Data Augmentation for Aiding Pneumonia Classification

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OVERVIEW

01

THE PROBLEM

Current Approaches to Pneumonia Detection,

Augmentation for Aiding Classification

DRIVING MOTIVATIONS

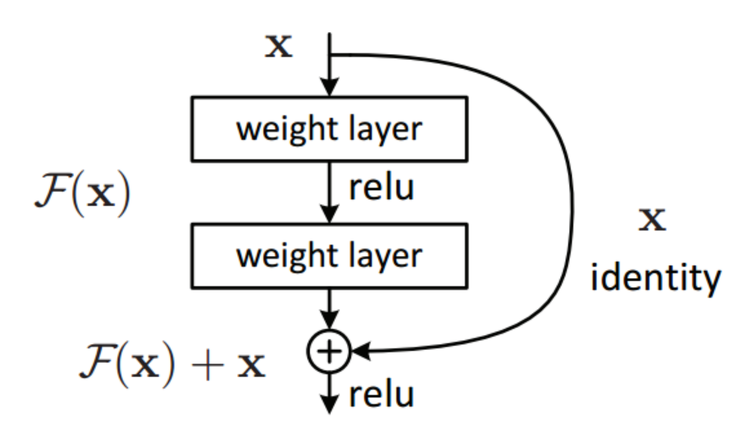
Accelerate medical diagnosis time with end-to-end deep learning

Improve performance of current pneumonia detection systems

Beneficial augmentation techniques may generalize to other tasks

PREVIOUS WORK

- Great results w/ forms of ResNet
- Preprocessing techniques
- Modified AlexNet w/ handcrafted features
- Transfer learning
- Reducing computational cost



Shortcut connection in ResNet

OUR WORK

- Baseline architecture vs. Established architecture
- Established architecture trained w/ data augmentations
- Leverage PyTorch, WandB framework for testing

02

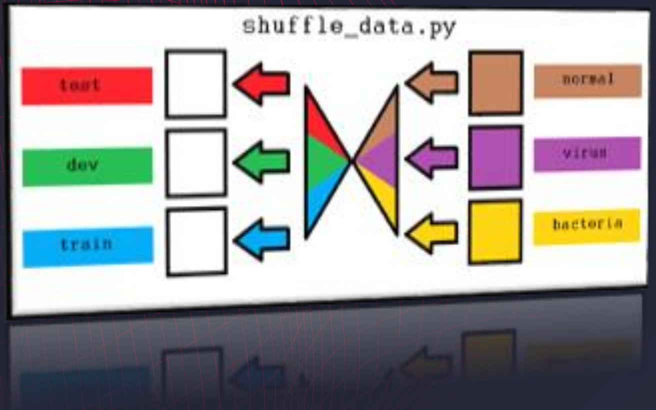
METHODOLOGIES

Data, Metrics, Augmentation,

Architecture, Training

OUR DATA SET

- 5,863 Chest X-Ray Images
- Labeled as Bacterial Pneumonia, Viral Pneumonia, or Normal
- 60% Train, 20% Dev, 20% Test



- ADVANTAGES:
  - High resolution images
  - Expert-verified labels
- LIMITATIONS:
  - Imbalanced
  - Relatively small

OUR TASK: BINARY CLASSIFICATION

Metrics:

- F1 Score
- PR Curve

True Positive: Pneumonia

True Negative: Normal

AUGMENTATIONS

Geometric Augmentations

- Rotations
- Mirroring
- Translations
- Noise Injection

Photometric Augmentations

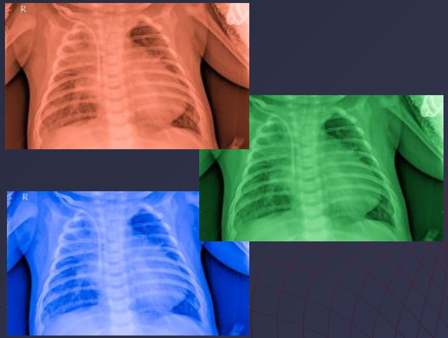
- Contrast
- Brightness
- Brightness & Contrast
- Color-space Transformations

Original

Mirrored

Original

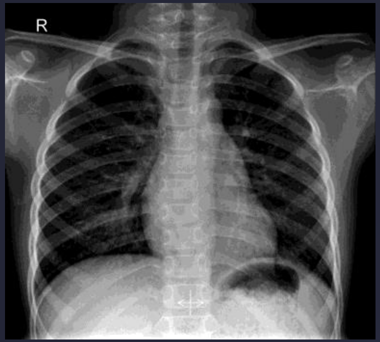
RGB Transforms

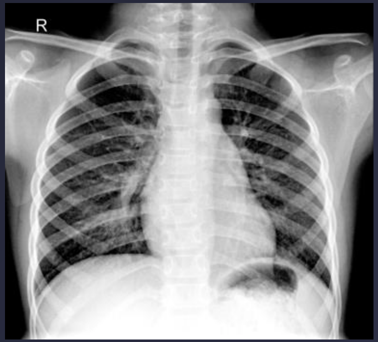


AUGMENTATIONS

Finalized on:

- Default
- Brightness
- Contrast
- Rotation
- Brightness + Contrast
- Brightness + Rotation
- Brightness + Contrast + Rotation

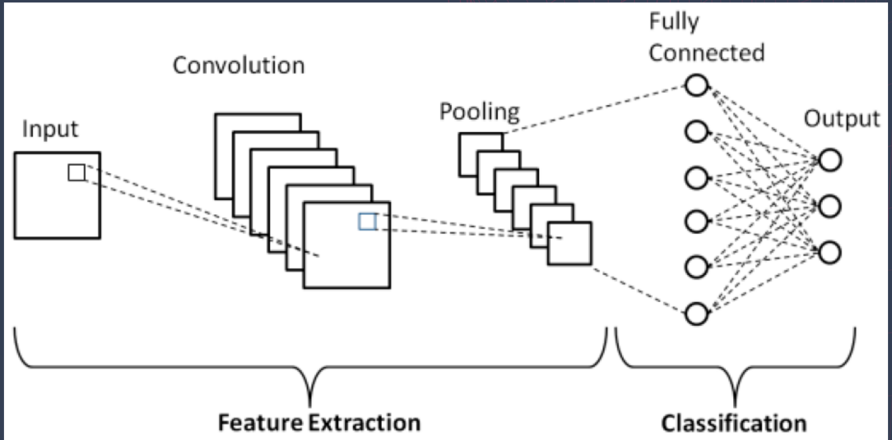




BASELINE ARCHITECTURE

Simple Convolutional Neural Network

- One convolutional layer
- Activation
- Pooling
- Fully connected linear layer
- Output – classification



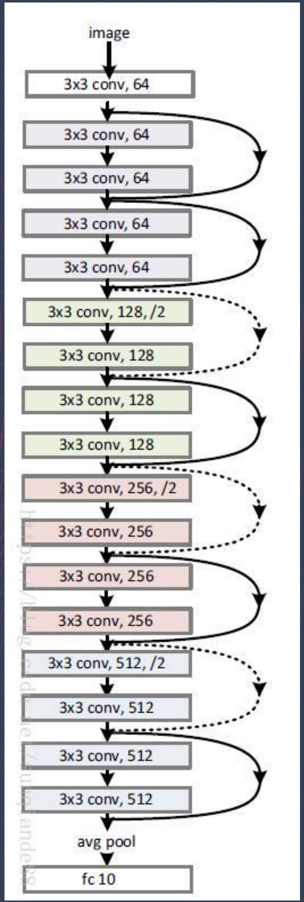
RESNET ARCHITECTURE

Residual Neural Networks

- Skip connections
- Prevents vanishing gradients
- Fewer layers when training
- Layers restored when feature spaced is learned
- Less prone to abnormalities within data

ResNet18

- 18 convolutional layers total
- Layers in blocks of four



03

RESULTS & ANALYSIS

ResNet Performance,

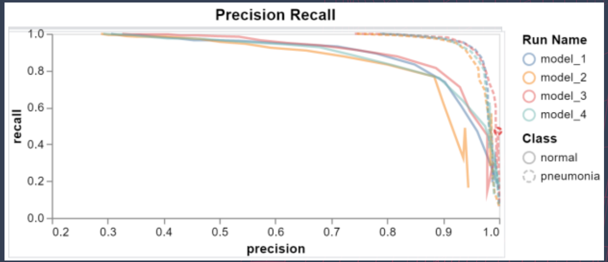
Scores Across Augmentations,

Interpretation of Results

BASELINE vs RESNET

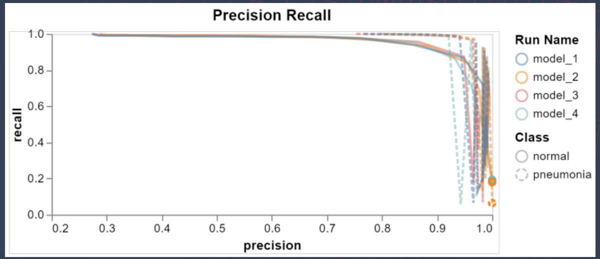
Actual \ Predicted	Pneumonia	Normal
Pneumonia	807	47
Normal	37	279

Results from Baseline Architecture



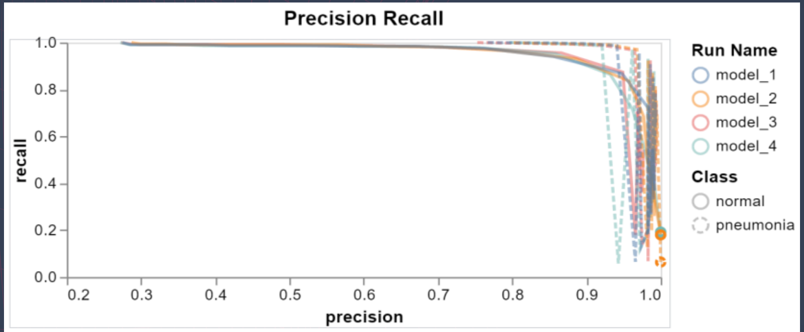
Actual \ Predicted	Pneumonia	Normal
Pneumonia	827	27
Normal	31	285

Results from ResNet18

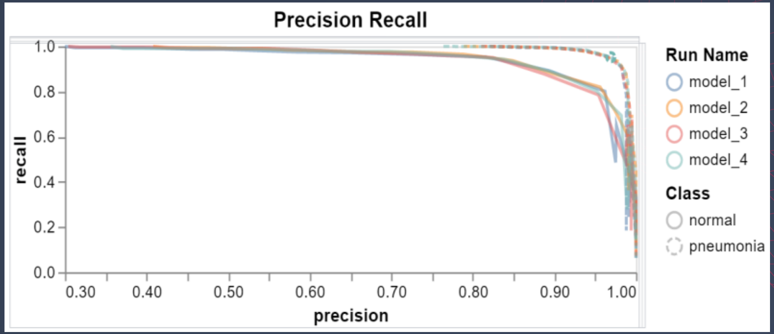


RESULTS ACROSS AUGMENTATIONS

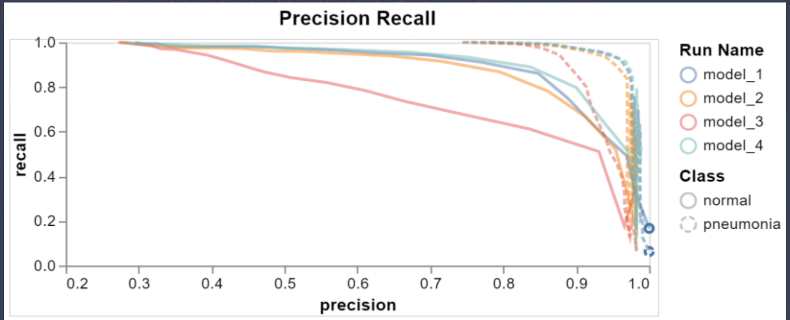
Default



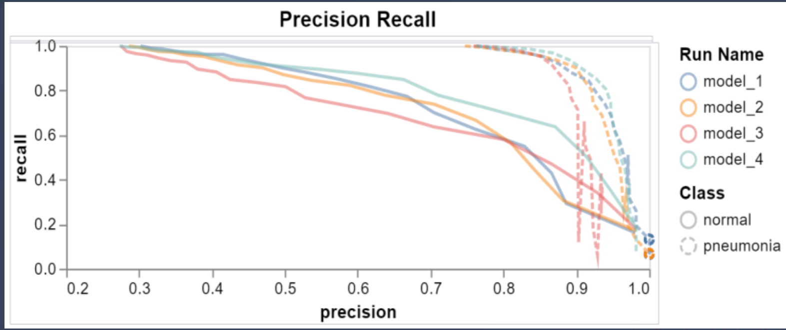
Rotation



Contrast

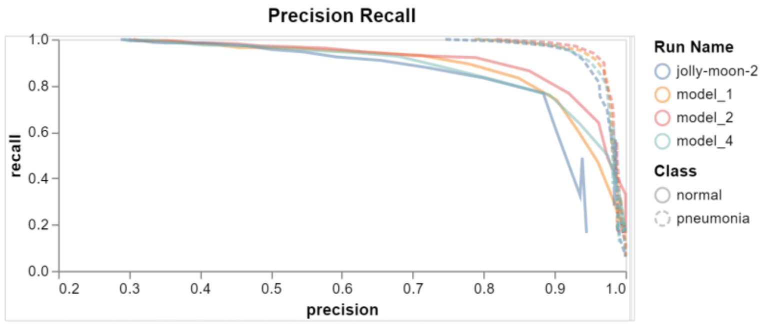


Brightness

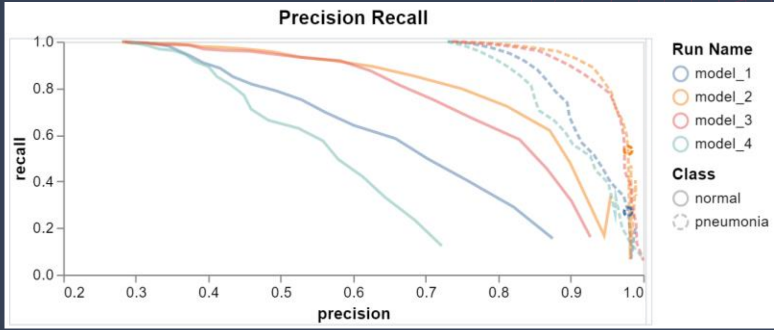


RESULTS ACROSS AUGMENTATIONS

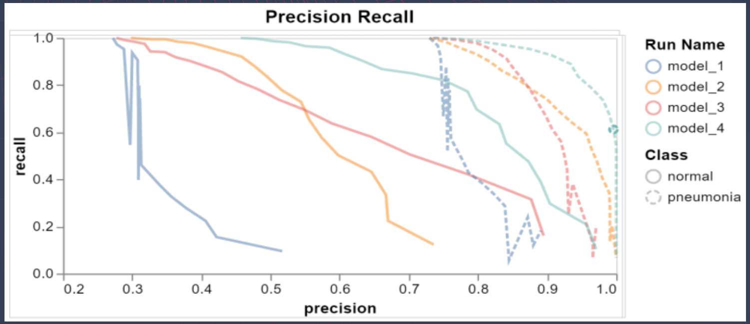
Contrast + Rotation



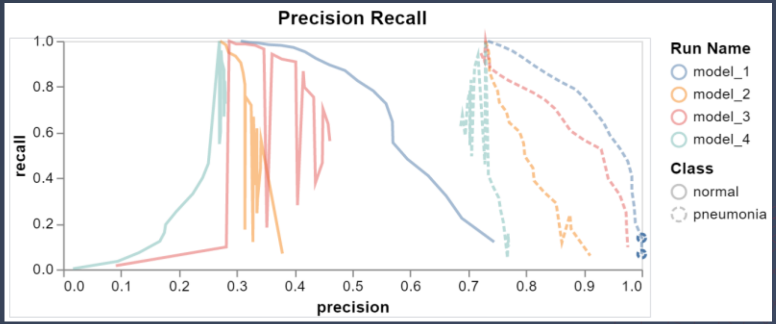
Brightness + Rotation



Brightness + Contrast



Brightness + Contrast + Rotation



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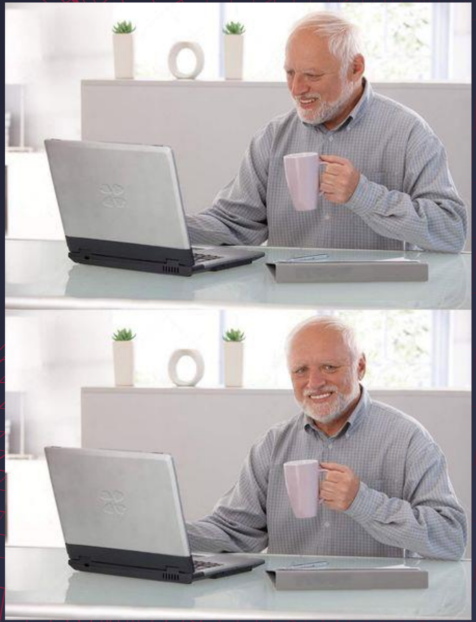
CLOSING THOUGHTS

Takeaways,

Future Work

KEY TAKEAWAYS

- ResNet18 still better than baseline
- Applicability of data augmentations
- Deep learning is hard



A visual representation of our team after result analysis

FUTURE WORK

- Incorporate new data
- Apply augmentations differently
- Adjust augmentation parameters
- Use augmentations in different architectures

THANKS FOR LISTENING!

** References available in report