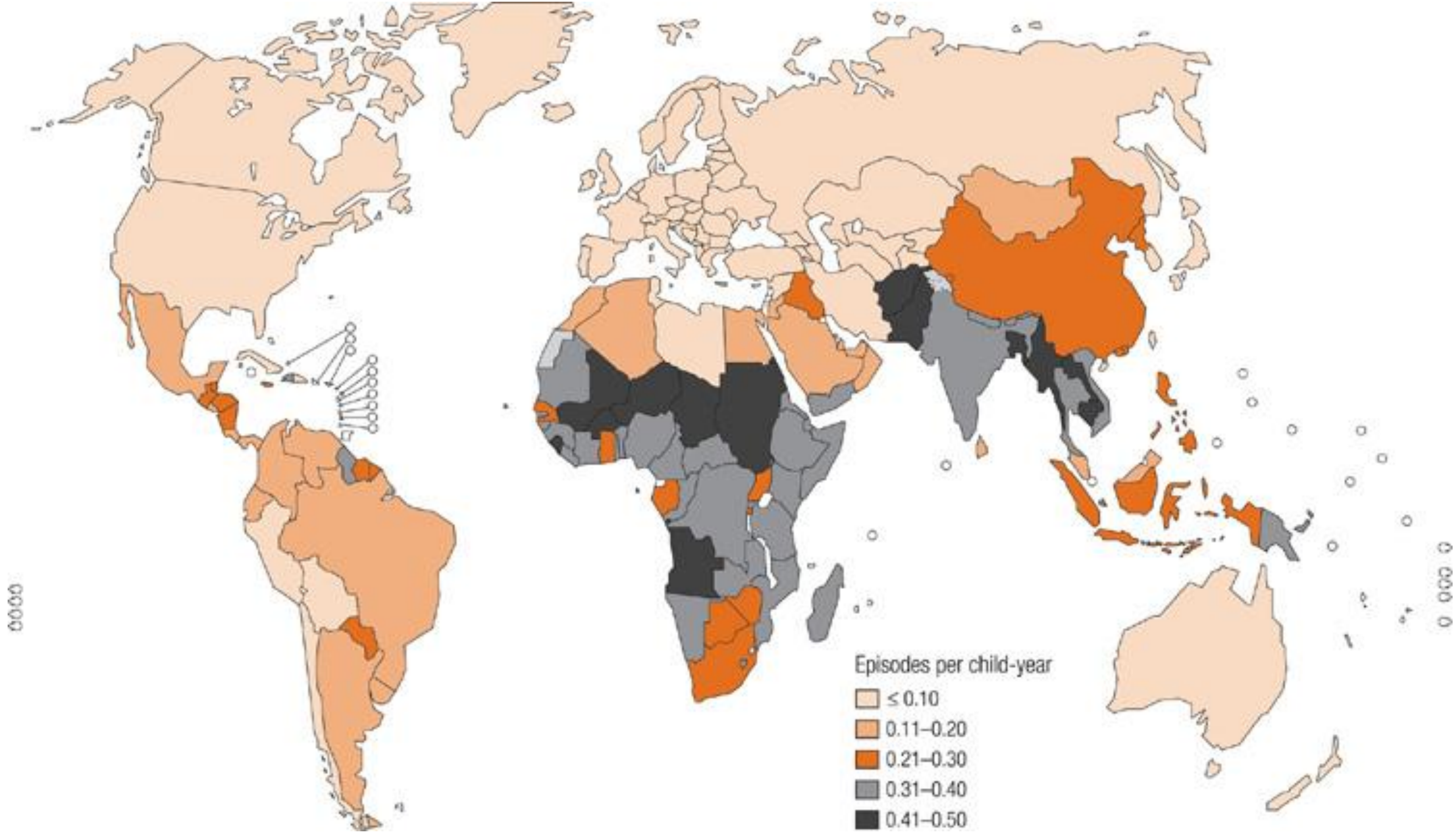
- Allergies (Allergy Meds)
- Asthma (Inhaler)

Bacterial Pneumonia

- Bedrest+Fluids
- Pain Medication
- Antibiotics IMMEDIATELY (Cases in children DO NOT often resolve on their own)

Interchangeable?

NO


Episodes per child-year
≤ 0.10
0.11–0.20
0.21–0.30
0.31–0.40
0.41–0.50

About the dataset

Categories

- 5216 Training Images
- 16 Validation Images
- 624 Test Images

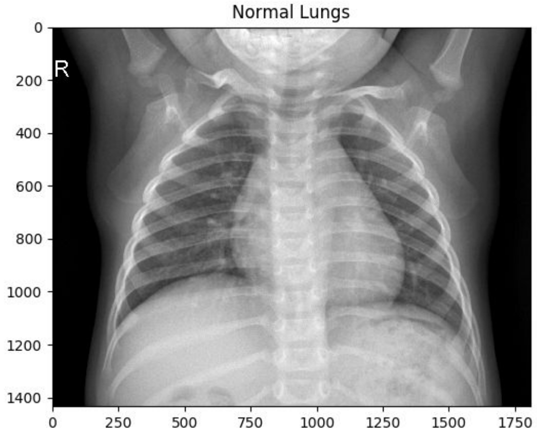
Problem Statement

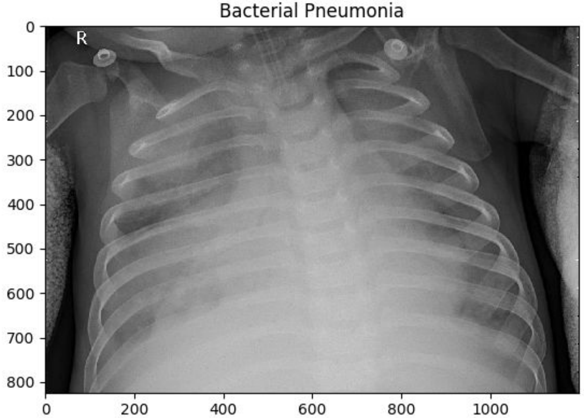
- Normal
- Pneumonia

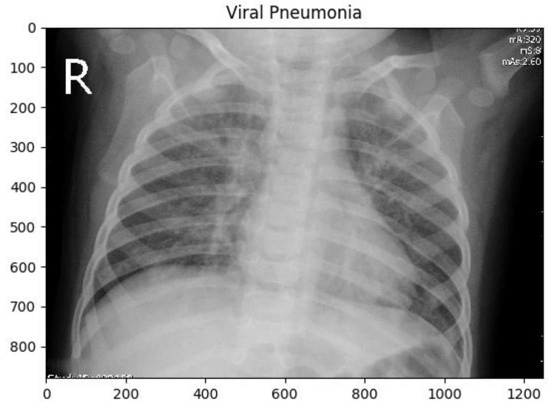
Modified Problem Statement

- Normal
- Viral Pneumonia
- Bacterial Pneumonia

Sample Images







Pre -Processing

Original Dataset Breakdown

Folder	Class	Number
train	Normal	1341
	Bacterial Pneumonia	2530
	Viral Pneumonia	1345
validation	Normal	8
	Bacterial Pneumonia	8
	Viral Pneumonia	0

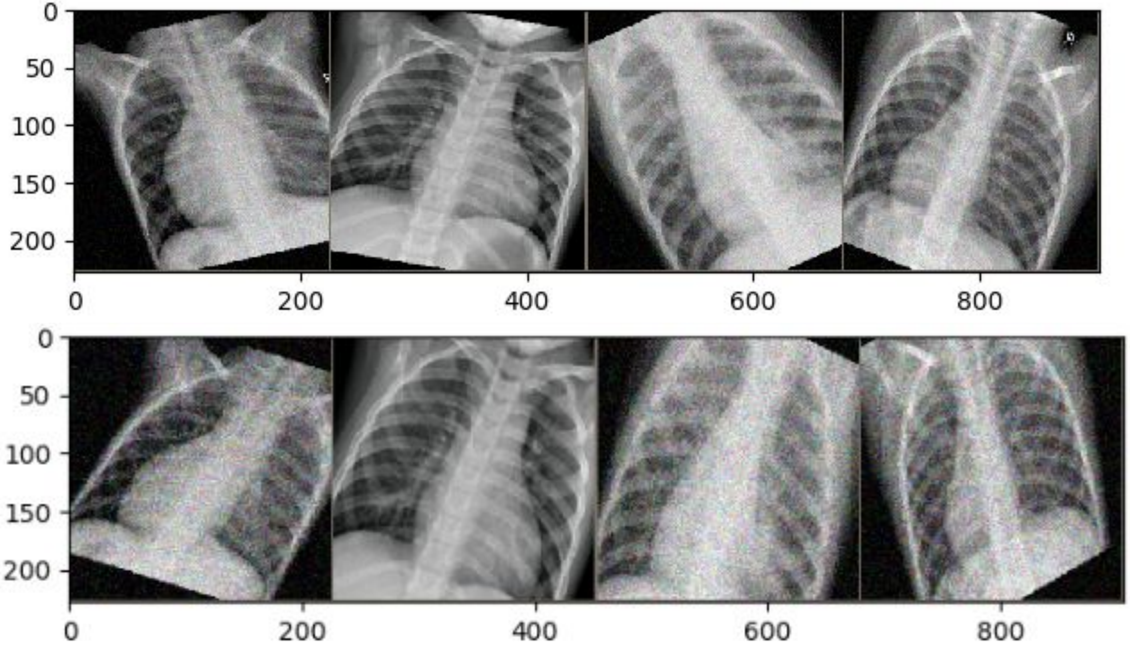
Resizing & Balancing

- Size of Images:
  - 28,200,**256**,350,800
- Transformations on Training Dataset
  - Resize
  - CenterCrop
  - Scaling
  - RandomHorizontalFlip
  - ToTensor
  - Normalization
  - RandomAffine
  - Gaussian Noise

After Data Balancing

Folder	Class	Number
train	Normal	1075
	Bacterial Pneumonia	2264
	Viral Pneumonia	1071
validation	Normal	277
	Bacterial Pneumonia	277
	Viral Pneumonia	277

Basic Transformations & Augmentations



Network and Training Algorithm

From the Scratch Algorithms & Basic Pre-Trained Networks

Basic CNN

MODEL

- Number of Layers(Conv2d()): 2-16
- **Activation Function**: relu(), LeakyRelu(),
- Batch Normalization:
- Pooling Layers: MaxPool2d(k=2)
- Output Layer: Linear(out_features = 3)
- **Optimizer**:Adam, SGD
- **Loss Function**: CrossEntropyLoss()

Results:

Val Loss: 2.24 - 1.16

Val Accuracy: 33% - 72.24%

Hyper Parameters:

- Batch Size = 32,64,128,200
- Learning Rate = 5e-3
- Decay = 0.001(Optimizer)
- EPOCHS = 30
- dropout = 0.2, 0.3

Densenet - Pre-Trained Networks

- Densenet121
  - 4 Blocks -
  - Layers/Block = (6,12,24,16)
- **Results:**

  Val Loss: 1.37- 1.12

  Val Accuracy: 39% - 71.24%

```
DenseNet(
  (features): Sequential(
    (conv0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (norm0): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu0): ReLU(inplace=True)
    (pool0): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
(denseblock1): _DenseBlock(
      (denselayer1): _DenseLayer(
        (norm1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu1): ReLU(inplace=True)
        (conv1): Conv2d(64, 128, kernel_size=(1, 1), stride=(1, 1), bias=False)
        (norm2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu2): ReLU(inplace=True)
        (conv2): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      )
```

Resnet - Pre-Trained Networks

- Resnet18
  - 4 Such Layers
  - 2 Basic Blocks / Layer
- Resnet34
  - 4 such layers
  - Blocks/Layer = (3,4,6,3)
- **Results:**

  Val Loss: 0.97- 0.83

  Val Accuracy: 48% - 76.24%

  Overfitting:

```
ResNet(
(conv1):
Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
 (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
```

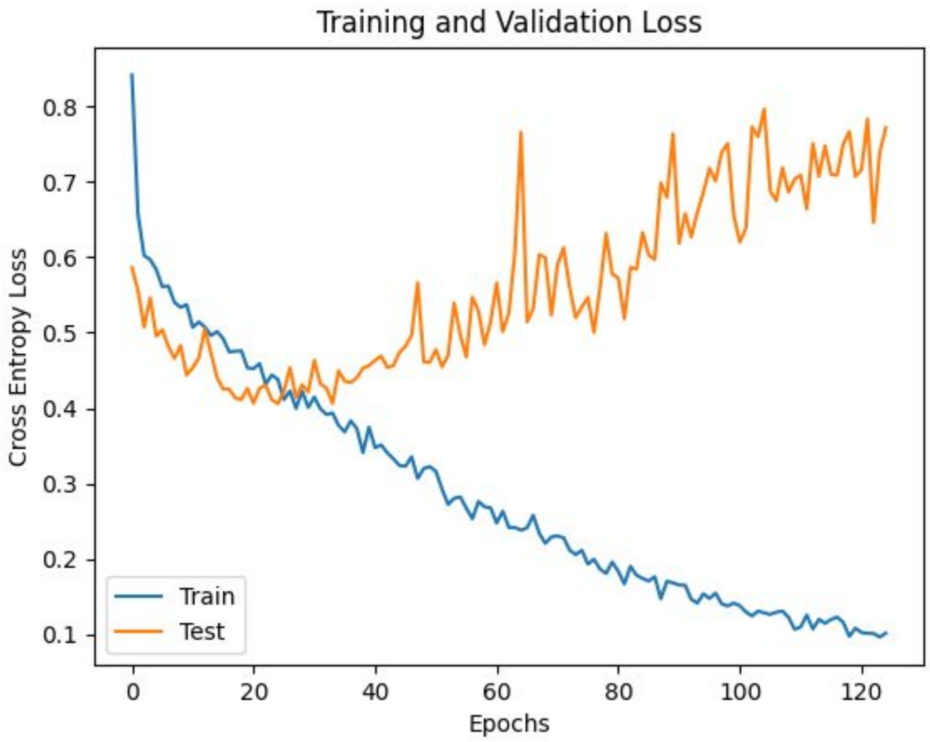
ResNet

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

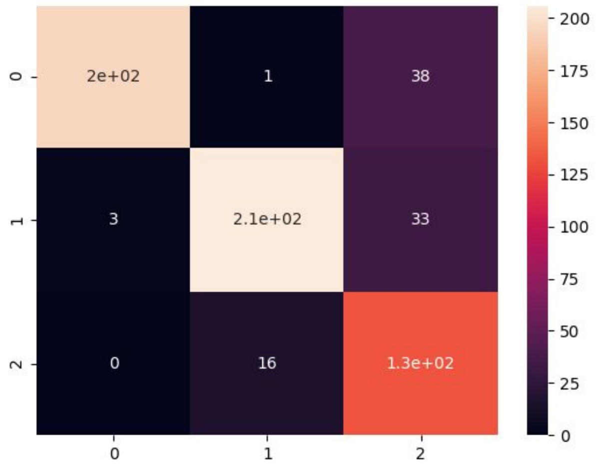
Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Down-sampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

ResNet18 with Classifier

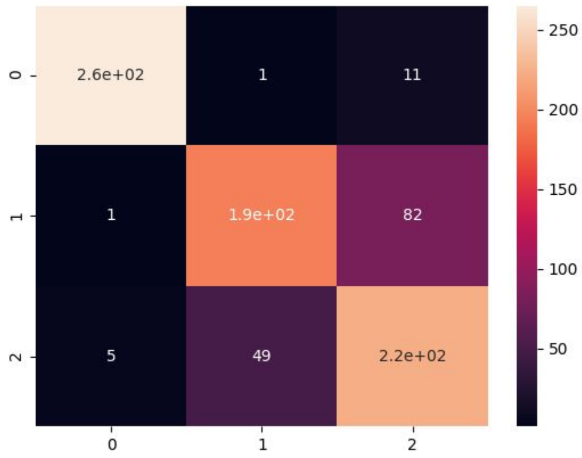
ResNet Only



Training and Validation Loss
Cross Entropy Loss
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
20
40
60
80
100
120
Epochs
Train
Test



2e+02
1
38
3
2.1e+02
33
0
16
1.3e+02
0
1
2
200
175
150
125
100
75
50
25
0



2.6e+02
1
11
1
1.9e+02
82
5
49
2.2e+02
0
1
2
250
200
150
100
50

ResNet Only

Validation:

Precision	0.826
Recall	0.821
F1 Score	0.821
Cohen’s Kappa	0.731

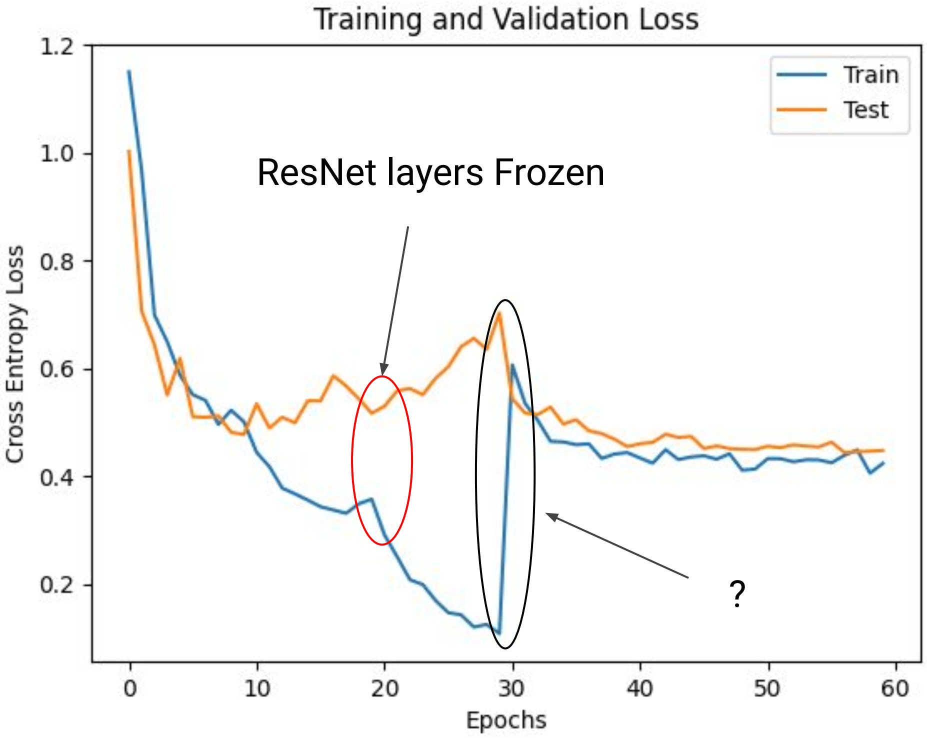
Test:

Precision	0.882
Recall	0.854
F1 Score	0.861
Cohen’s Kappa	0.781

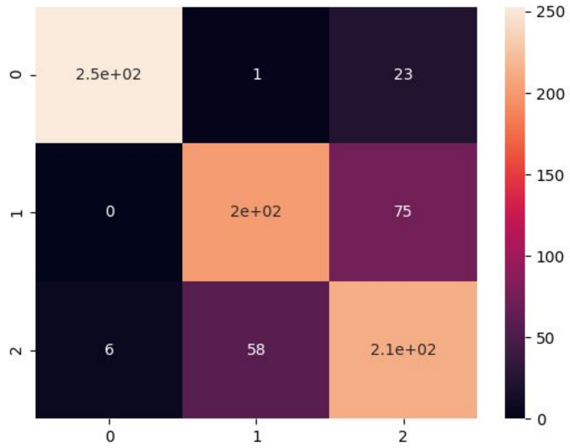
Fully Connected Classifier

```
(1): LeakyReLU(negative_slope=0.01)
(2): Dropout(p=0.5, inplace=False)
(3): BatchNorm1d(4096, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(4): Linear(in_features=4096, out_features=4096, bias=True)
(5): LeakyReLU(negative_slope=0.01)
(6): Dropout(p=0.5, inplace=False)
(7): BatchNorm1d(4096, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(8): Linear(in_features=4096, out_features=2048, bias=True)
(9): LeakyReLU(negative_slope=0.01)
(10): Dropout(p=0.5, inplace=False)
(11): BatchNorm1d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(12): Linear(in_features=2048, out_features=2048, bias=True)
(13): LeakyReLU(negative_slope=0.01)
(14): Dropout(p=0.5, inplace=False)
(15): BatchNorm1d(2048, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(16): Linear(in_features=2048, out_features=1024, bias=True)
(17): LeakyReLU(negative_slope=0.01)
(18): Dropout(p=0.5, inplace=False)
(19): BatchNorm1d(1024, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
(20): Linear(in_features=1024, out_features=3, bias=True)
```

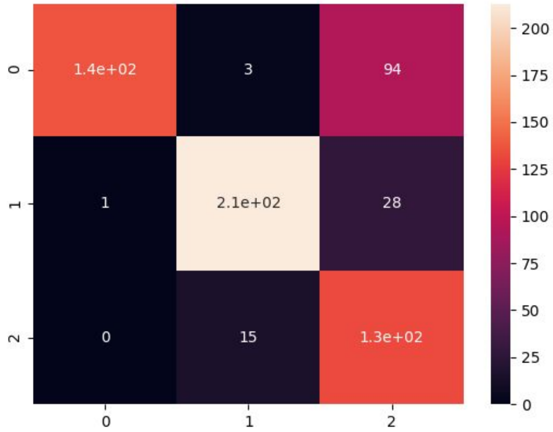
ResNet w/ FCC



Training and Validation Loss
Train
Test
ResNet layers Frozen
?
Cross Entropy Loss
Epochs
1.2
1.0
0.8
0.6
0.4
0.2
0
10
20
30
40
50
60



2.5e+02
1
23
0
2e+02
75
6
58
2.1e+02
0
1
2
250
200
150
100
50



1.4e+02
3
94
1
2.1e+02
28
0
15
1.3e+02
0
1
2
200
175
150
125
100
75
50
25

Resnet, VGG16 & Inception V3 Ensembling

VGG16 & Inception V3

- transforms.ColorJitter

```
model1 = torchvision.models.inception_v3(aux_logits=False)
for param in model1.parameters():
    param.requires_grad = False
model1.fc = nn.Linear(model1.fc.in_features, 3)
model1 = model1.cuda()
```

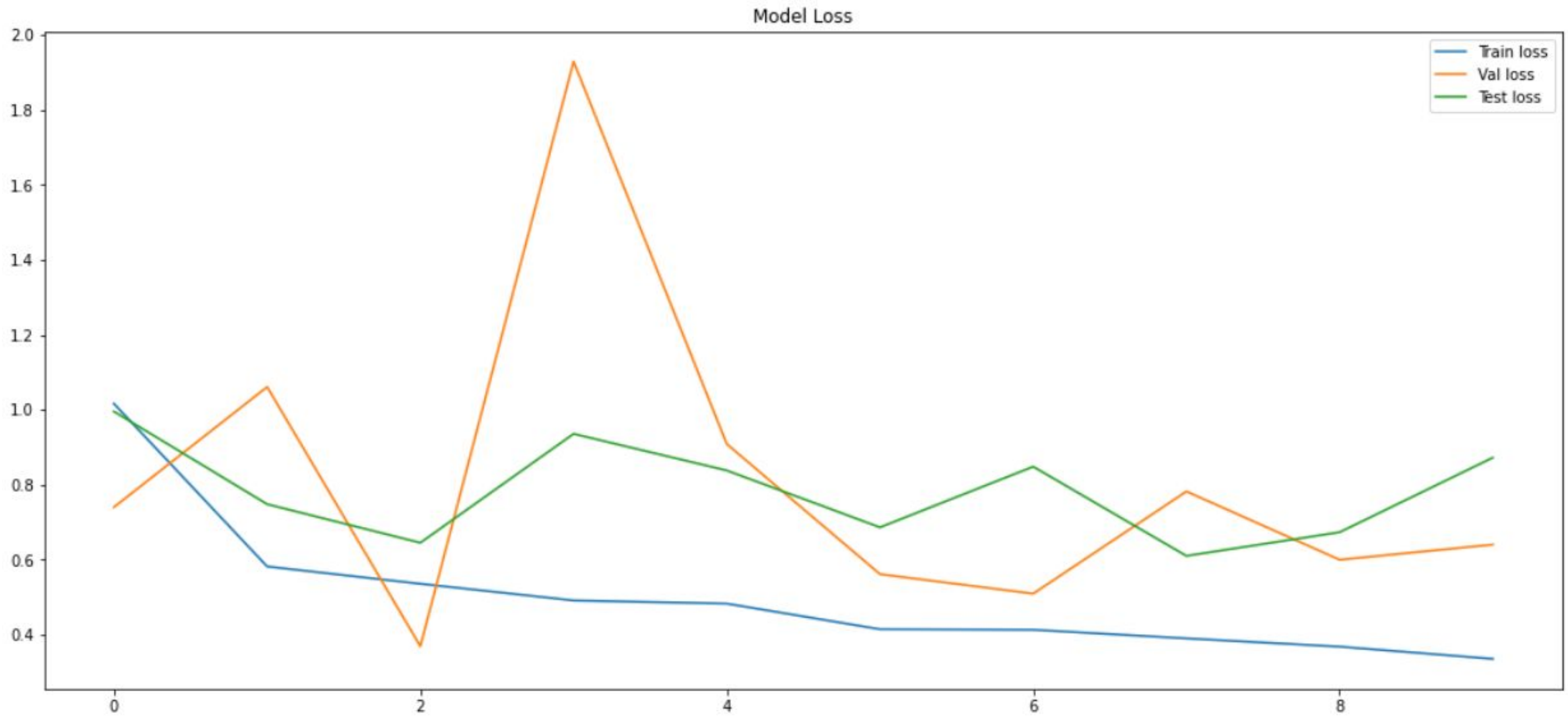
```
model2 = torchvision.models.vgg16_bn()
for param in model2.parameters():
    param.requires_grad = False
model2.classifier = nn.Sequential(nn.Linear(model2.classifier[0].in_features, 4096),
                                  nn.ReLU(),
                                  nn.Dropout(0.5),
                                  nn.Linear(4096,4096),
                                  nn.ReLU(),
                                  nn.Dropout(0.5),
                                  nn.Linear(4096, 3))
model2 = model2.cuda()
```

```
train batch [1303/1304]: loss 0.168365538120269786
val batch [3/4]: loss 0.5017175078392029
test batch [155/156]: loss 0.820534169673919785
Train loss: 0.4435696732252836, Train accuracy: 0.8002300613496933
Val loss: 1.0874995440244675, Val accuracy: 0.5
Test loss: 1.0613460964881456, Test accuracy: 0.7243589743589743
```

Variations

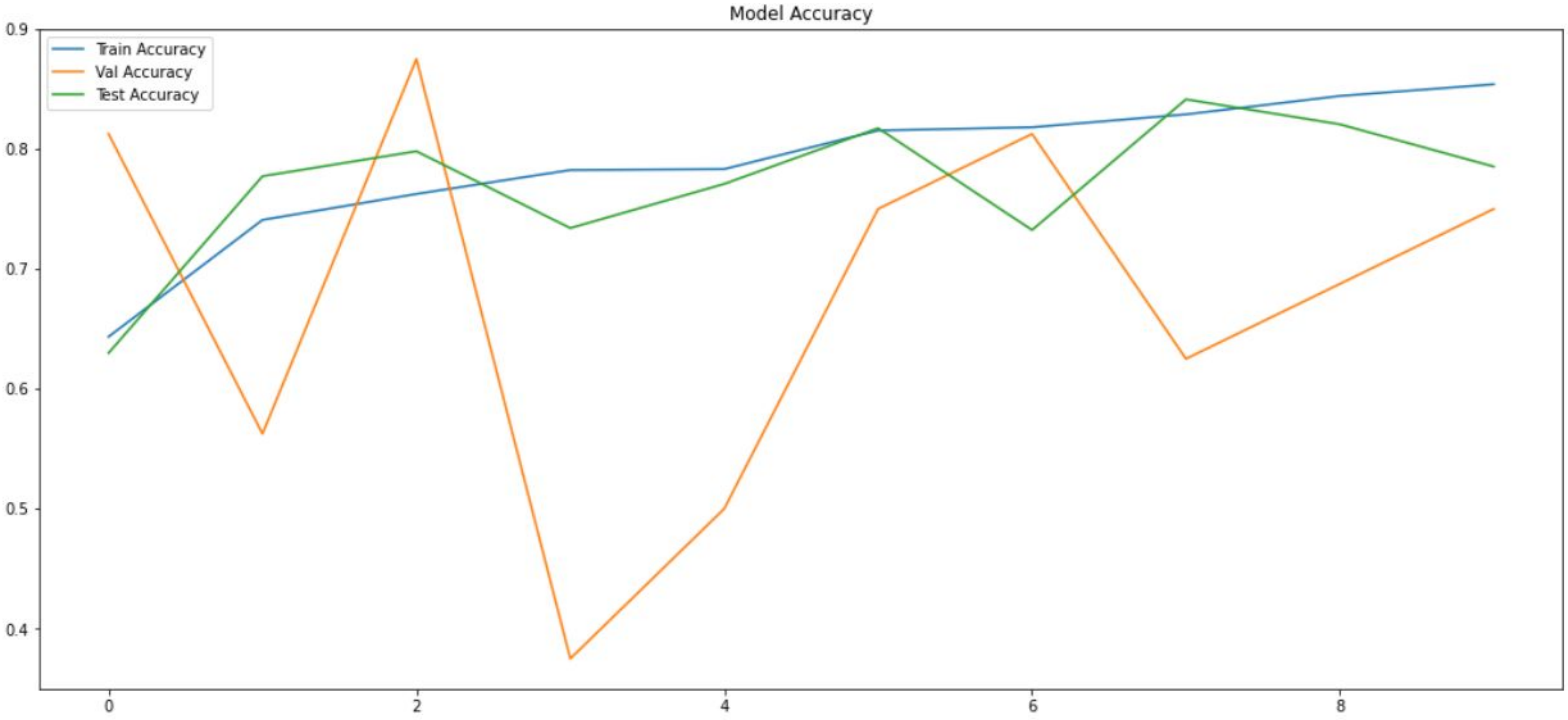
- vgg16_bn() - VGG16 with Batch Normalization
- Resize
    - 256, 350
- Optimizers
    - SDG
    - **Adam**
- Epoch
    - 10 - 50
    - **20**

Result



Model Loss
Train loss
Val loss
Test loss
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0
2
4
6
8

Result



Model Accuracy
Train Accuracy
Val Accuracy
Test Accuracy
0.9
0.8
0.7
0.6
0.5
0.4
0
2
4
6
8

Summary and conclusions

Summary & Observations

- The stand alone **ResNet 18 model** with only one layer classifier performed the best of our models.
    - **Accuracy = 0.851**
    - **Precision = 0.882**
    - **Recall = 0.854**
    - **F1 Score = 0.861**
    - **Cohen's Kappa = 0.781**
- Metrics in Kaggle kernels
    - Maximum Precision = 0.97
    - Maximum Recall = 0.93
    - Maximum Accuracy = 0.93

Observations:

- Optimizer : SGD
- Balanced Dataset is better
- Complex Problem - Complex Solution
- Image size : 256
- Dropout in FC6 may be too high

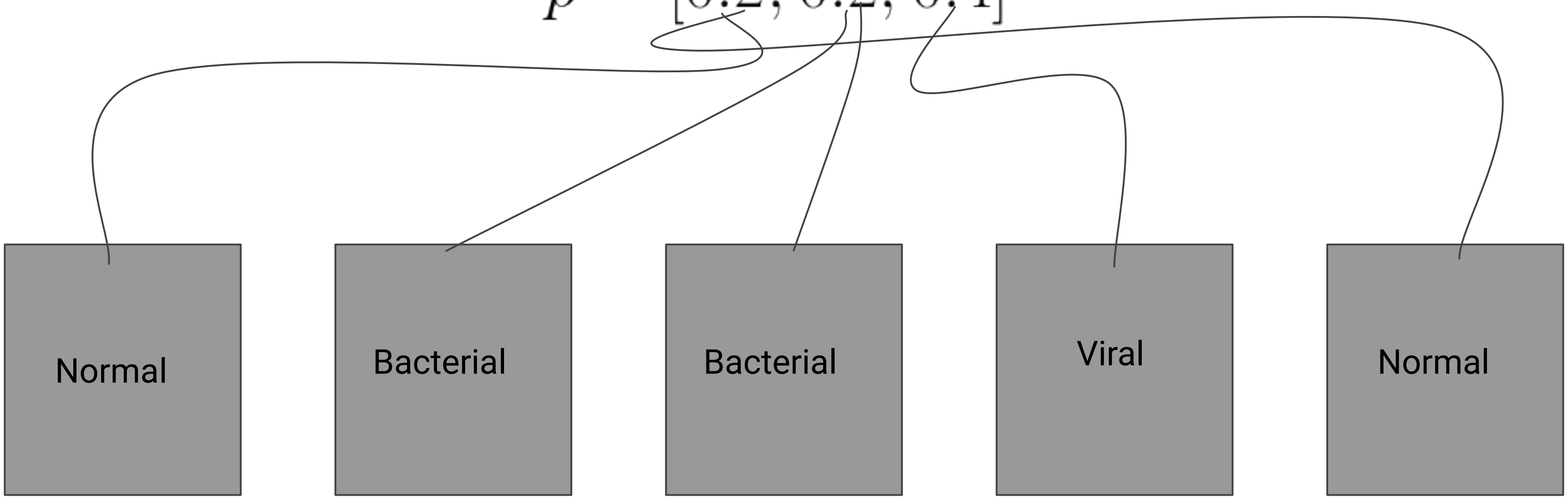
Future Improvements

- Two models
  - Normal vs Pneumonia
  - Bacteria vs Virus
- Modify the ColorJitter
  - brightness, contrast, saturation and hue of an image
- Batch Size and Epochs
- Collect More Data

WeightedRandomSampler

Normal, Bacterial Pneumonia, Viral Pneumonia

$$p = [0.2, 0.2, 0.4]$$




Thank You !