Assessing Ventilator-Associated Pneumonia (VAP) Using Deep Learning

Computer Integrated Surgery II
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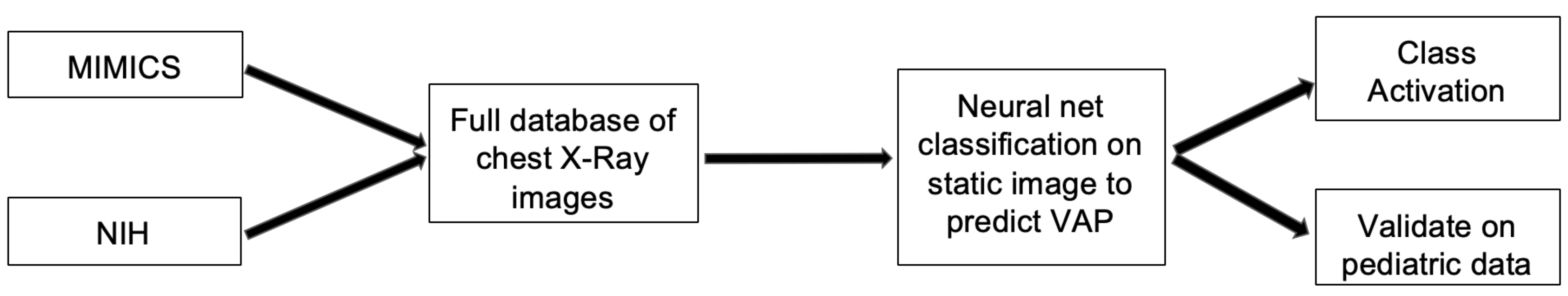
Introduction

- There is currently a lack of machine-augmented techniques that can be applied in critical-care settings (ICU and PICU) to classify pneumonia
- To address this problem, I implemented several deep learning techniques to classify pneumonia with high accuracy and visualize the actual features on which the machine detected pneumonia
  - This was built with an adult chest X-ray pipeline, but can be applied to pediatrics (with enough data)

Problem

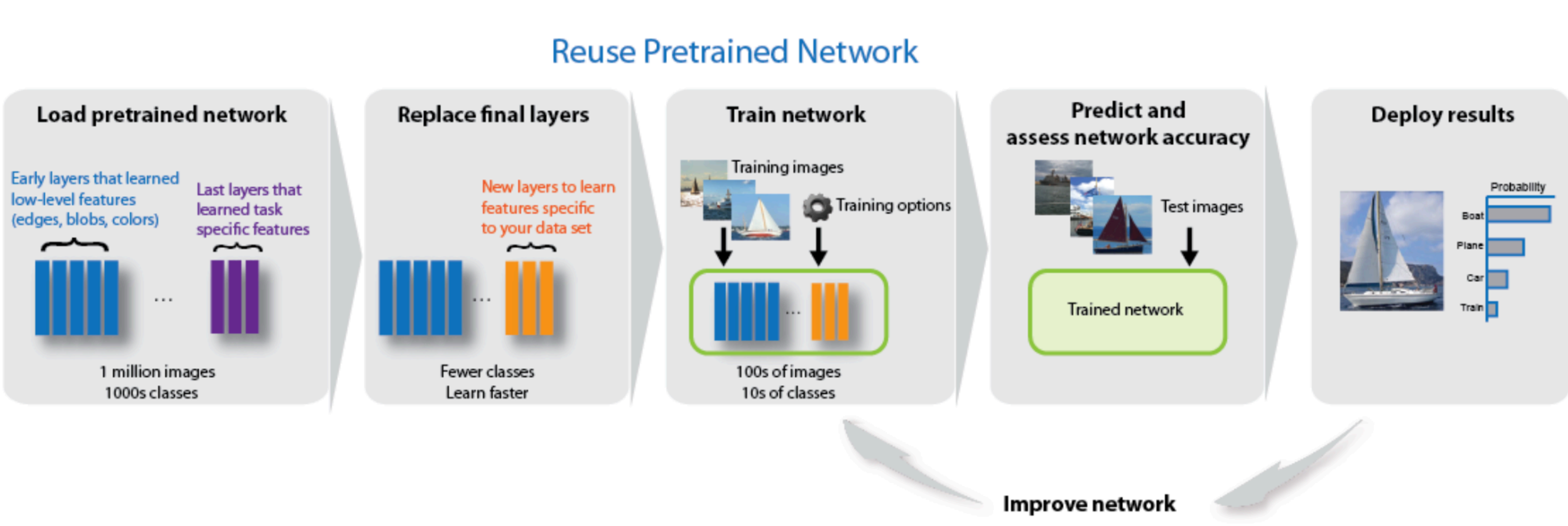
- Chest X-rays are the empirical standard in diagnosing pneumonia but are subject to trained radiologist diagnoses
- Mechanical ventilation is a critical, life-sustaining ICU therapy (more than half of patients ventilated within 24 hours) but results in increased mortality for many
- 10-20% of patients every year are diagnosed with VAP, and contracting VAP amplifies risk of mortality by 30%
- Radiologists are often unavailable to diagnose chest X-rays in real-time in critical-care settings
- Thus, there is a need for an automatic classifier to diagnose VAP in these situations

The Solution



Ingestion and Learning Pipeline for Project

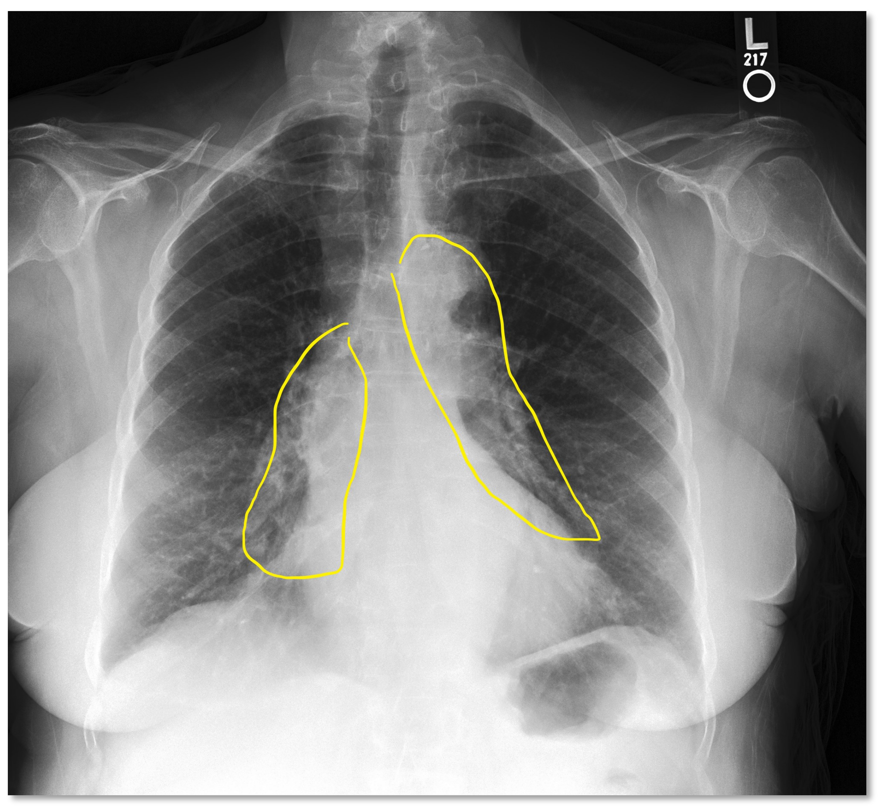
Overview of Transfer Learning



- First, assembled a pipeline for easy manipulation of publicly available data; able to sort data easily into model-ready inputs after assembly
- Built models off of existing pre-trained convolutional neural networks, and adjusted feature size and optimization accordingly, *example implementation is shown below*
- After training the model, ran class activation algorithms to display to physicians where feature extraction most occurs
- Models were tested and cross-verified across both datasets

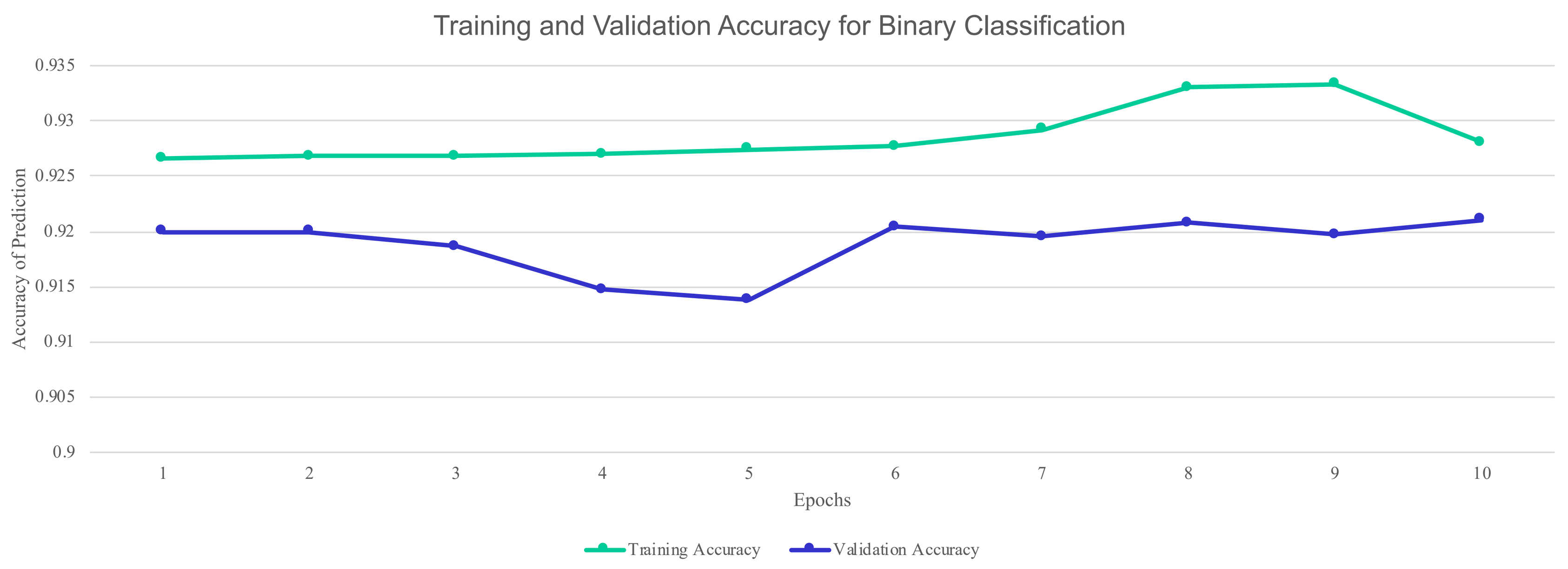
Network Parameters for Binary Classification	
Loss Function	Binary Cross Entropy Loss
Optimization Function	SGD (stochastic gradient descent)
Output Activation Function	Probabilistic Softmax
Iterations	50
Epochs	10

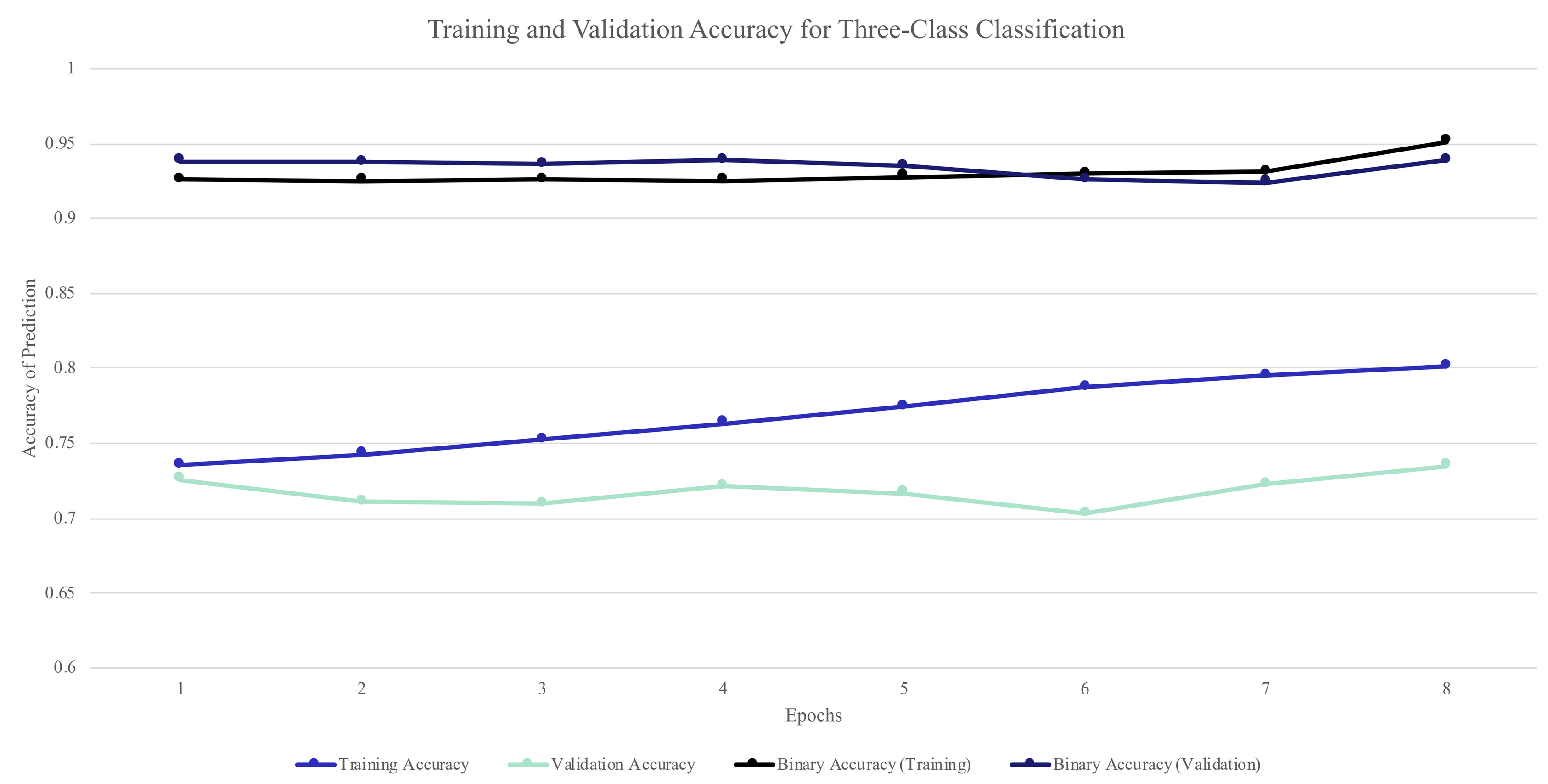
Outcomes and Results



Patient with Pneumonia

Class Activation Filtering





Achieved 94% accuracy on binary classification (trained on 65K images)

Future Work

- I will be graduating and starting a full-time job in August, so cannot continue work on my own
- **Computational:** include applying deep clustering methods on top of the neural network to extract most relevant features
- **Experimental:** testing on a more robust set of pediatric patients (especially validating on patients who are specifically ventilated)

Lessons Learned

- Generalization of convolutional neural networks derives a convenient way to train own datasets
- Publicly available time-series data is difficult to ingest
- Very accurate diagnosis of pneumonia can often depend on non-imaging data points

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