# Using Machine Learning to Classify Chest X-Rays

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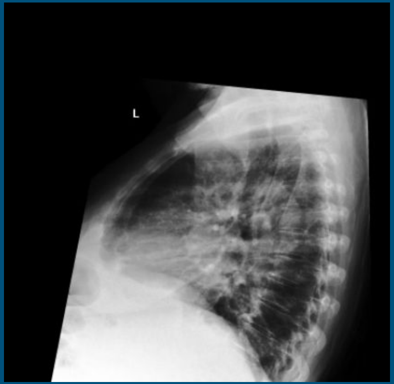
Avi Komarlingam

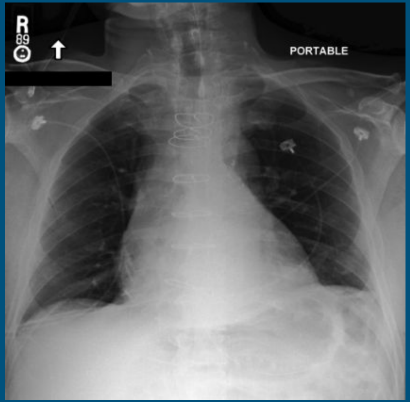
# Dataset: MIMIC-CXR-JPEG

| metadata | | | | | |
|---|---|---|---|---|---|
| dicom_id | subject_id | study_id | ViewPosition | Rows | Columns |
| b5f871e6- | 10002428 | 58601917 | AP | 3056 | 2544 |

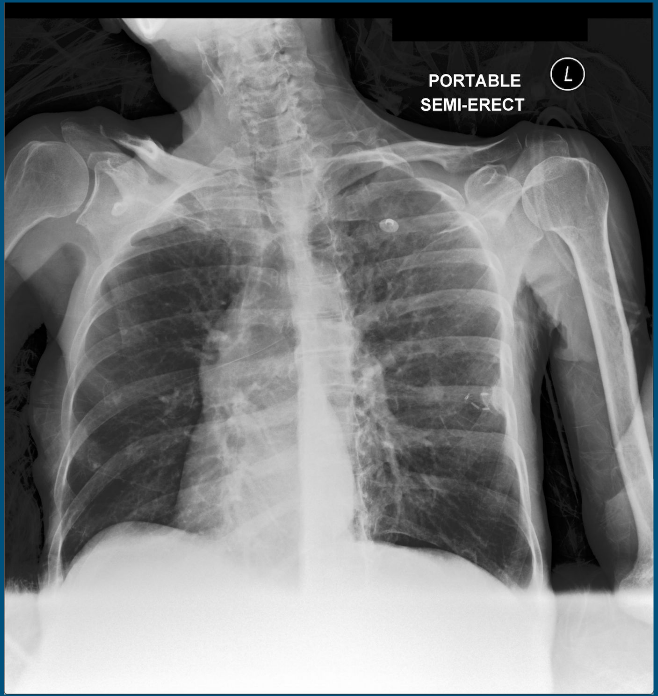
| negbio | | | |
|---|---|---|---|
| subject_id | study_id | Atelectasis | Cardiomegaly |
| 10002428 | 58581921 | | 0 |
| 10002428 | 58601917 | 1 | -1 |

# Data Processing

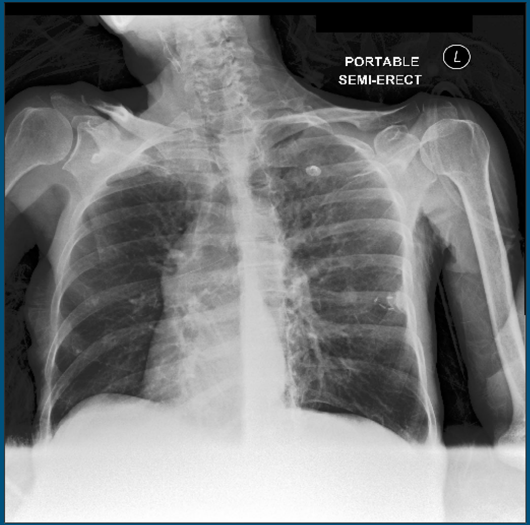


# Bilinear Interpolation

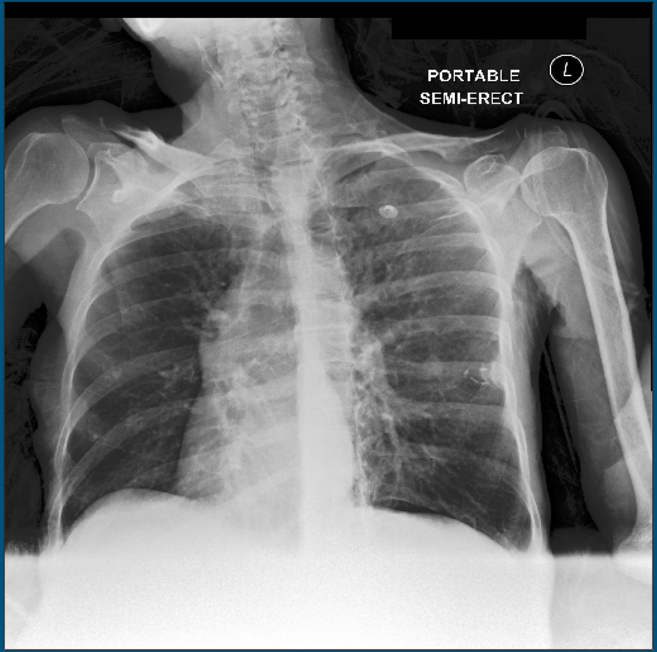



(2539, 2705)

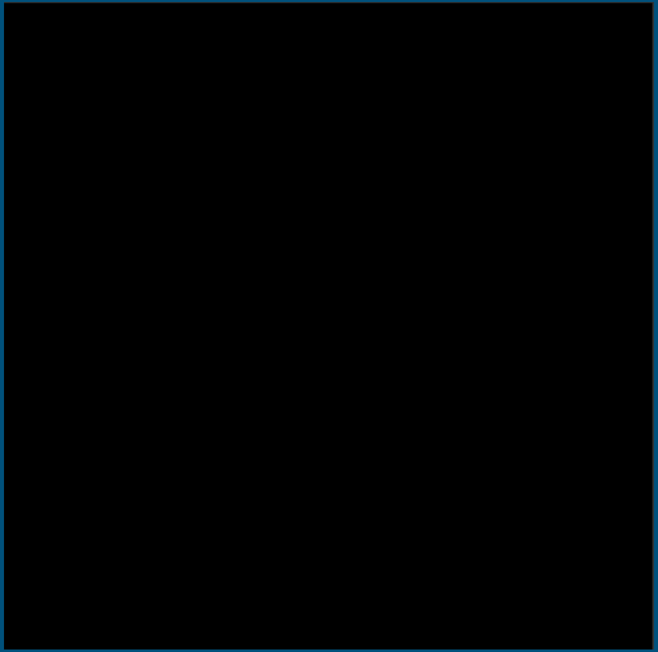



(512, 512)

# Pixel Normalization

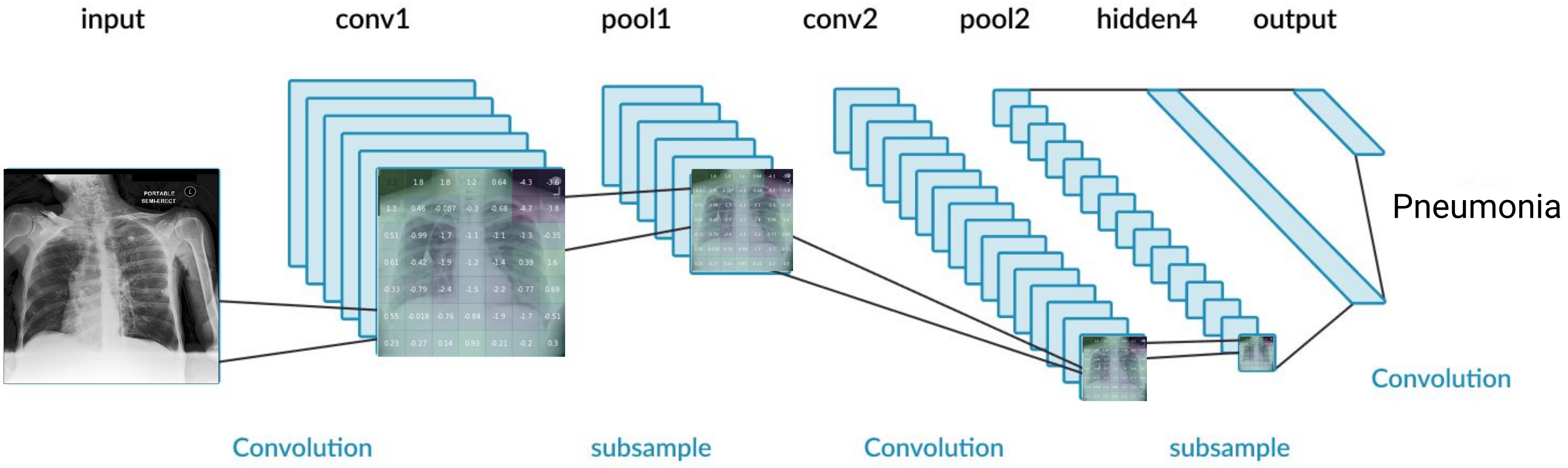



Min: 0.000, Max: 255.000



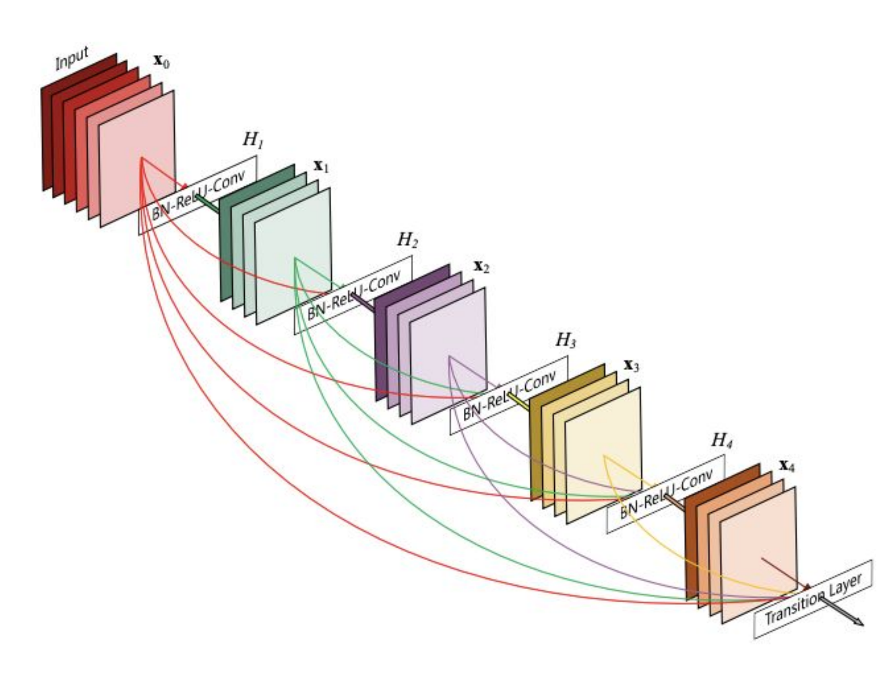
Min: 0.000, Max: 1.000

# Developing CNNs



# DenseNet

DenseNet-121
DenseNet-161



# Model Performance

DenseNet-121

Layers: 121

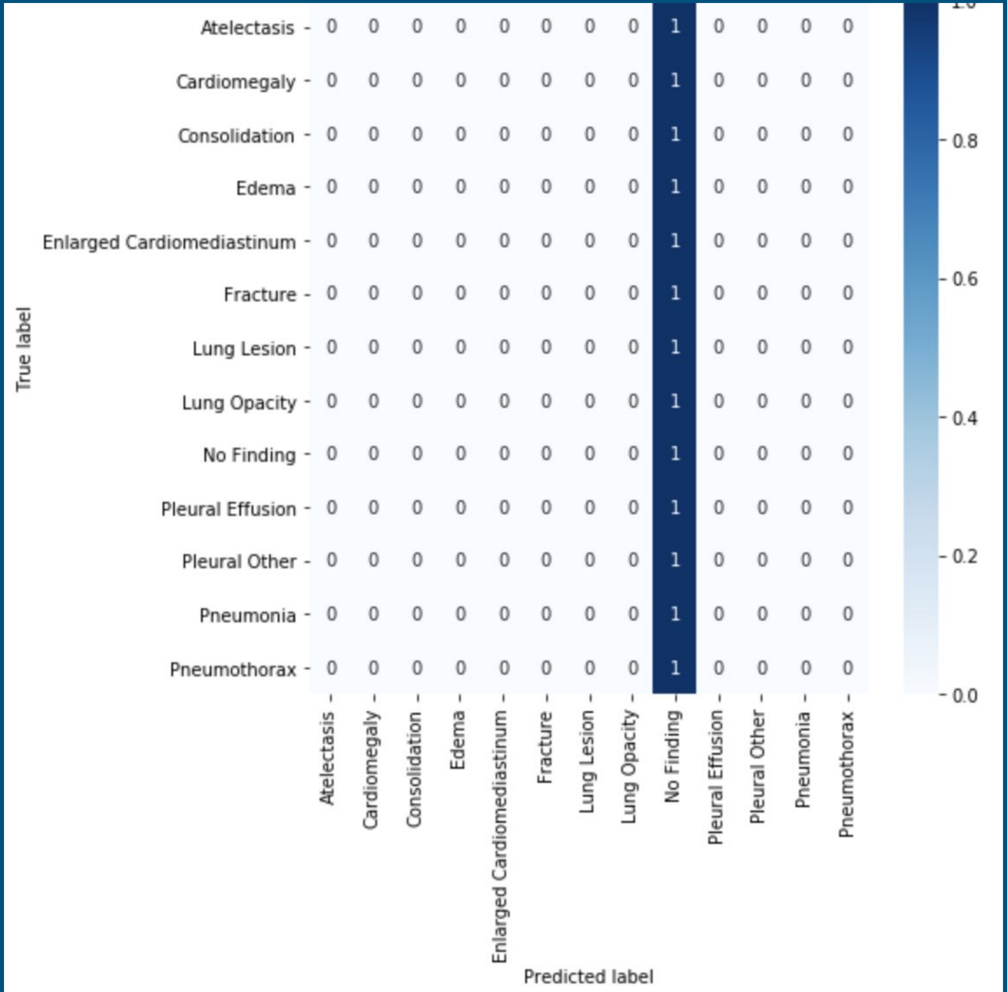
Accuracy: 92.30%

DenseNet-161

Layers: 161

Accuracy: 92.15%

# “Results”

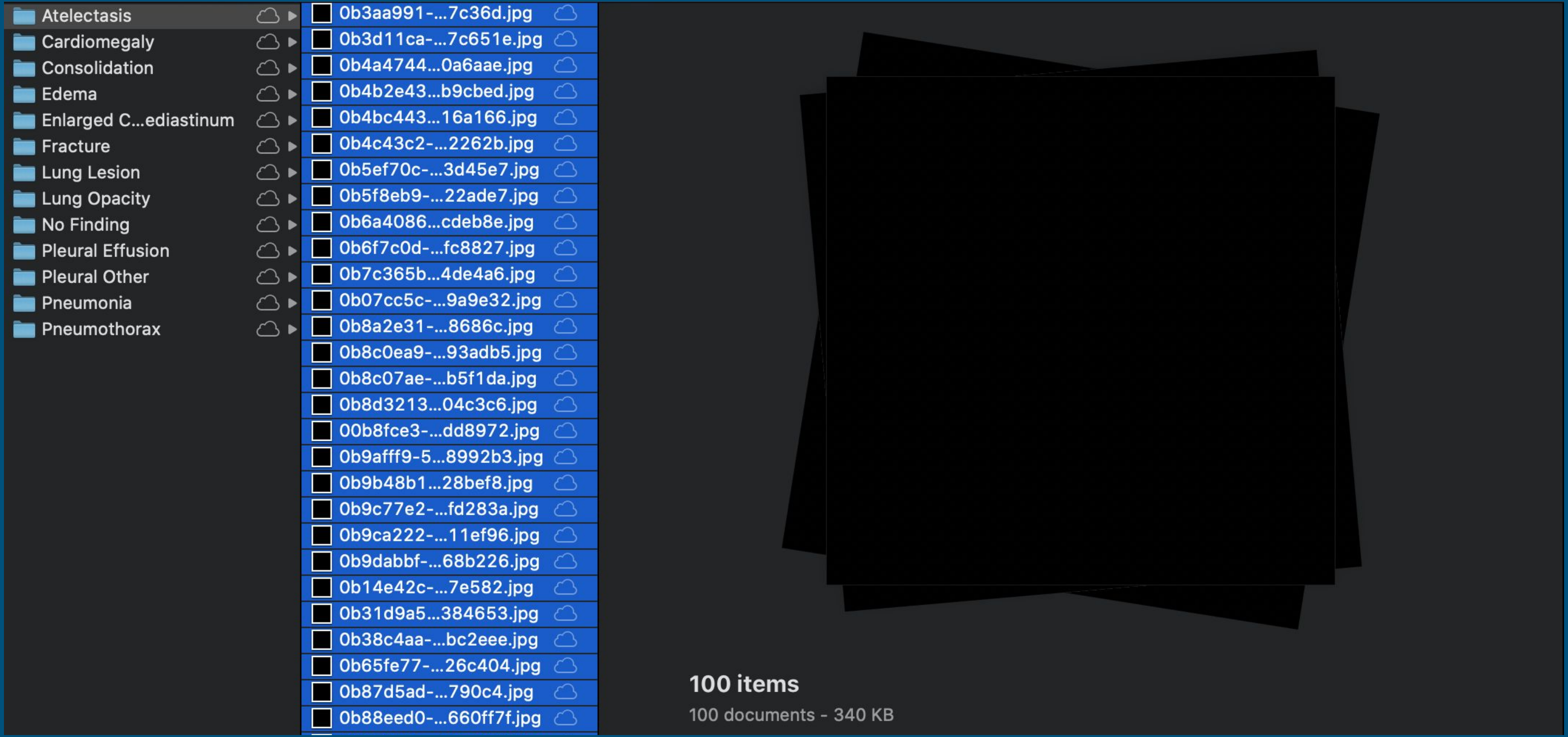


Atelectasis 0 0 0 0 0 0 0 0 1 0 0 0 0
Cardiomegaly 0 0 0 0 0 0 0 0 1 0 0 0 0
Consolidation 0 0 0 0 0 0 0 0 1 0 0 0 0
Edema 0 0 0 0 0 0 0 0 1 0 0 0 0
Enlarged Cardiomediastinum 0 0 0 0 0 0 0 0 1 0 0 0 0
Fracture 0 0 0 0 0 0 0 0 1 0 0 0 0
Lung Lesion 0 0 0 0 0 0 0 0 1 0 0 0 0
Lung Opacity 0 0 0 0 0 0 0 0 1 0 0 0 0
No Finding 0 0 0 0 0 0 0 0 1 0 0 0 0
Pleural Effusion 0 0 0 0 0 0 0 0 1 0 0 0 0
Pleural Other 0 0 0 0 0 0 0 0 1 0 0 0 0
Pneumonia 0 0 0 0 0 0 0 0 1 0 0 0 0
Pneumothorax 0 0 0 0 0 0 0 0 1 0 0 0 0
True label
Atelectasis
Cardiomegaly
Consolidation
Edema
Enlarged Cardiomediastinum
Fracture
Lung Lesion
Lung Opacity
No Finding
Pleural Effusion
Pleural Other
Pneumonia
Pneumothorax
Predicted label
0.8
0.6
0.4
0.2
0.0

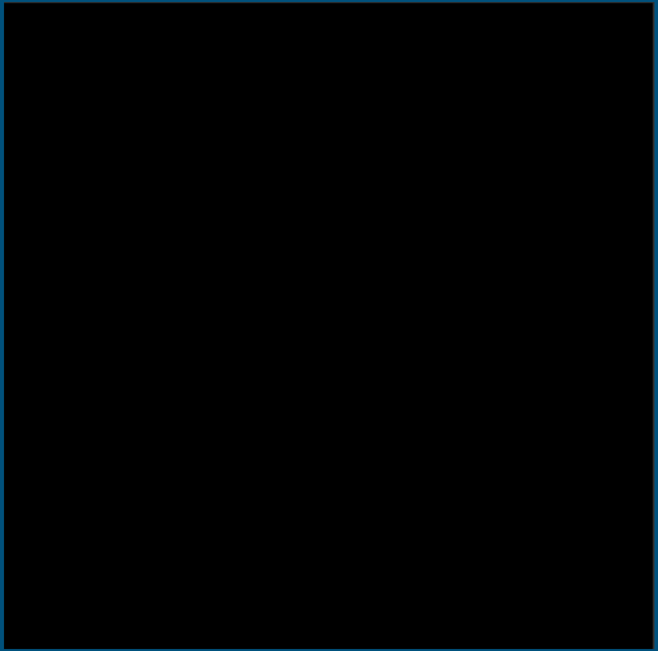
# Possible Causes

1. Domination of one class over the others due to overrepresentation
2. Errors in preprocessing images
3. Issues with model architecture

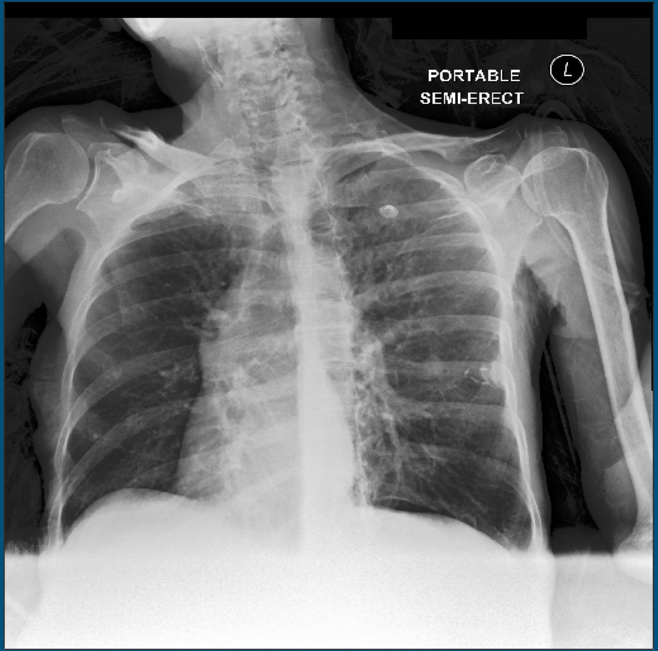
# Equalizing Class Sizes



# Pixel Denormalization



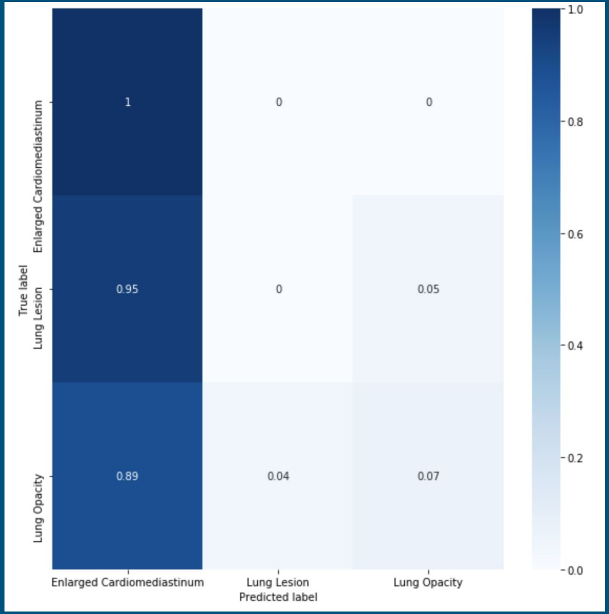
Min: 0.000, Max: 1.000



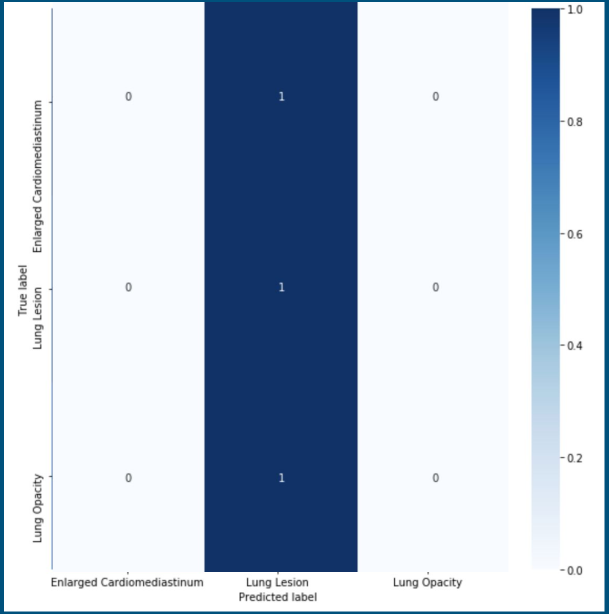

Min: 0.000, Max: 255.000

# Different Model Architectures

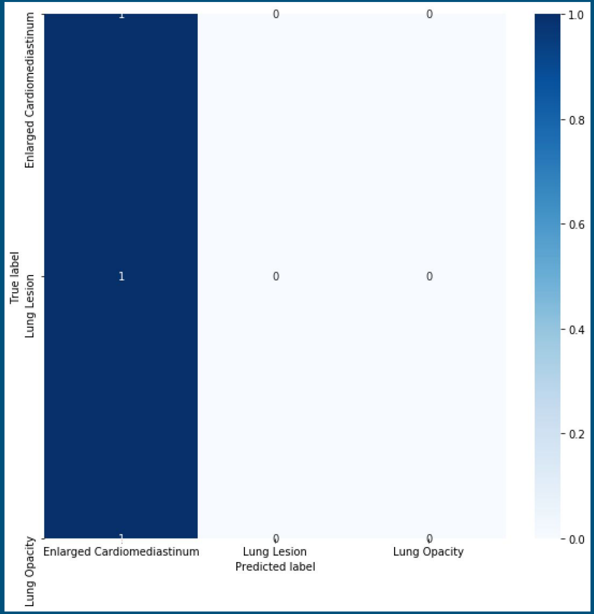
DenseNet-121




ResNet-50




CNN-7



# Future Work: Finding a solution to the single-class prediction problem

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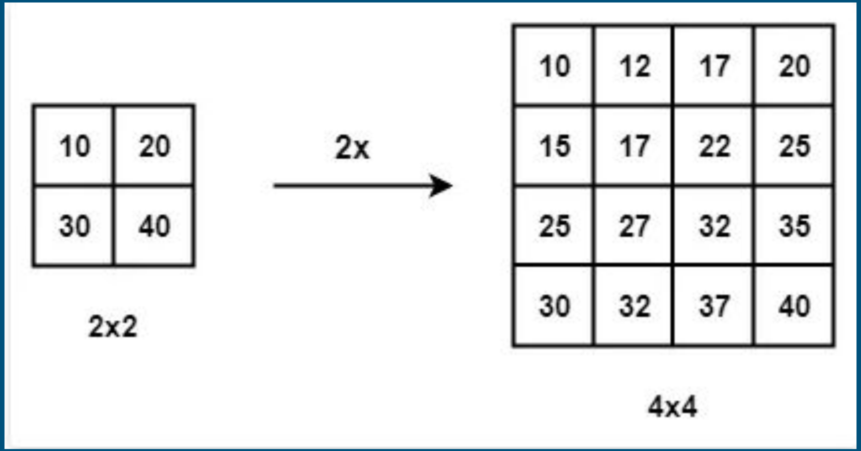
Raoof, S., Feigin, D., Sung, A., Raoof, S., Irugulpati, L., & Rosenow, E. C. (2012). Interpretation of Plain Chest Roentgenogram. Chest,141(2), 545-558. doi:10.1378/chest.10-1302

Riggs, W., & Parvey, L. (1976). Differences between right and left lateral chest radiographs. American Journal of Roentgenology,127(6), 997-1000. doi:10.2214/ajr.127.6.997

# Reserve

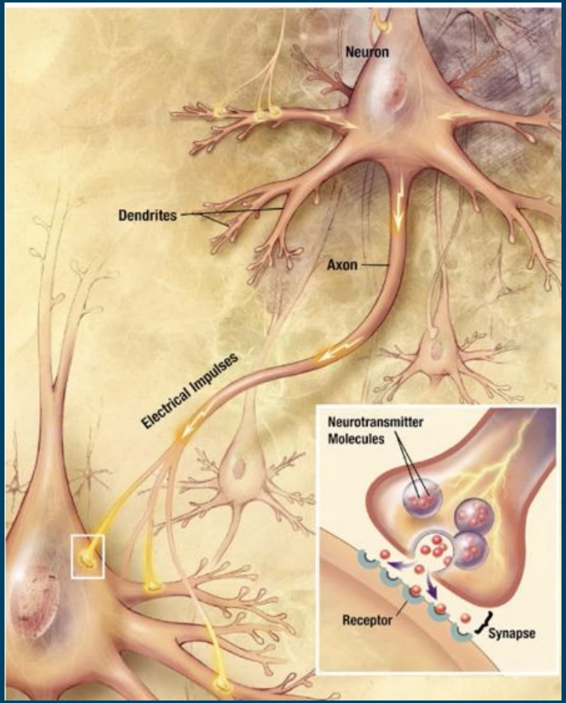
# Bilinear Interpolation



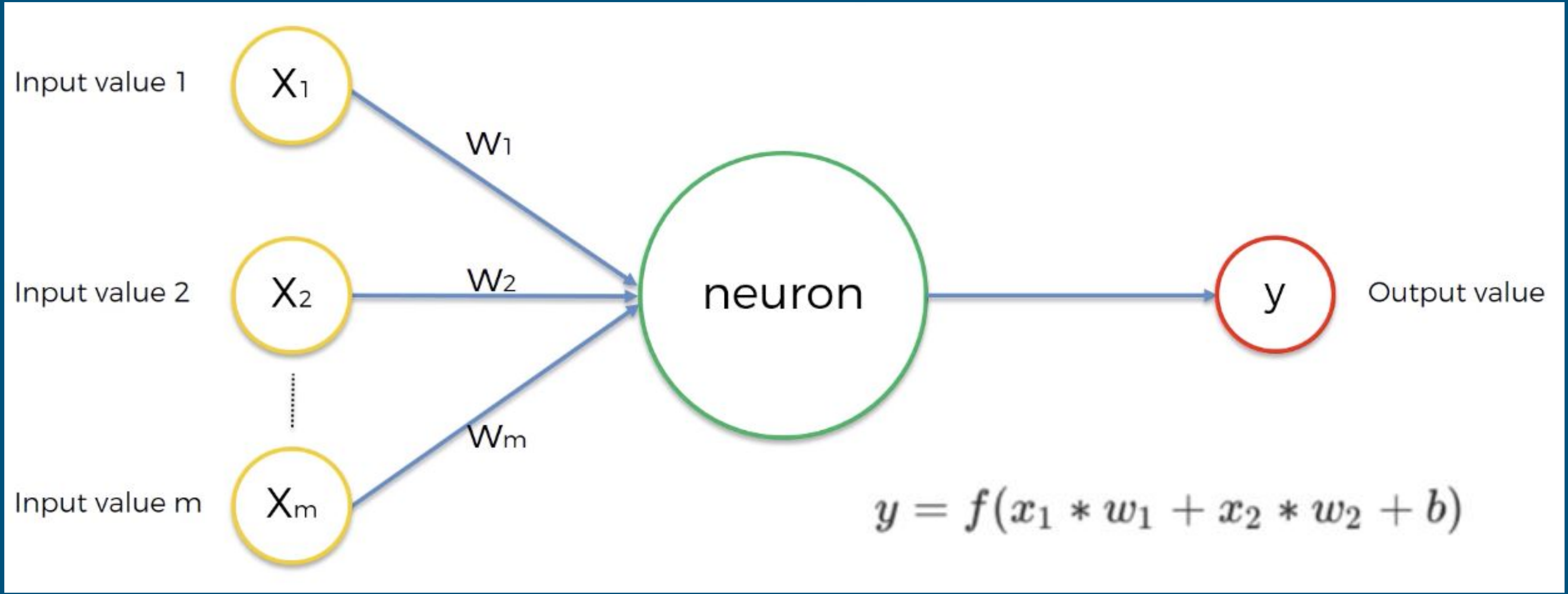
# Deep Learning

Rohan Bhansali and Avi Komarlingam

# Artificial Neural Networks



# The Neuron

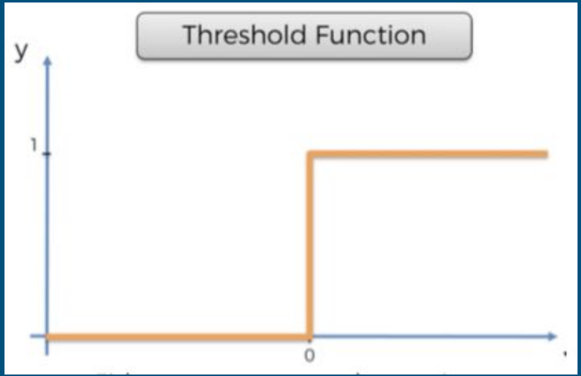


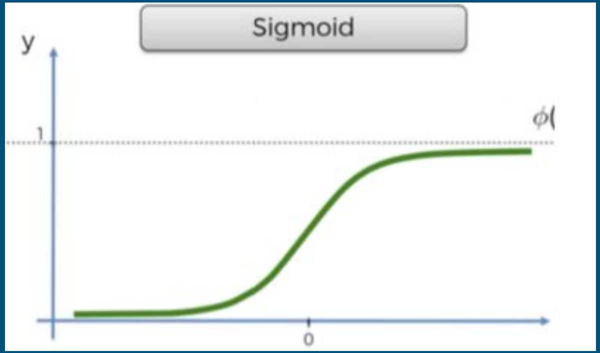
Input value 1
X1
Input value 2
X2
Input value m
Xm
W1
W2
Wm
neuron
y
Output value
$y = f(x_1 * w_1 + x_2 * w_2 + b)$

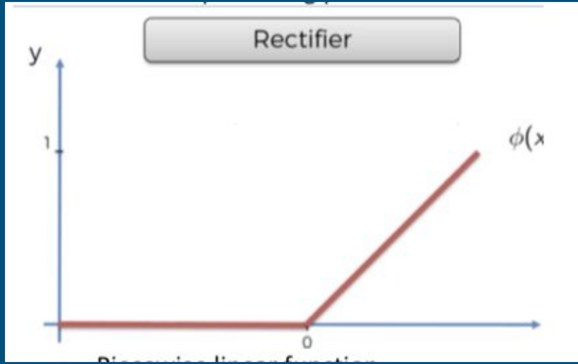
# Activation function

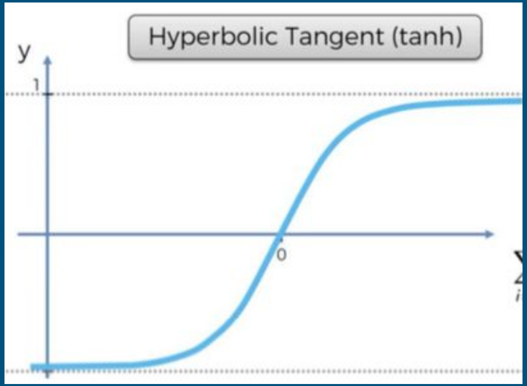
Used to determine if a certain neuron will “fire” or not

Four main functions



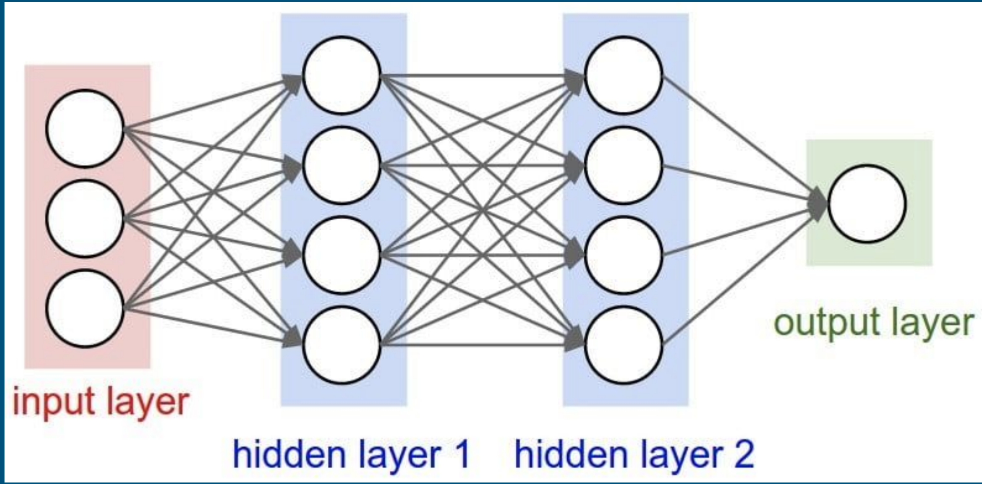



# How do NN’s learn?

- Weights adjust based on cost function to minimize cost
- Back propagation is the process of adjusting the weights to find ideal network





$$C = \sum \tfrac{1}{2}(\hat{y} - y)^2$$

# Back propagation

**STEP 1:** Randomly initialise the weights to small numbers close to 0 (but not 0).

**STEP 2:** Input the first observation of your dataset in the input layer, each feature in one input node.

**STEP 3:** Forward-Propagation: from left to right, the neurons are activated in a way that the impact of each neuron's activation is limited by the weights. Propagate the activations until getting the predicted result y.

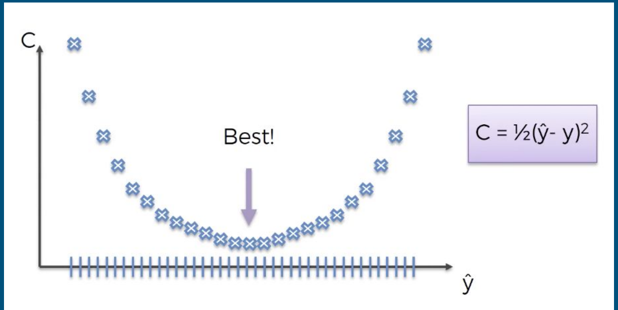
**STEP 4:** Compare the predicted result to the actual result. Measure the generated error.

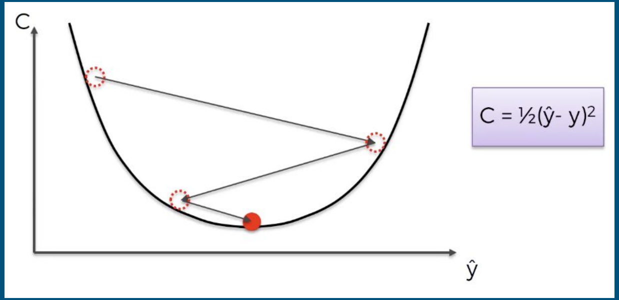
**STEP 5:** Back-Propagation: from right to left, the error is back-propagated. Update the weights according to how much they are responsible for the error. The learning rate decides by how much we update the weight

**STEP 6:** Repeat Steps 1 to 5 and update the weights after each observation (Reinforcement Learning). Or:
Repeat Steps 1 to 5 but update the weights only after a batch of observations (Batch Learning).

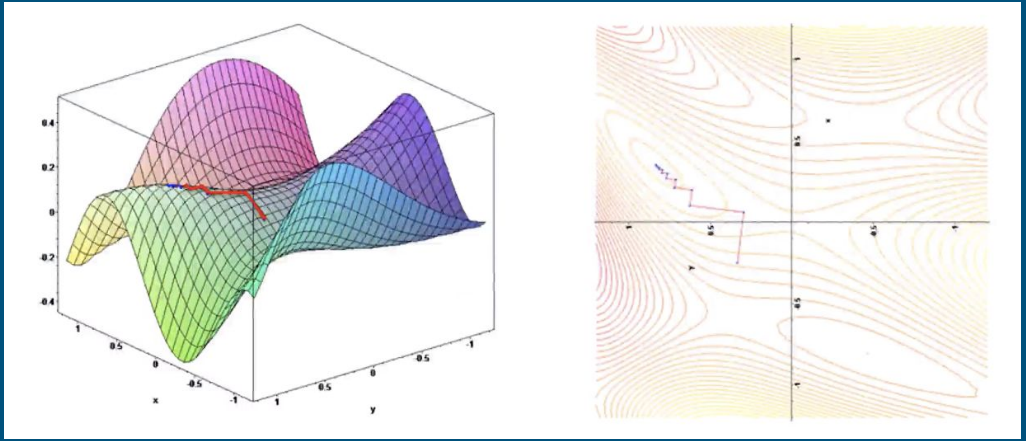
**STEP 7:** When the whole training set passed through the ANN, that makes an epoch. Redo more epochs.

# Gradient descent

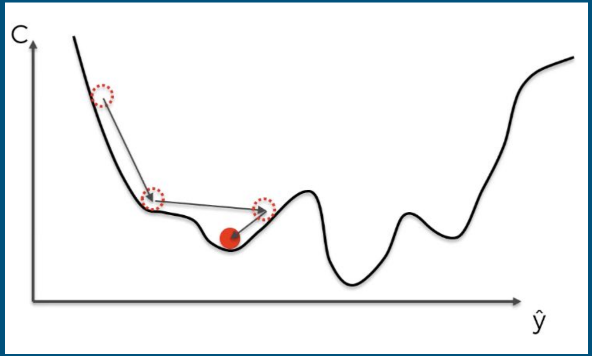



Using the slope at various points in the cost function lets you find the direction in which the weights are optimized



# Stochastic Gradient Descent




Upd w's

| Row ID | Study Hrs | Sleep Hrs | Quiz | Exam |
|---|---|---|---|---|
| 1 | 12 | 6 | 78% | 93% |
| 2 | 22 | 6.5 | 24% | 68% |
| 3 | 115 | 4 | 100% | 95% |
| 4 | 31 | 9 | 67% | 75% |
| 5 | 0 | 10 | 58% | 51% |
| 6 | 5 | 8 | 78% | 60% |
| 7 | 92 | 6 | 82% | 89% |
| 8 | 57 | 8 | 91% | 97% |

Batch Gradient Descent

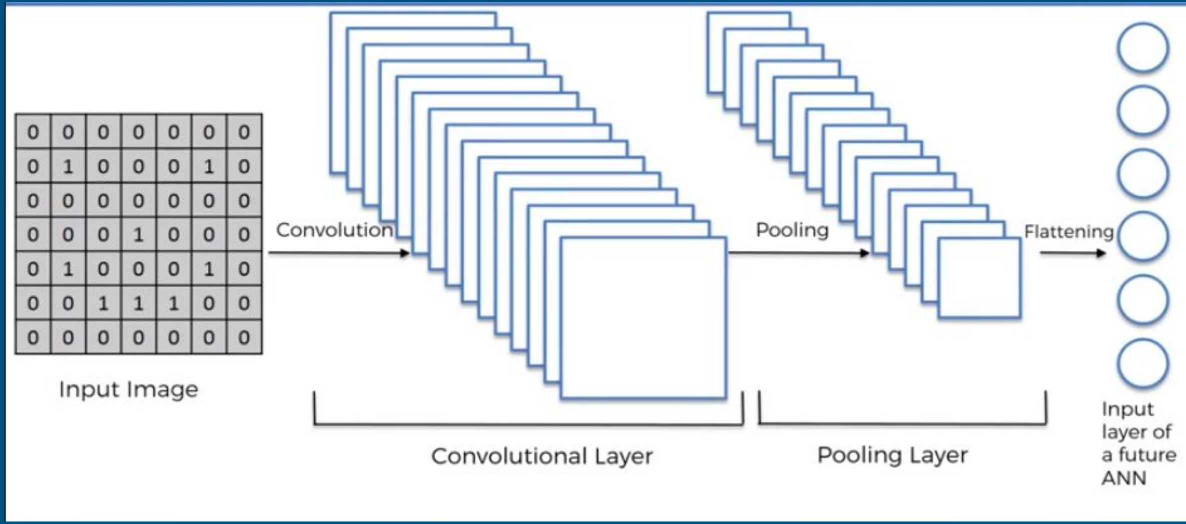
| | Row ID | Study Hrs | Sleep Hrs | Quiz | Exam |
|---|---|---|---|---|---|
| Upd w's | 1 | 12 | 6 | 78% | 93% |
| Upd w's | 2 | 22 | 6.5 | 24% | 68% |
| Upd w's | 3 | 115 | 4 | 100% | 95% |
| Upd w's | 4 | 31 | 9 | 67% | 75% |
| Upd w's | 5 | 0 | 10 | 58% | 51% |
| Upd w's | 6 | 5 | 8 | 78% | 60% |
| Upd w's | 7 | 92 | 6 | 82% | 89% |
| Upd w's | 8 | 57 | 8 | 91% | 97% |

Stochastic Gradient Descent

# Convolutional Neural Networks

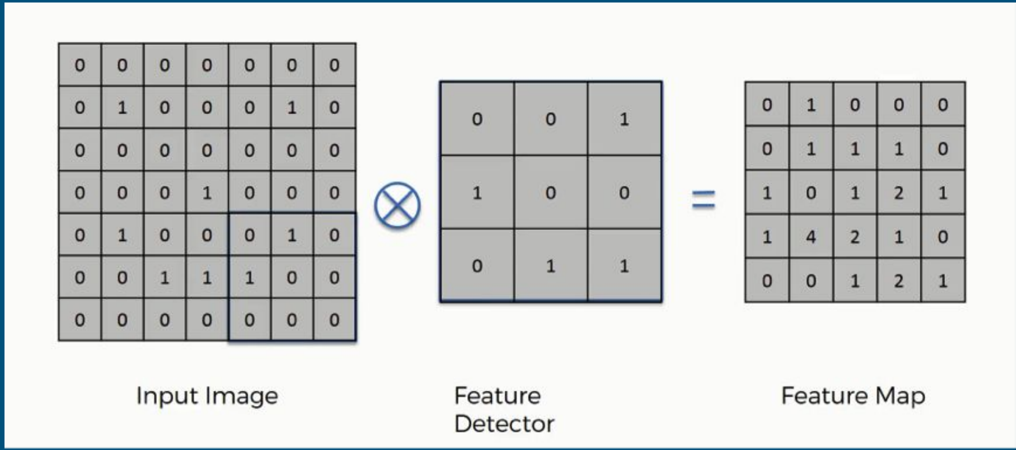
# Usage

- Mainly used for image recognition



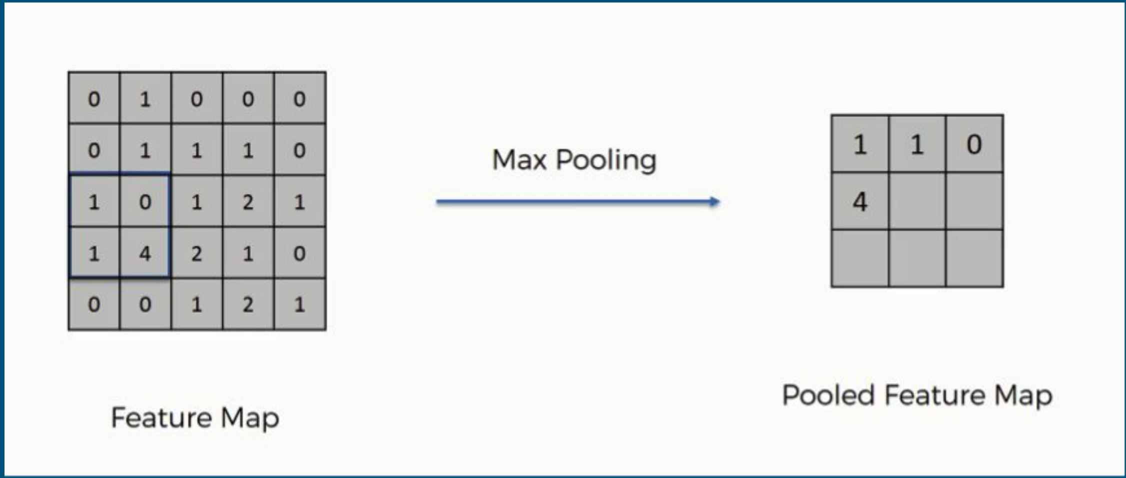
# Convolution Layer

- Feature maps are applied to images in order to extract certain features



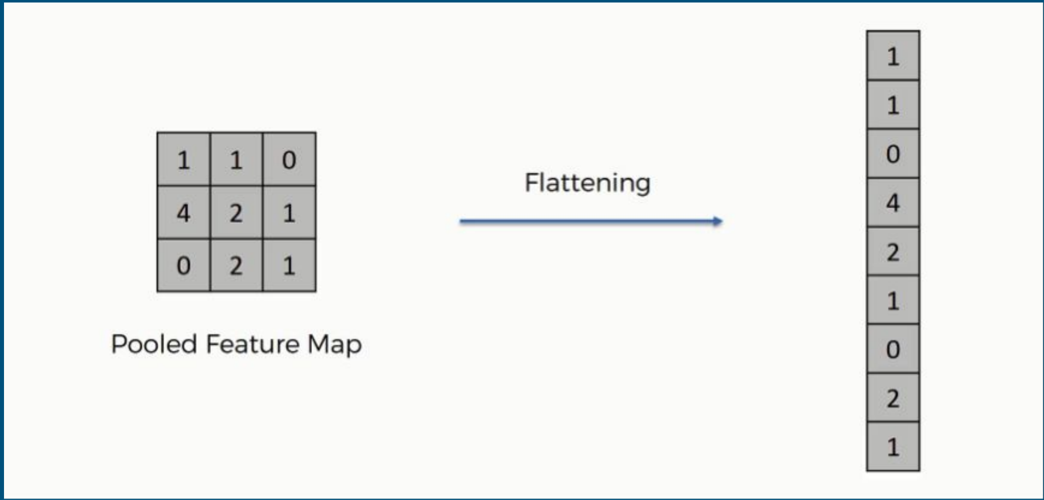
# Pooling

- Average and max pooling, used to reduce the amount of data to work with



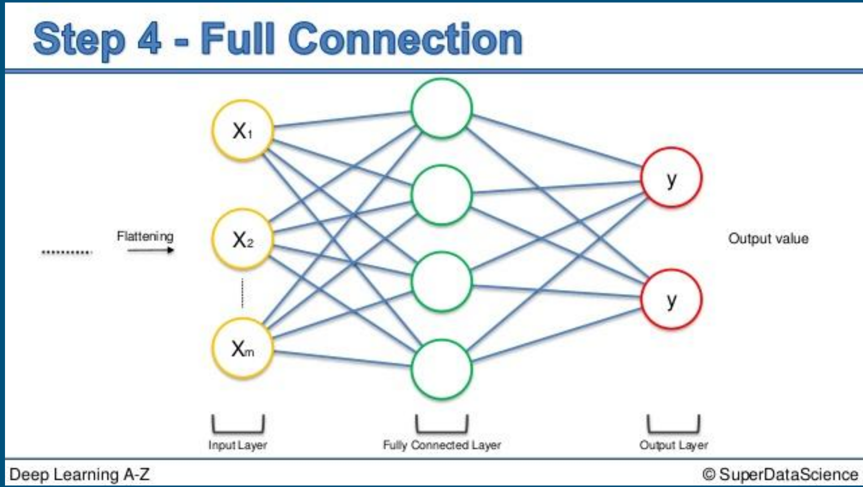
# Flatenning

- Images are converted into a single vector to input into an ANN



# Full Connection

- Flattened vectors are inputted into an ANN

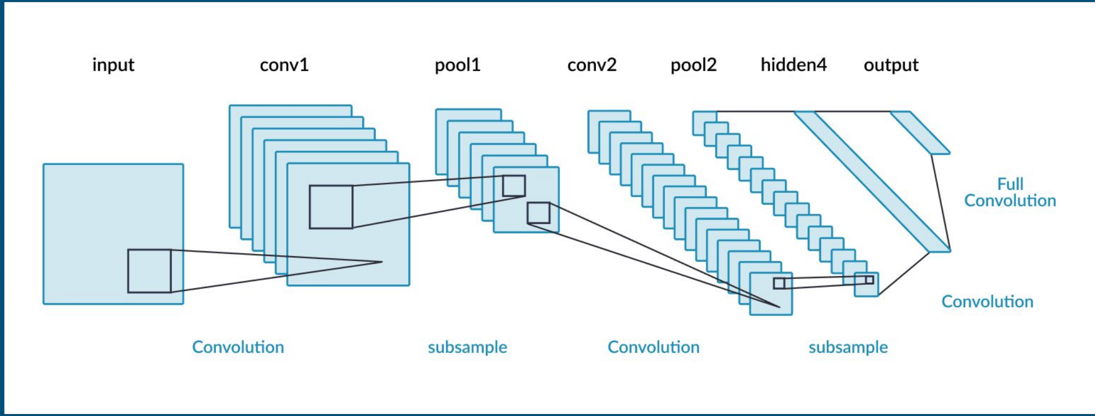


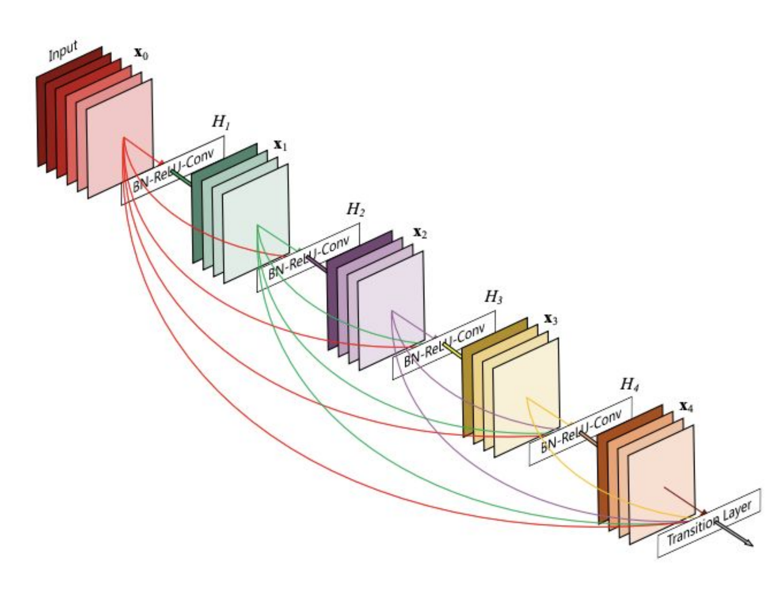
# Softmax & Cross Entropy

- Softmax is applied to the values of an output vector to generate probabilities
- Cross Entropy is used as a method to determine how accurate a model is
- More efficient than other methods such as classification or mean squared error

# DenseNet

- Alleviates the vanishing-gradient problem
- Strengthens feature propagation and reuse
- Substantially reduces the number of parameters



# Even More Different Model Architectures

kNN

| Actual \ Predicted | Enlarged Cardiomediastinum | Lung Lesion | Lung Opacity | Σ |
|---|---|---|---|---|
| Enlarged Cardiomediastinum | 51.7 % | 38.7 % | 9.6 % | 551 |
| Lung Lesion | 36.0 % | 55.3 % | 8.8 % | 684 |
| Lung Opacity | 46.9 % | 43.0 % | 10.1 % | 435 |
| Σ | 735 | 778 | 157 | 1670 |

Logistic Regression

| Actual \ Predicted | Enlarged Cardiomediastinum | Lung Lesion | Lung Opacity | Σ |
|---|---|---|---|---|
| Enlarged Cardiomediastinum | 43.0 % | 35.6 % | 21.4 % | 551 |
| Lung Lesion | 27.2 % | 52.5 % | 20.3 % | 684 |
| Lung Opacity | 32.9 % | 38.4 % | 28.7 % | 435 |
| Σ | 566 | 722 | 382 | 1670 |

SVM

| Actual \ Predicted | Enlarged Cardiomediastinum | Lung Lesion | Lung Opacity | Σ |
|---|---|---|---|---|
| Enlarged Cardiomediastinum | 53.9 % | 22.7 % | 23.4 % | 551 |
| Lung Lesion | 51.3 % | 29.2 % | 19.4 % | 684 |
| Lung Opacity | 54.5 % | 19.5 % | 26.0 % | 435 |
| Σ | 885 | 410 | 375 | 1670 |

# Purpose