X-Ray Image Classification with Deep Learning

Flatiron School Phase 4 Project

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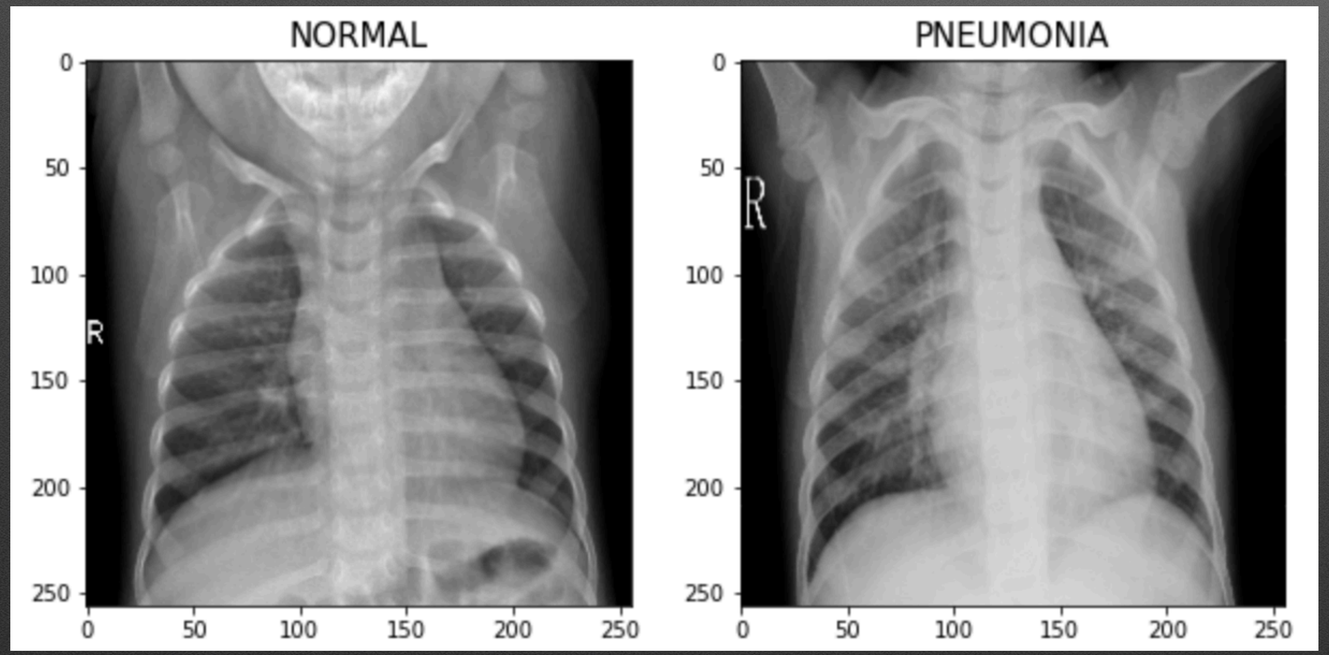
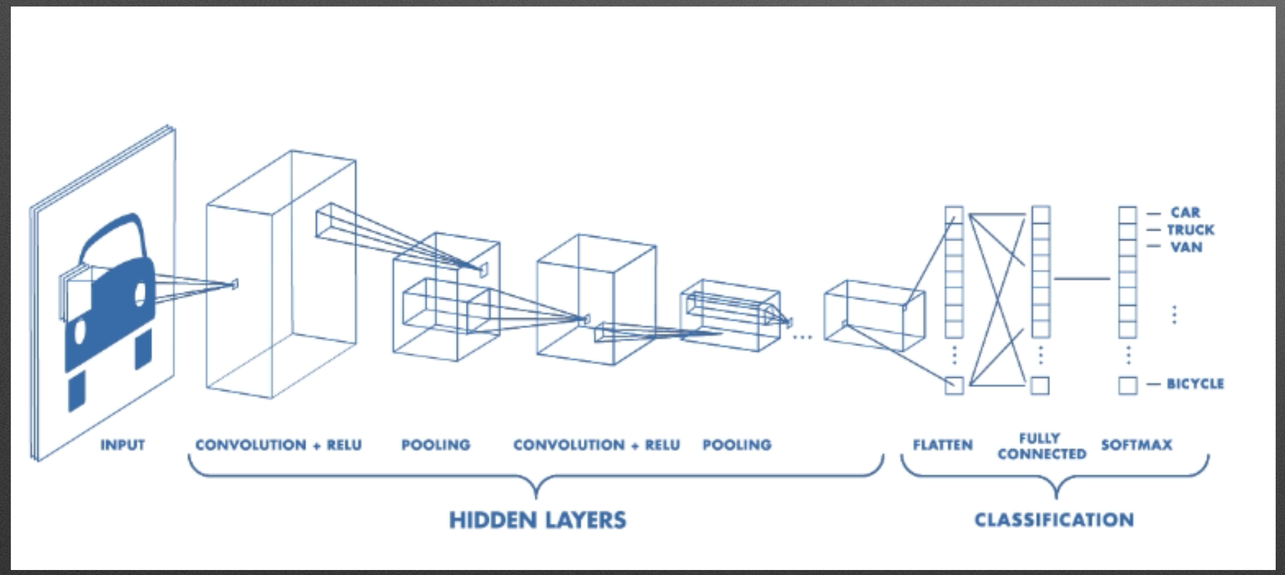
Introduction

- Data analysis and modeling of pediatric chest x-rays using a dataset provided by Mendeley Data



- Project goal is to train a neural network to classify x-rays as containing pneumonia or not as accurately as possible
- X-ray assessment is a time consuming process for radiologists. A robust model would save them time and increase their productivity
- X-rays are expensive for insurance companies and patients. Part of their cost is the amount of time they take to be reviewed. An accurate model would shorten review time and decrease costs
- A model can analyze images much faster than a human. The sooner medical professionals and patients get results the sooner they can begin treating the patient, which gives the patient a better potential outcome

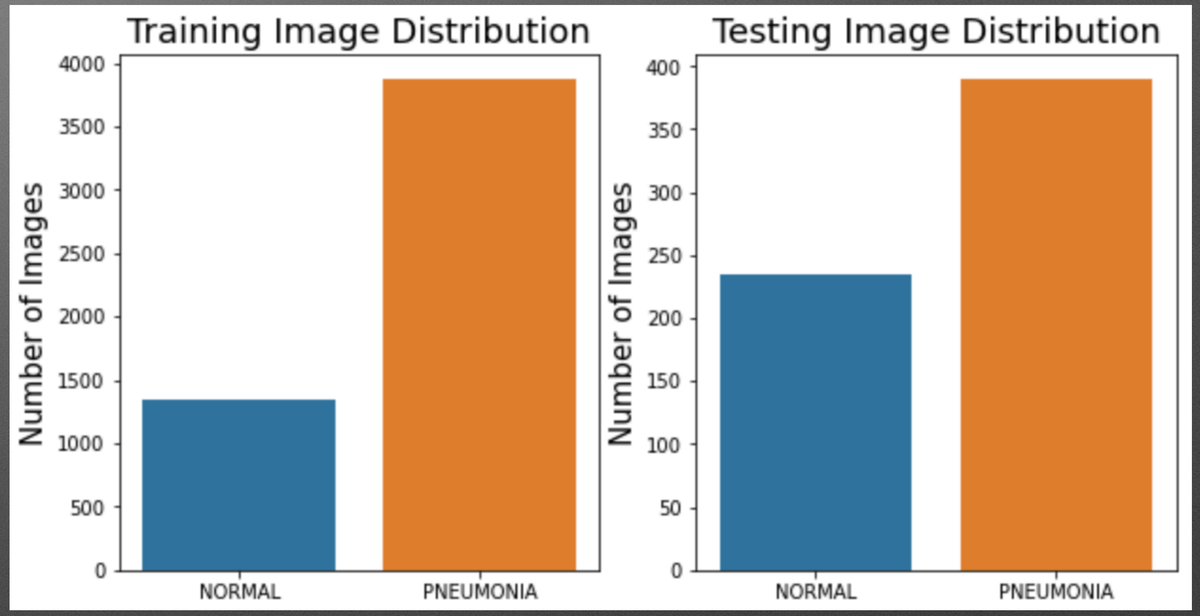
Methodology



- Prepare data to be modeled
- Explore different CNN modeling architectures
- Iterate through different ranges of data augmentation and hyper-parameter values

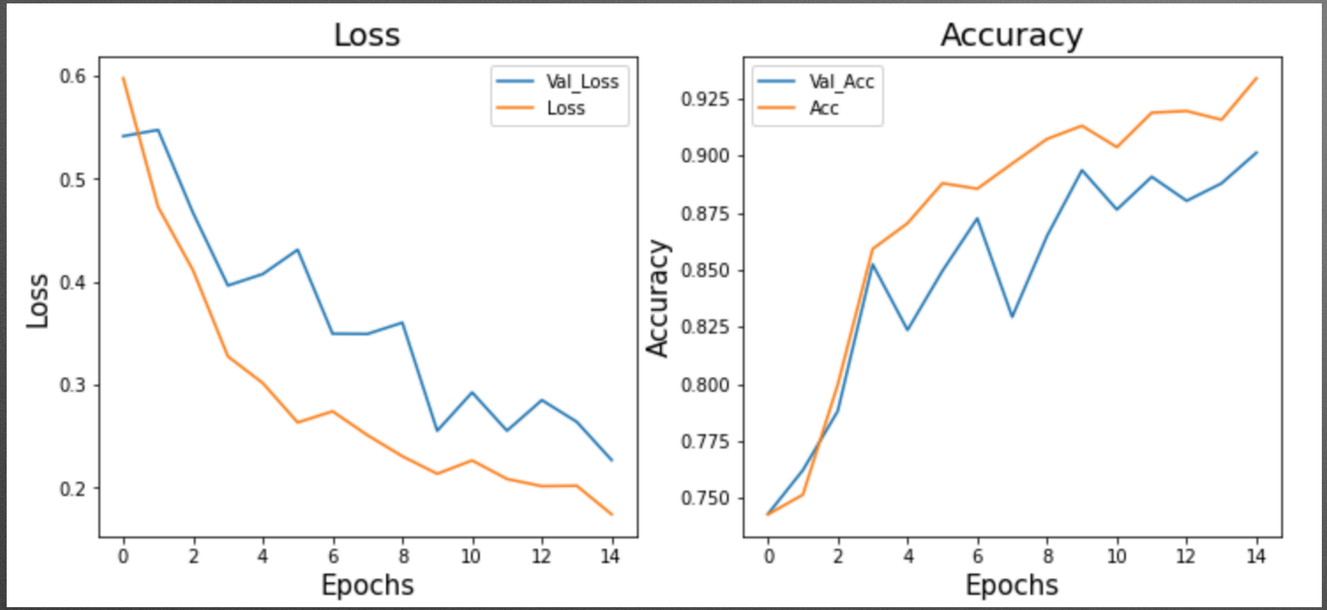
EDA & Preprocessing

- Assess dataset split (5,216 training, 16 validation, 624 testing) and label distributions
- Found that dataset split and label distribution display class imbalance



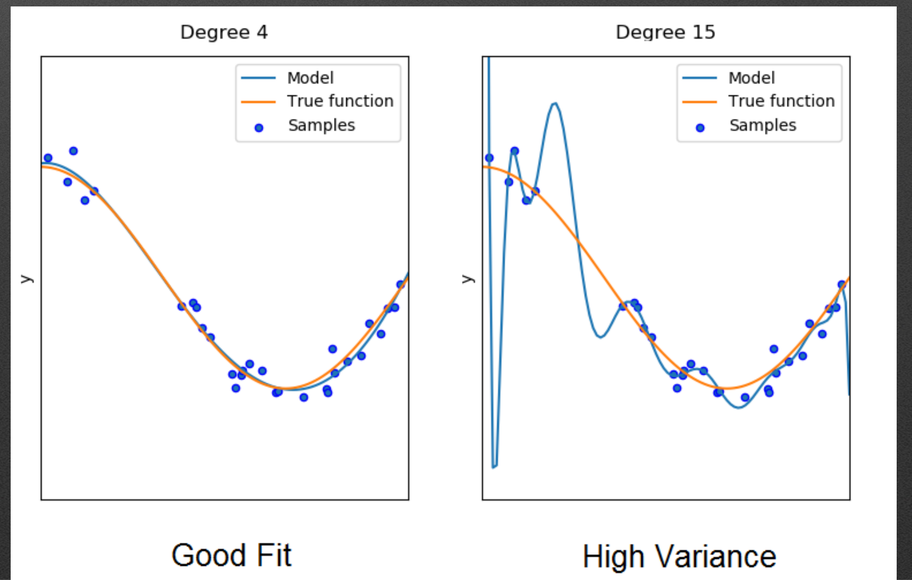
- Utilize data augmentation to provide added variance
- Data augmentation alters images to give you multiple variations of same image

Modeling



- Modeled data iteratively through different values of augmentation and hyper-parameters with goal of optimizing accuracy and reducing loss
- Data augmentation made biggest performance difference, but once applied, changing values didn't make difference
- Generating larger validation set increased accuracy, but not significantly

- Explored regularization techniques and transfer learning in attempt to reduce model over-fitting
- Dropout decreased loss during training and evaluating
- L1 & L2 regularization and transfer learning greatly improved performance during training, but did not generalize to evaluation
- Transfer learning will require more time to properly tune



Model Evaluation

- After iterating through many combinations of data augmentation and model configurations, select model with best combination of high accuracy and low loss to evaluate
- Evaluate best model with confusion matrix and classification report
- Best model returned 92% accuracy, 81.2% precision (44 false positives), and 95.5% recall (9 false negatives)

```
Confusion Matrix
[[190  44]
 [  9 381]]
Classification Report
              precision    recall  f1-score   support

      NORMAL       0.95      0.81      0.88       234
   PNEUMONIA       0.90      0.98      0.93       390

    accuracy                           0.92       624
   macro avg       0.93      0.89      0.91       624
weighted avg       0.92      0.92      0.91       624
```

Conclusion

- The size and scope of this project was limited by time and still performed very well. It is currently as accurate as medical professionals on average
- With more time to optimize the model it could become more accurate than medical professionals, while being able to process a much higher volume of images exponentially faster

Thank you!

- If you have additional questions about this presentation or opportunities for me to help solve your business problems with a data driven analysis and modeling, please contact me at the following links
- LinkenIn: https://www.linkedin.com/in/joshua-blumer-6180591b2/
- GitHub: https://github.com/joshblumer
- Email: josh.e.blumer@gmail.com