Convolutional Neural Networks in Radiology

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Introduction

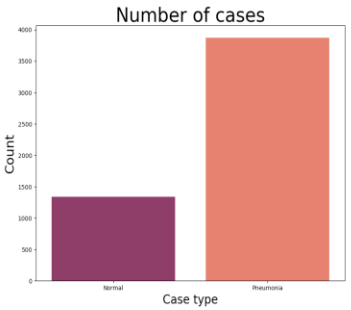
Motivation: The goal of using CNNs in Radiology is to help Radiologists more accurately diagnose patients, to reduce fatigue-based errors, and to help patients who lack access to Radiologists diagnose themselves using their chest X-Ray images. My CNN specifically checks for pneumonia, which can cause coughs, fevers, shortness of breath, chills, shaking, fatigue, sweating, and muscle pain, so it would be excellent to have a fast, accurate method for detecting such a disease before symptoms worsen.

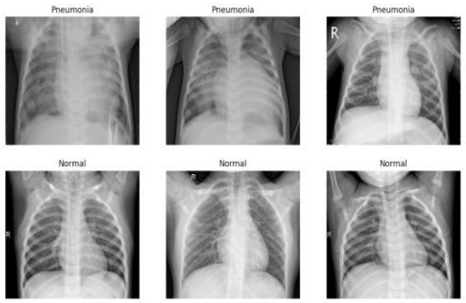
Approach: I used partial transfer learning from VGG16 and a 24-layer CNN and I split my image data into a training set (N normal = 1341, N pneumonia = 3875), a cross validation set (N normal = 8, N pneumonia = 8), and a test set (N normal = 234 normal, N pneumonia = 390).

Results: Pneumonia is not easy to see with the naked eye—when interpreting an X-Ray, a professional Radiologist will look for white spots in the lungs (called infiltrates) that identify an infection. Nevertheless my best model achieved a F1-score on the test data of 0.86.

Data and Features

- 5863 infant X-Ray images from Guangzhou Women and Children's Medical Center in China
- Every image was labeled with the ground truth (pneumonia vs. normal)
- I performed data augmentation (horizontal flips, rotation, random brightness changes) to correct for class imbalance (as seen below there are more pneumonia examples)
- The image data varied in dimensions, so I converted all images to a standard 224x224x3—the standard input for the VGG16 CNN.





Models

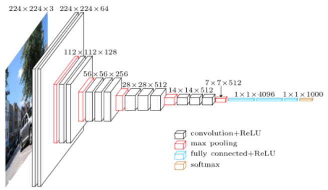
- Rather than using random initialization for my first four convolution layers, which capture general details like blobs, patches, edges, etcetera, I found much more success through loading pre-trained weights from VGG16 (built by Visual Geometry Group) and fine tuning them.
- Next I use convolutional, batch norm, and max pooling, layers, ending with a softmax layer for binary prediction. I use a 24-layer CNN instead of the 16-layer VGG16 CNN and update my parameters according to Adaptive Moment Estimation (Adam)
- I use binary cross entropy as my loss function $BCE = -\frac{1}{N}\sum_{i=0}^{N} y_i \cdot log(\hat{y}_i) + (1 - y_i) \cdot log(1 - \hat{y}_i)$
- I experimented with different weight initializations, different learning rates, and different batch sizes.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$
$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$$
$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

Adam

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

Note : default values of 0.9 for β_1, 0.999 for β_2, and 10^{-8} for ϵ



Results

Training: N Pneumonia = 3875, N Normal = 1341

Testing: N Pneumonia = 390, N Normal = 234

Weight Initializations	Batch Size	Learning Rate	Effective Error Train	F1 Score Train	Effective Error Test	F1 Score Test
Random	16	1x10^-3	0.50	0.85	0.50	0.77
Random	16	1x10^-4	0.50	0.85	0.50	0.77
VGG16	16	1x10^-3	0.50	0.85	0.50	0.77
VGG16	16	1x10^-4	0.01	0.99	0.16	0.86
VGG16	64	1x10^-3	0.50	0.85	0.50	0.77
VGG16	64	1x10^-4	0.01	0.99	0.16	0.86

Discussion and Future

The CheXNeXt team at Stanford, which includes Professor Andrew Ng and CS 230 guest speaker Pranav Rajpurkar, has developed a CNN that classifies 14 different thoracic diseases roughly as well as the top Radiologists. Additionally, using class activation mappings (CAMs), their model outputs a heatmap pinpointing the location in the chest that caused the CNN to make its prediction, as seen in their colorized example below. Now they are working to deploy a website where anyone in the world who lacks access to a Radiologist can upload their own X-Ray image file to get a fast, free diagnosis. With six more months, I would work to try to replicate or improve upon their model. Since their results were so promising, I expected my top model to achieve a high F1 Score as well.

	F1 Score (95% CI)
Radiologist 1	0.383 (0.309, 0.453)
Radiologist 2	0.356 (0.282, 0.428)
Radiologist 3	0.365 (0.291, 0.435)
Radiologist 4	0.442 (0.390, 0.492)
Radiologist Avg.	0.387 (0.330, 0.442)
CheXNet	0.435 (0.387, 0.481)

Acknoledgements and References

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Works Cited:

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