Convolutional Neural Networks: Machine Learning and Pneumonia

Clay Swisher, Iryna Marchiano, Simon Castellanos, and Elijah Abuel

Project justification

According to the American Thoracic Society and the American Lung Association:

- Pneumonia is the world’s leading cause of death among children under 5 years of age
- Pneumonia killed approximately 2,400 children a day in 2015
- Pneumonia killed an estimated 880,000 children under the age of five in 2016
- More than 150,000 people are estimated to die from lung cancer each year
- Infections, including pneumonia, are the second most common cause of death in people with lung cancer
- Medical system is overworked due to COVID-19 pandemic and can use novel applications of AI to assist in prompt pneumonia diagnostics

Demystifying Machine Learning

- Kaggle dataset composed of chest x-rays differentiating between healthy patients and those with pneumonia
- Used a convolutional neural network to analyze image dataset
- Objective:
  - Build a model to accurately predict the diagnosis of a patient (NORMAL or PNEUMONIA) based on a submitted image of a chest x-ray
  - Achieve a high accuracy and precision rate
  - Avoid false positives and false negatives

Data Model Implementation

Tensorflow Keras
- Model - VGG16 as a basis for CNN model
- Image size = 224, 224

Compiling Model
- Loss = categorical crossentropy
- Optimizer = adam

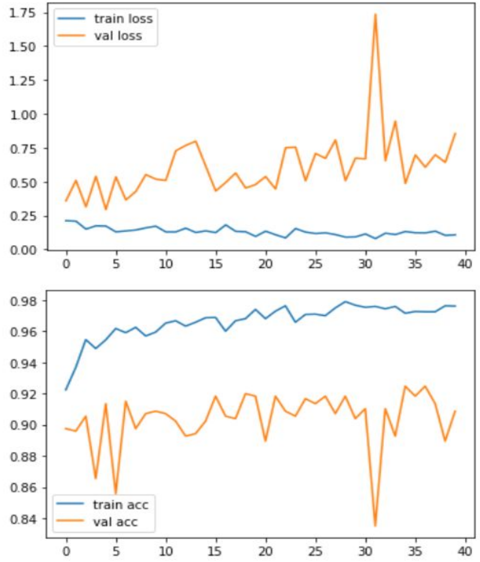
Creating Generator
- Keras ImageDataGenerator
- Scaled (1./255) *(to scale RGB pixel values from range [0,255] -> [0,1]*

Building and Fitting Models
- 10, 20, 30, 40, 100 Epochs
- Precision and Recall scores
- Validation/Loss Accuracy
- Train/Loss Accuracy
- Confusion Matrix

Final Training Model (hdf5 file)
- 1-30 Epochs
- 62% Precision
- 67% Recall
- 92% Accuracy

Data Model Optimization

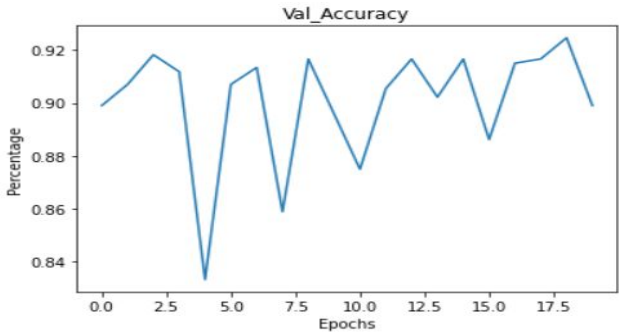
- Training the model to be more accurate at predictions required several steps
- Training for more epochs with different iterations of 1, 10, 20, 100 etc.
- Avoid overfitting to the training data
- Created a usable confusion matrix to determine true positive/negative and false positive/negative values



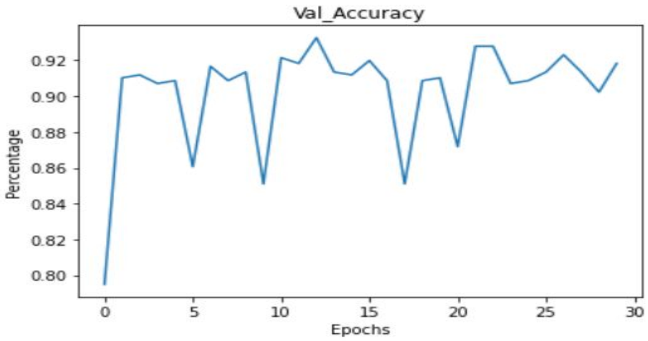
- With more epochs used, validation loss and training accuracy increased
- Validation accuracy remained at around ~90%
- Risk of overfitting to training data remained

Validation Accuracy

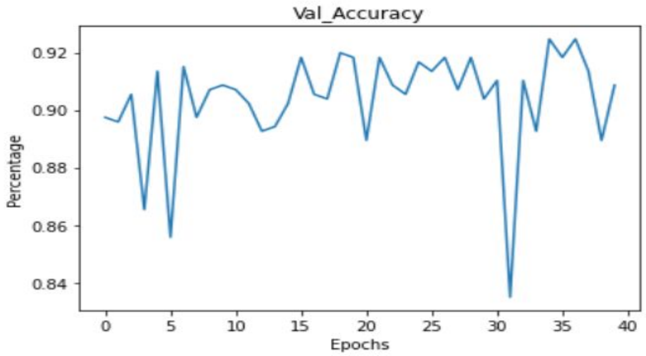
20 Epochs



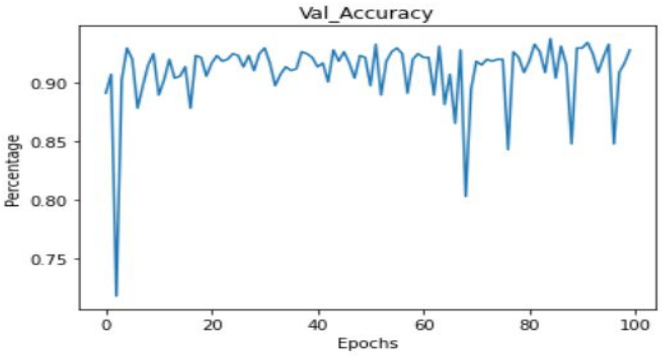
30 Epochs



40 Epochs

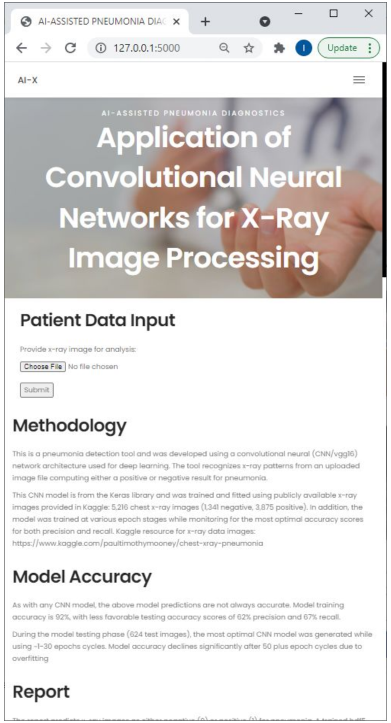


100 Epochs

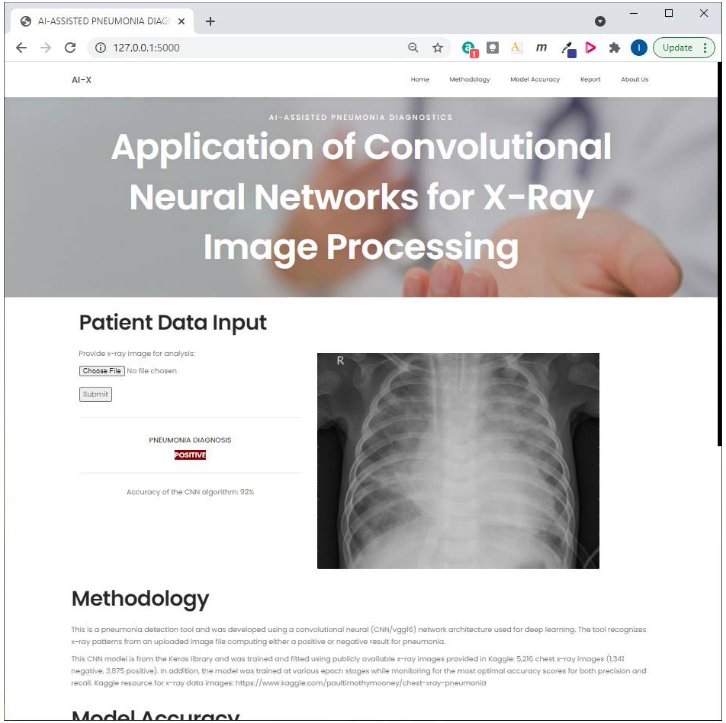


Front End Implementation

SMALL SCREEN Landing page



LARGE SCREEN Page post model prediction



- X-ray image upload via Flask
- Flexibility in permitted image file formats (*.jpg, *.jpeg, *.png, *.gif)
- Once uploaded, image is stored in the “library”, pre-processed and fed to the model

Questions & Recommendations

Challenge

- CNN models take considerable time to train

If we had more time…

- Improve data augmentation - explore different techniques to enhance the size and quality of the x-ray images for training
- Added noise and random permutations to original dataset to clone it, increasing number of training images and hopefully improving robustness
- Adjusted resolution of images received by model for more accurate reading
- To train using the ResNet model vs VGG16/19 pretrained models

Resources/Back up

Data Source: Kaggle

x-ray images provided in Kaggle: 5,216 chest x-ray images (1,341 negative, 3,875 positive). https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

Keras Applications VGG16:
https://keras.io/api/applications/vgg/#vgg16-function