



# Machine Learning for Medical Imaging

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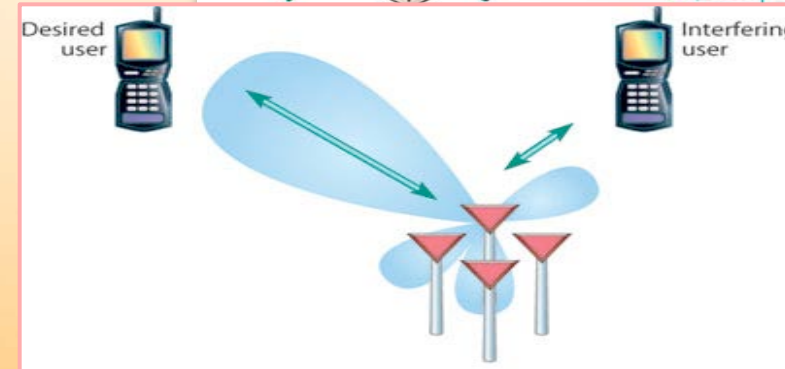
# Wireless Internet Research Laboratory

- Director: Shahrokh Valaee
- Professors on Sabbatical: 13
- Visiting Researchers: 5,  
(LG Electronics, SONY, ETRI, Siradel)
- Post-doctoral Fellows: 9
- PhD Students: 18
- MSc Students: 20
- Visiting PhD Students: 12
- Visiting MSc Students: 3
- Undergrad students: > 60

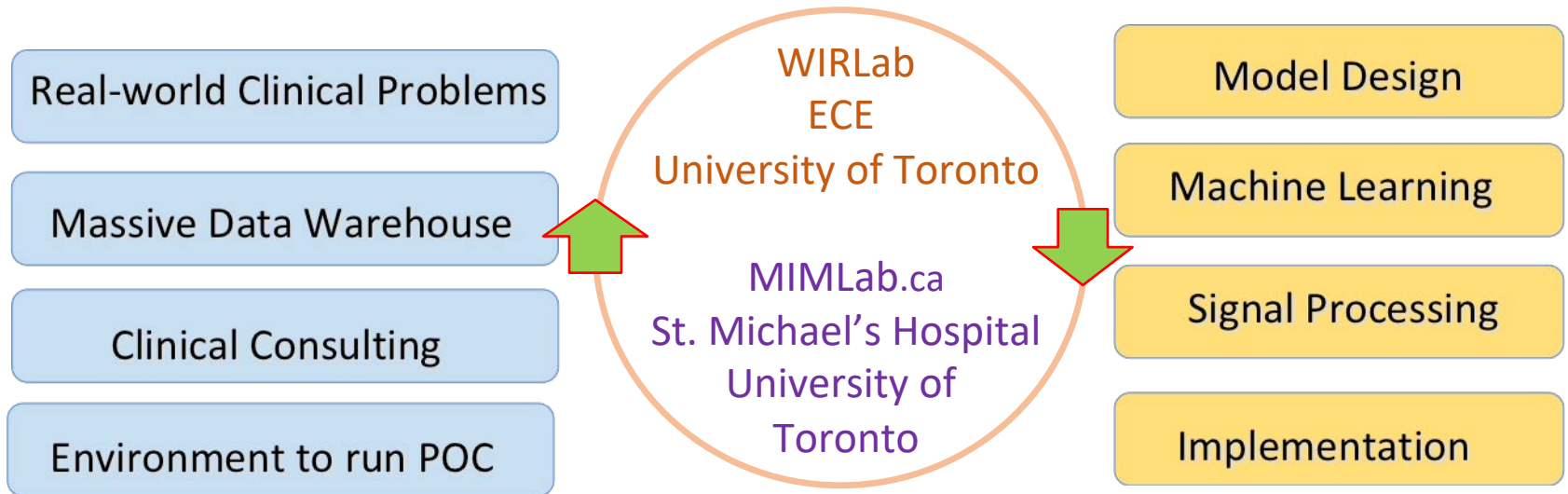


# Research Directions

- Machine learning for medical imaging
- 5G/6G wireless systems
- Localizations of WiFi and LTE terminals
- Vehicular communication



# WIRLab's Collaboration with Two Hospitals to Solve Real-World Medical Problems



About St. Michael's Hospital:

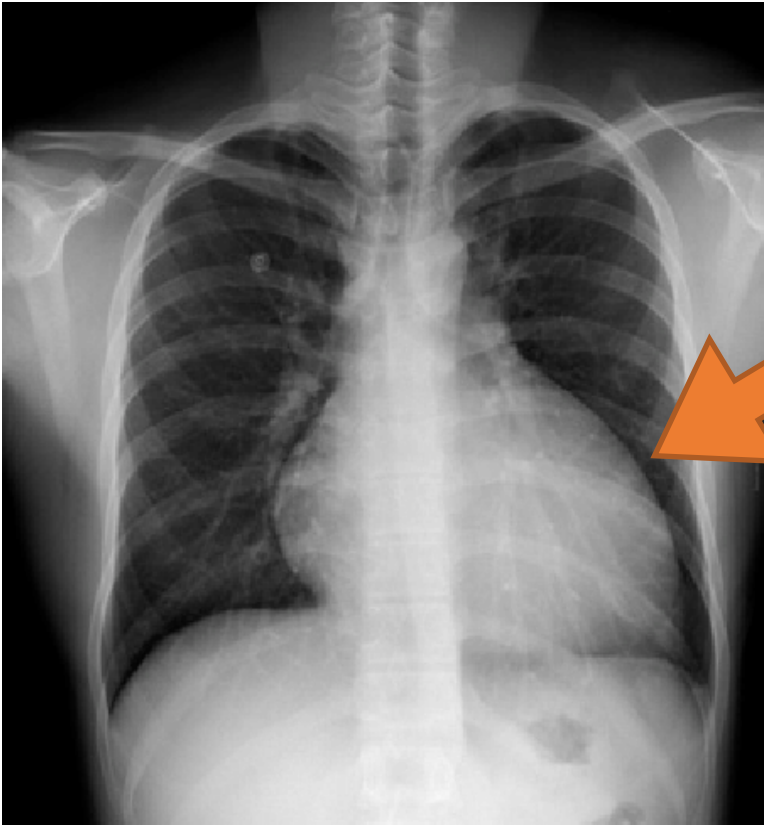
- Downtown Toronto's adult trauma center Hub for neurosurgery, complex cardiac and cardiovascular care, diabetes and osteoporosis care
- Well-known for ICU
- More than 10 Staff Radiologists, Clinical Scientists, and Surgeons Collaborating with our team

**What makes this team-up different:**

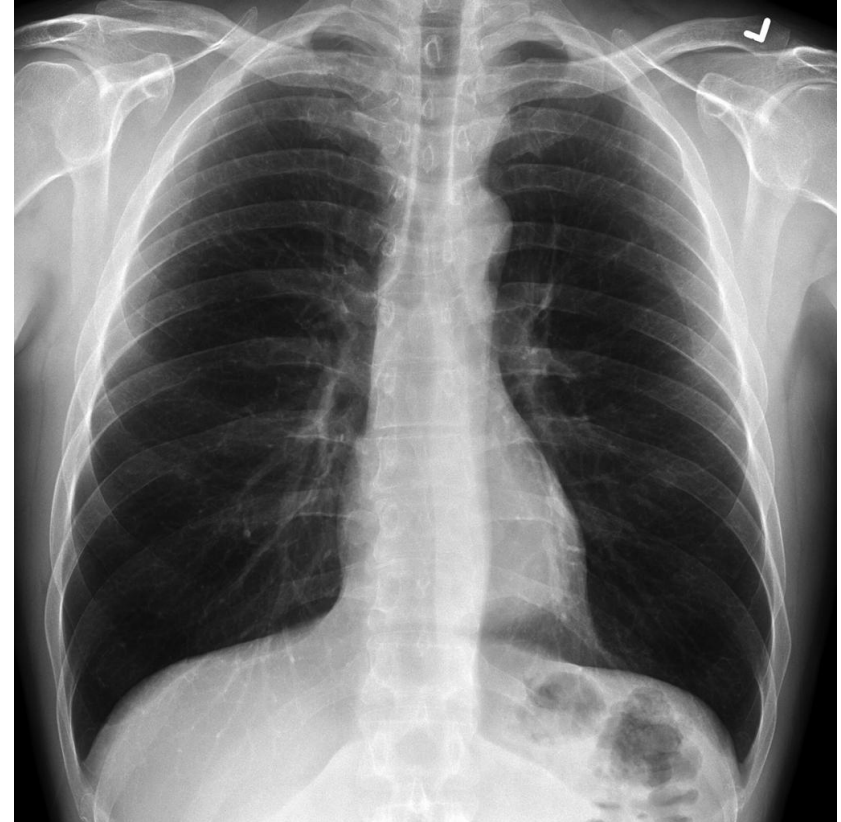
- Daily exposure to clinical problems
- Modeling open real-world clinical problems
- Providing tangible solutions
- Implementing algorithm
- Dynamic team - Moving fast



# What is wrong with this image?



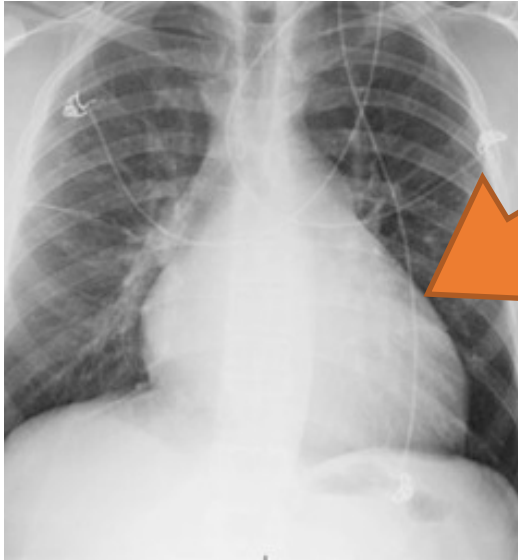
Enlarged Heart (Cardiomegaly)



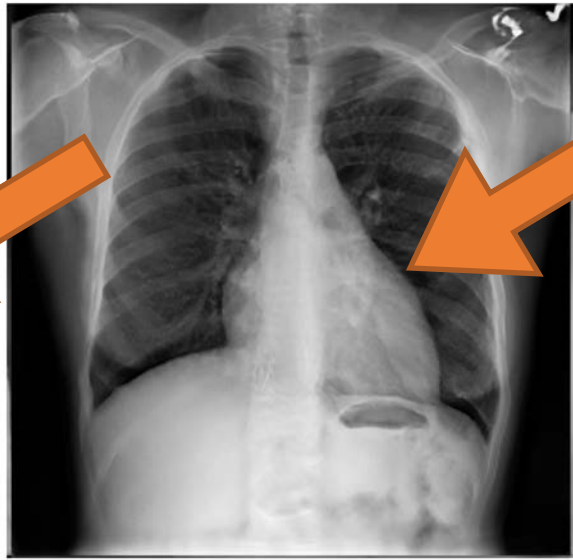
This is a normal case

# Some more Training Images

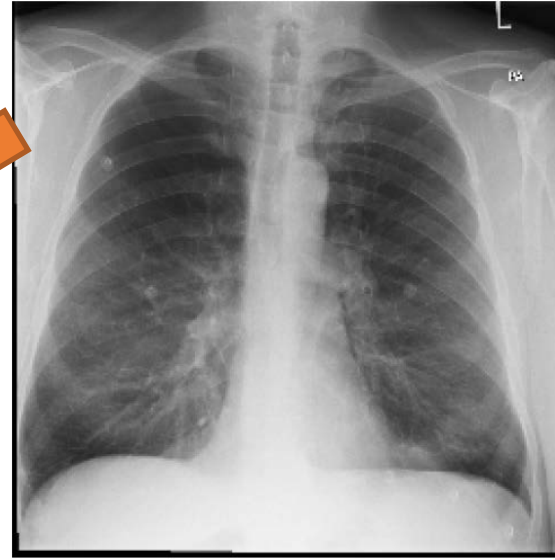
Cardiomegaly



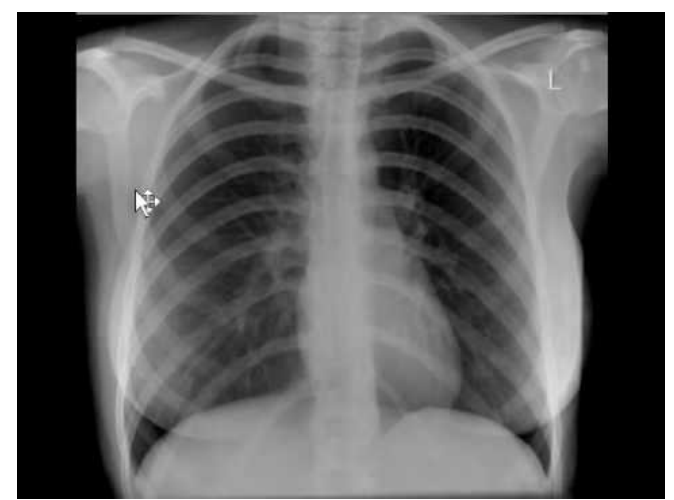
Cardiomegaly



Normal



Normal



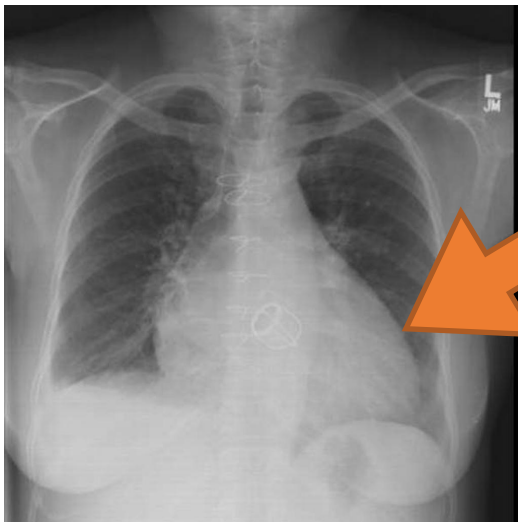
<https://www.sciencedirect.com/topics/neuroscience/cardiomegaly>

<https://lhncbc.nlm.nih.gov/system/files/pub9938.pdf>

# Find the Cardiomegaly X-Ray



We just trained your eyes

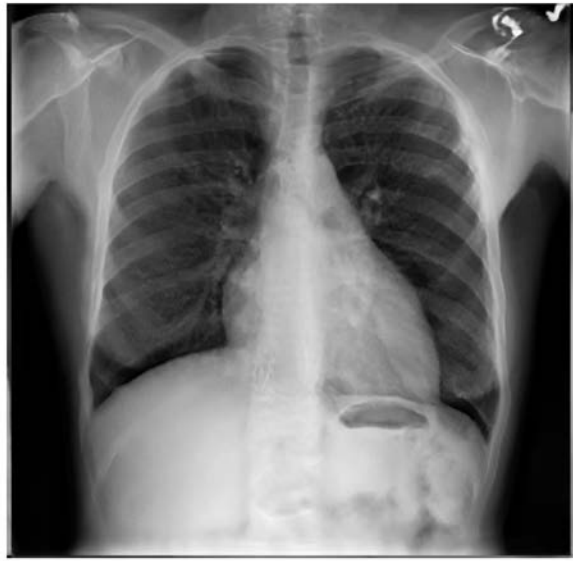


# Back to Training Images



Real Image

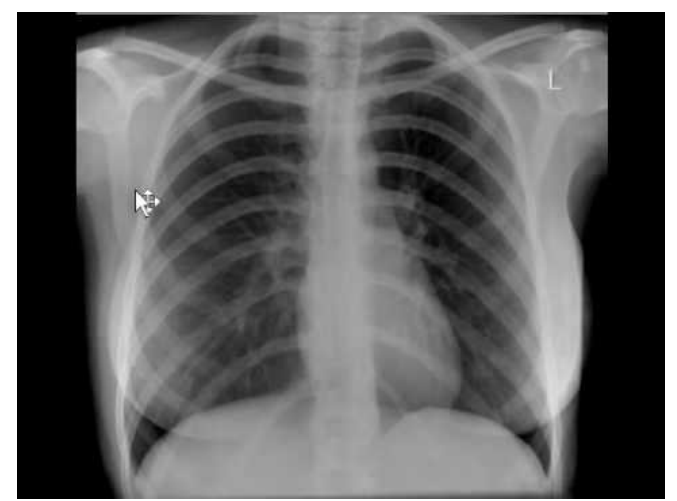
<https://www.sciencedirect.com/topics/neuroscience/cardiomegaly>



Synthesized Image



Real Image



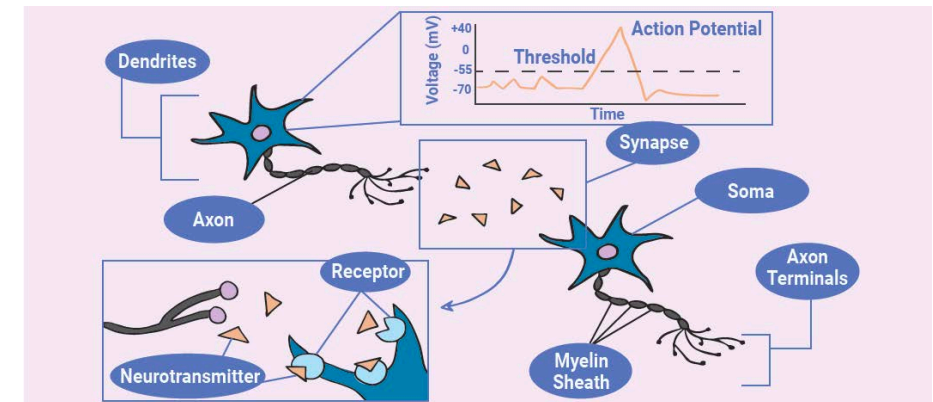
Synthesized Image

<https://lhncbc.nlm.nih.gov/system/files/pub9938.pdf>



# How Does Brain Work?

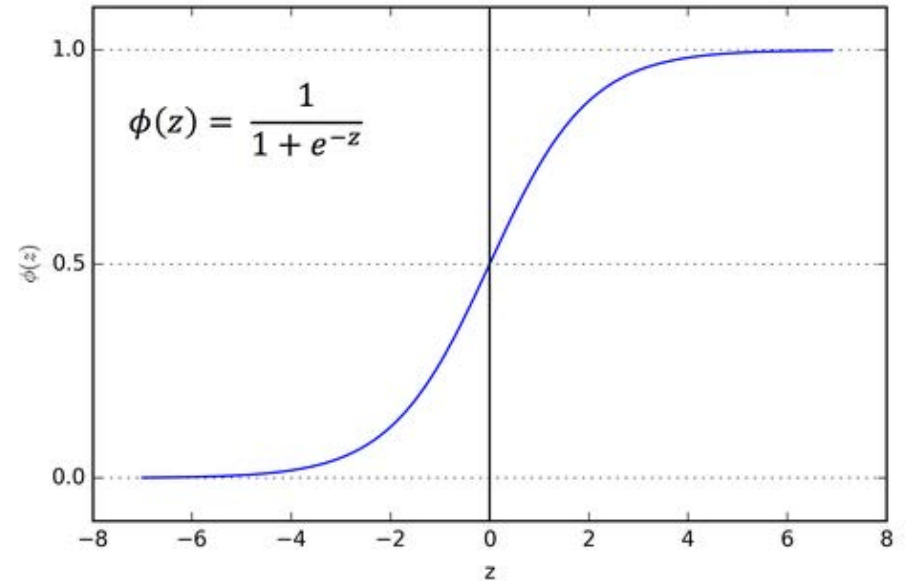
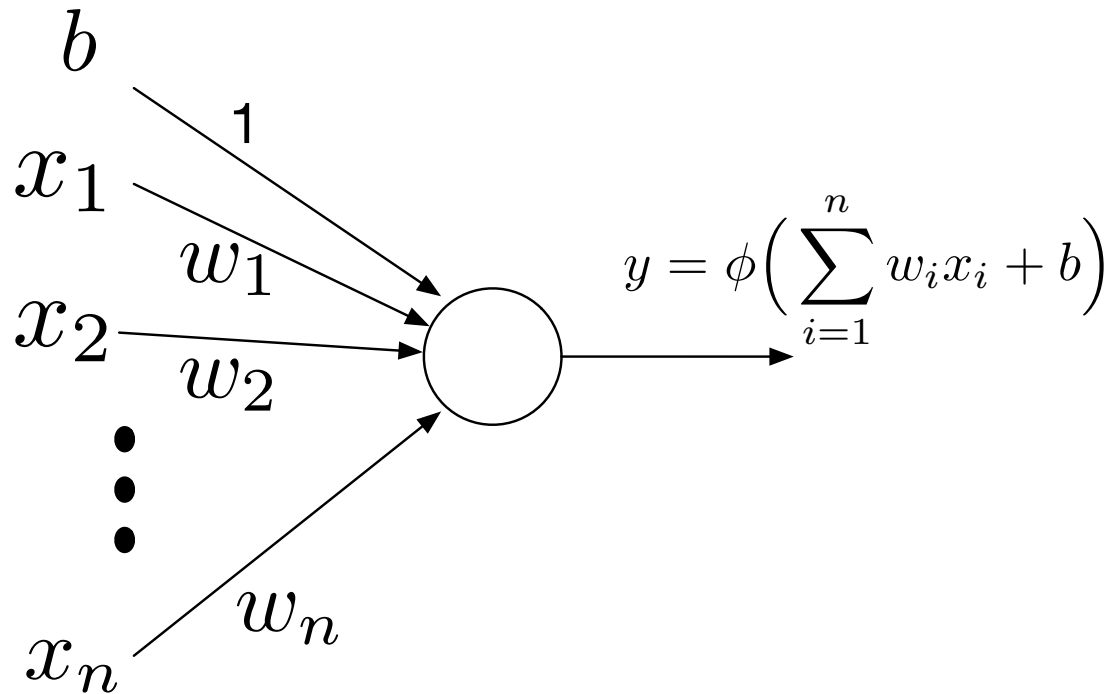
- ❖ Neurons : 80-100 billion nerve cells
  - soma, axon, and dendrites
- ❖ Each neuron is connected to more than 1,000 other neurons
- ❖ A neuron has a negative charge of -70 mV
- ❖ Once the neuron reaches a threshold of -55mV, the neuron to “fire” Electrical signals are converted into chemical signals that travel between neurons



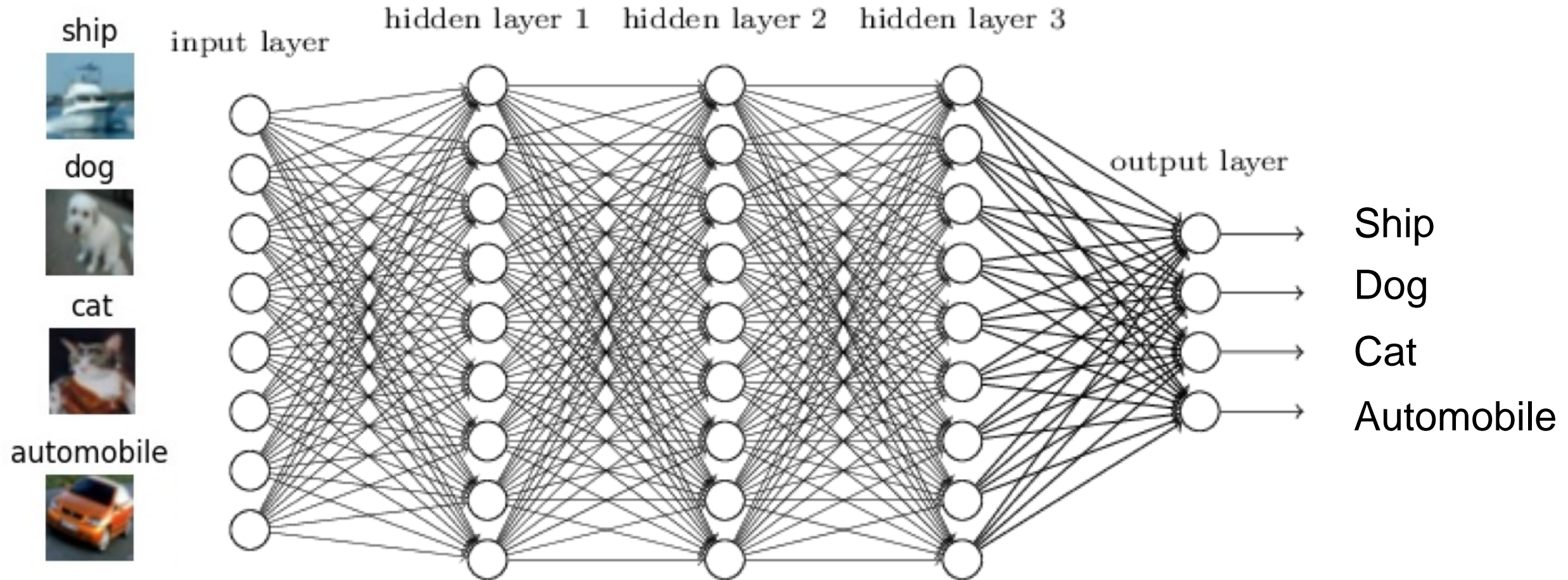
<https://www.dana.org/article/how-does-the-brain-work/>

# How can we train machines to diagnose?

- First we need to build a (machine) neuron

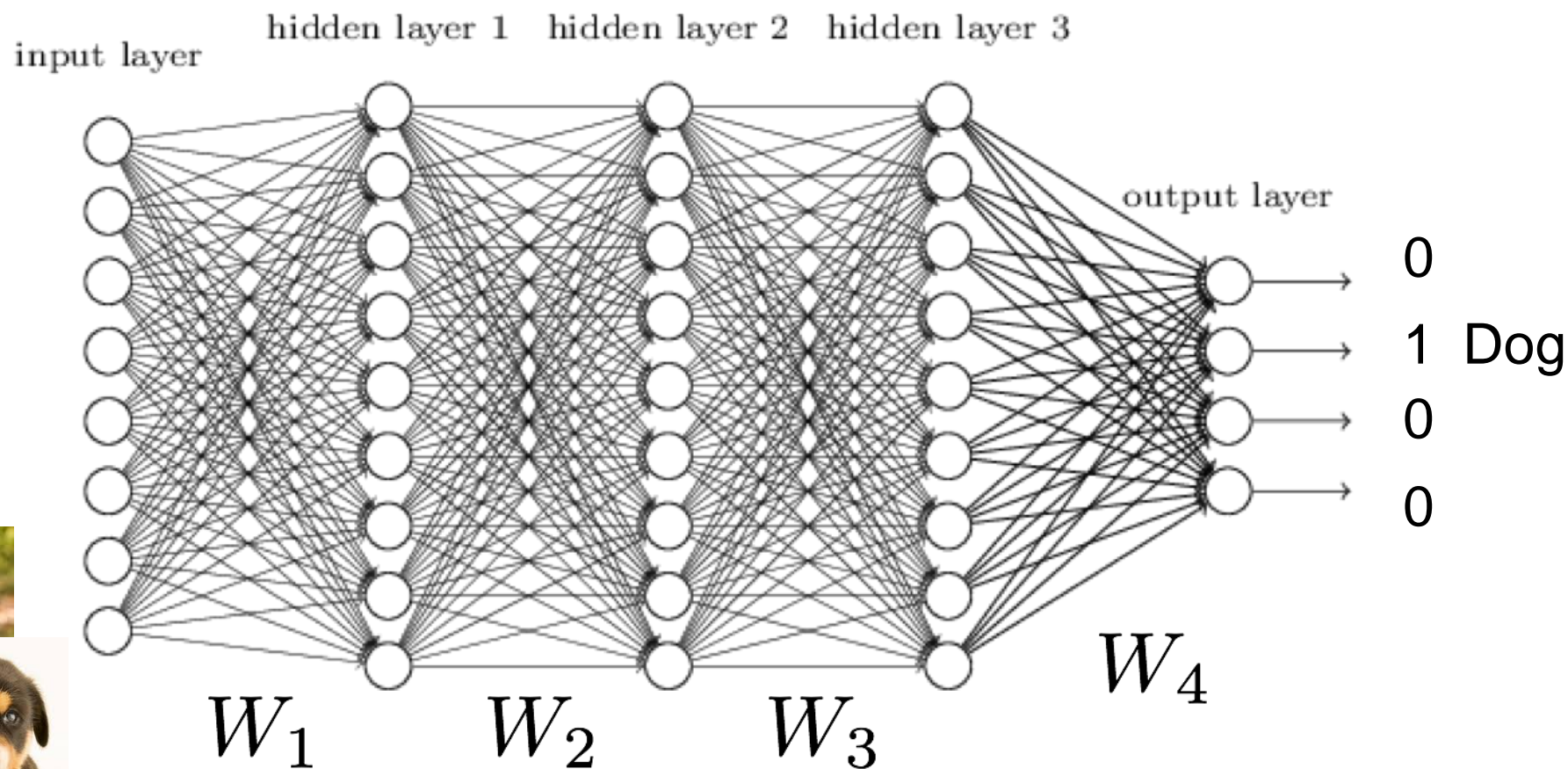


# Network of Neurons





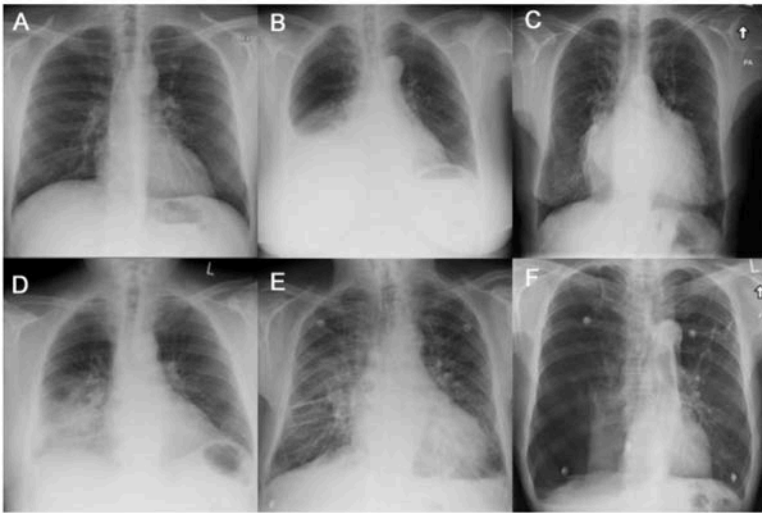
# Training Neural Networks





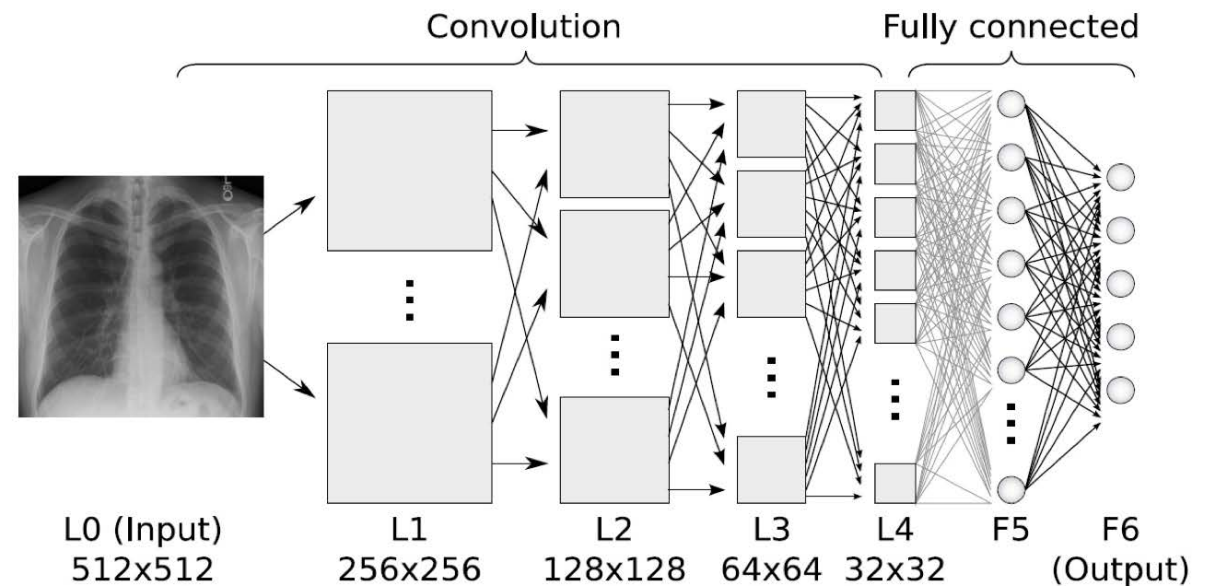
# Classification of Chest Pathology

## Applying Deep Convolutional Networks to Chest X-rays



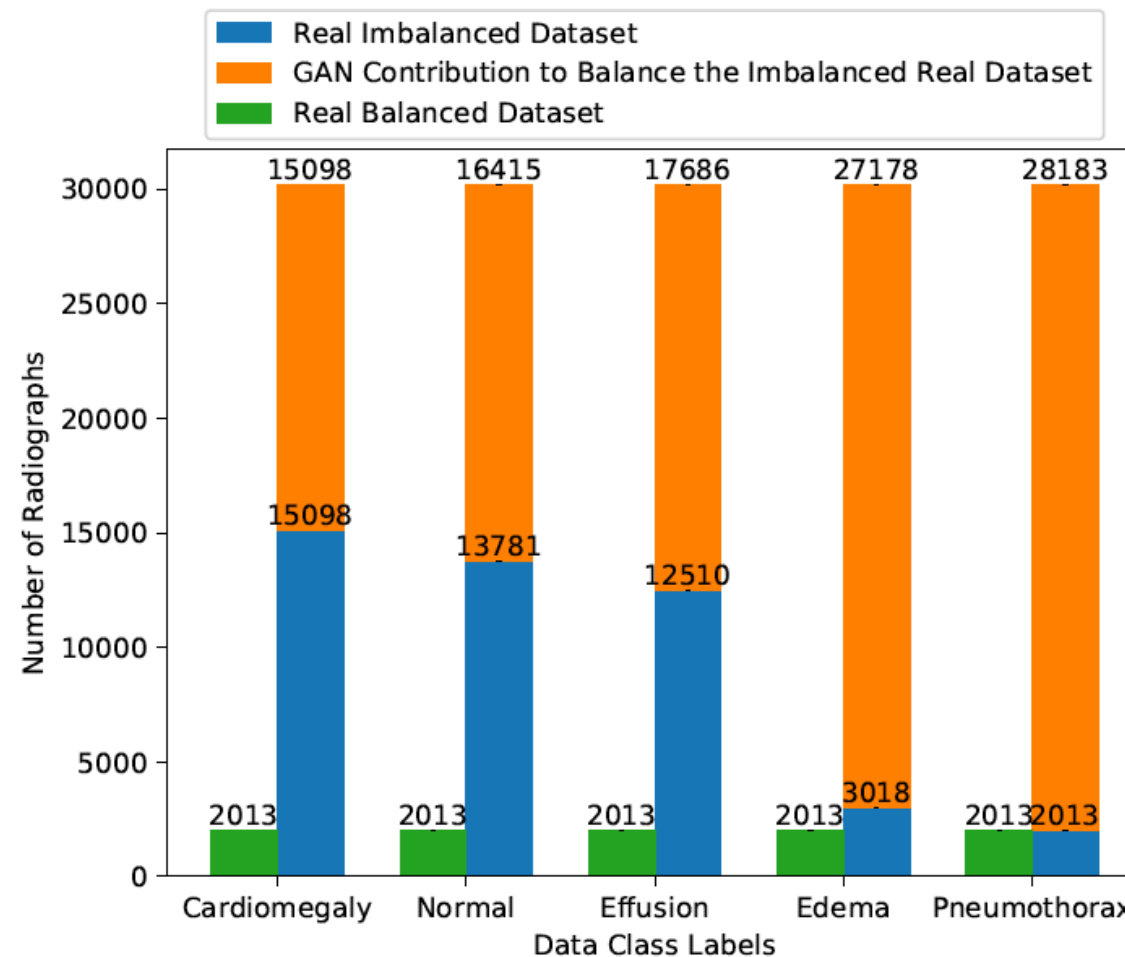
- A - Normal
- B - Effusion
- C - Cardiomegaly
- D - Consolidation
- E - Edema
- F - Pneumothorax

About 20,000 Real Radiographs



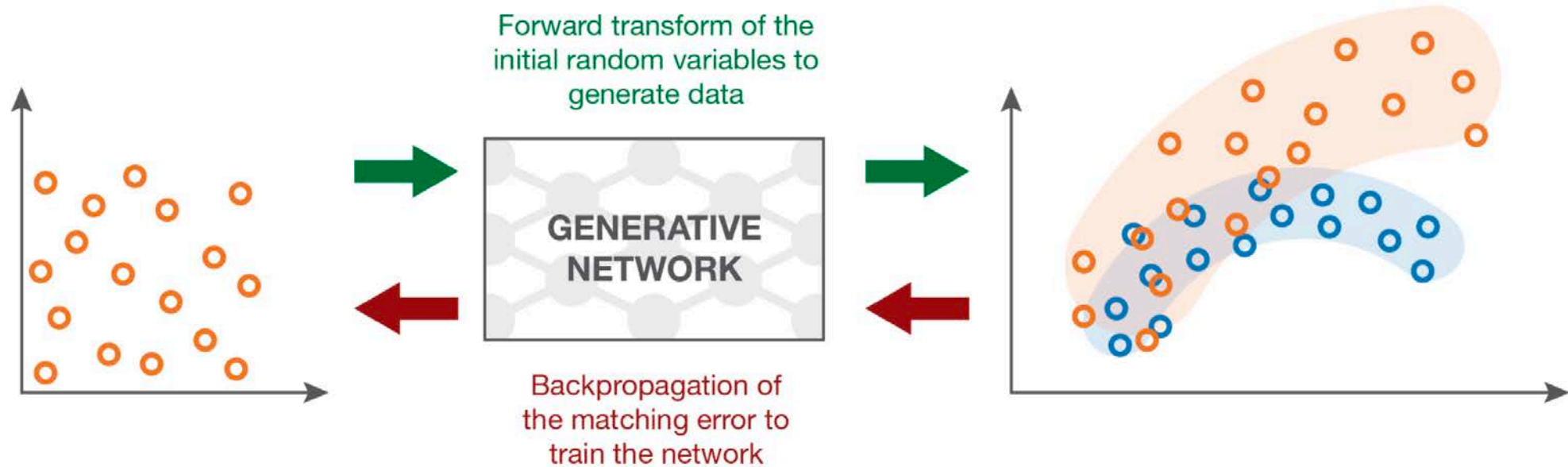
# Unbalanced Labeled Data

- Data is mostly unbalanced in practice
  - More Cardiomegaly cases than Pneumothorax
- Several options:
  - Use all the available data (blue)
  - Use the same number of data samples for each class (green)
  - Synthesize data (blue + orange)



# Generative Adversarial Networks (GAN)

# Generative Networks



Input random variables  
(drawn from a uniform).

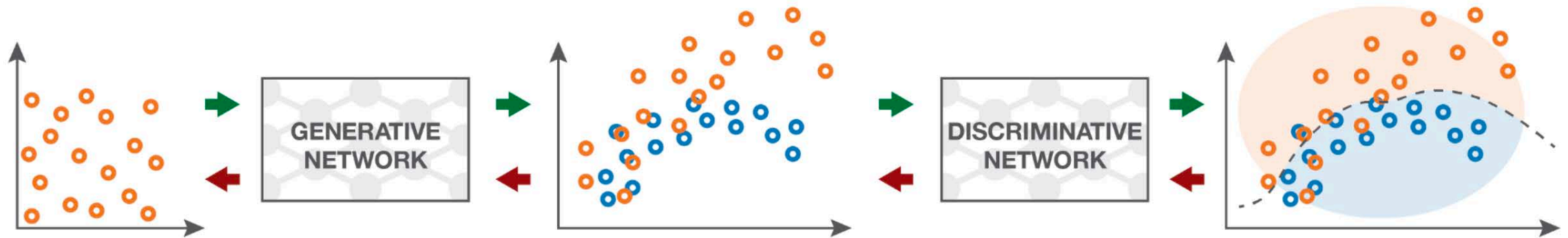
Generative network  
to be trained.

The **generated distribution** is compared  
to the **true distribution** and the "matching error"  
is backpropagated to train the network.

<https://towardsdatascience.com/understanding-generative-adversarial-networks-gans-cd6e4651a29>



# Generative Adversarial Networks (GAN)



Input random variables.

The generative network is trained to **maximise** the final classification error.

The **generated distribution** and the **true distribution** are not compared directly.

The discriminative network is trained to **minimise** the final classification error.

The classification error is the basis metric for the training of both networks.

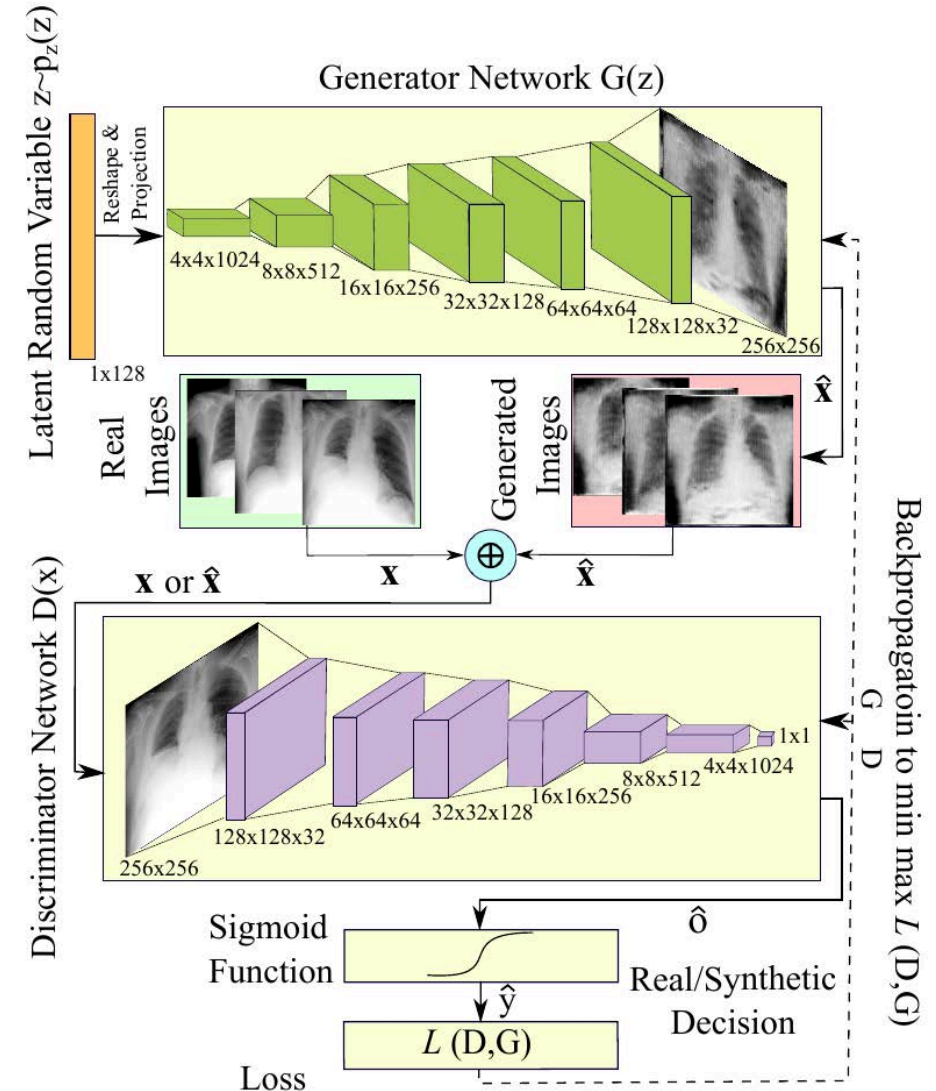
<https://towardsdatascience.com/understanding-generative-adversarial-networks-gans-cd6e4651a29>

# Who are these celebrities?



# Synthesizing Chest X-Rays

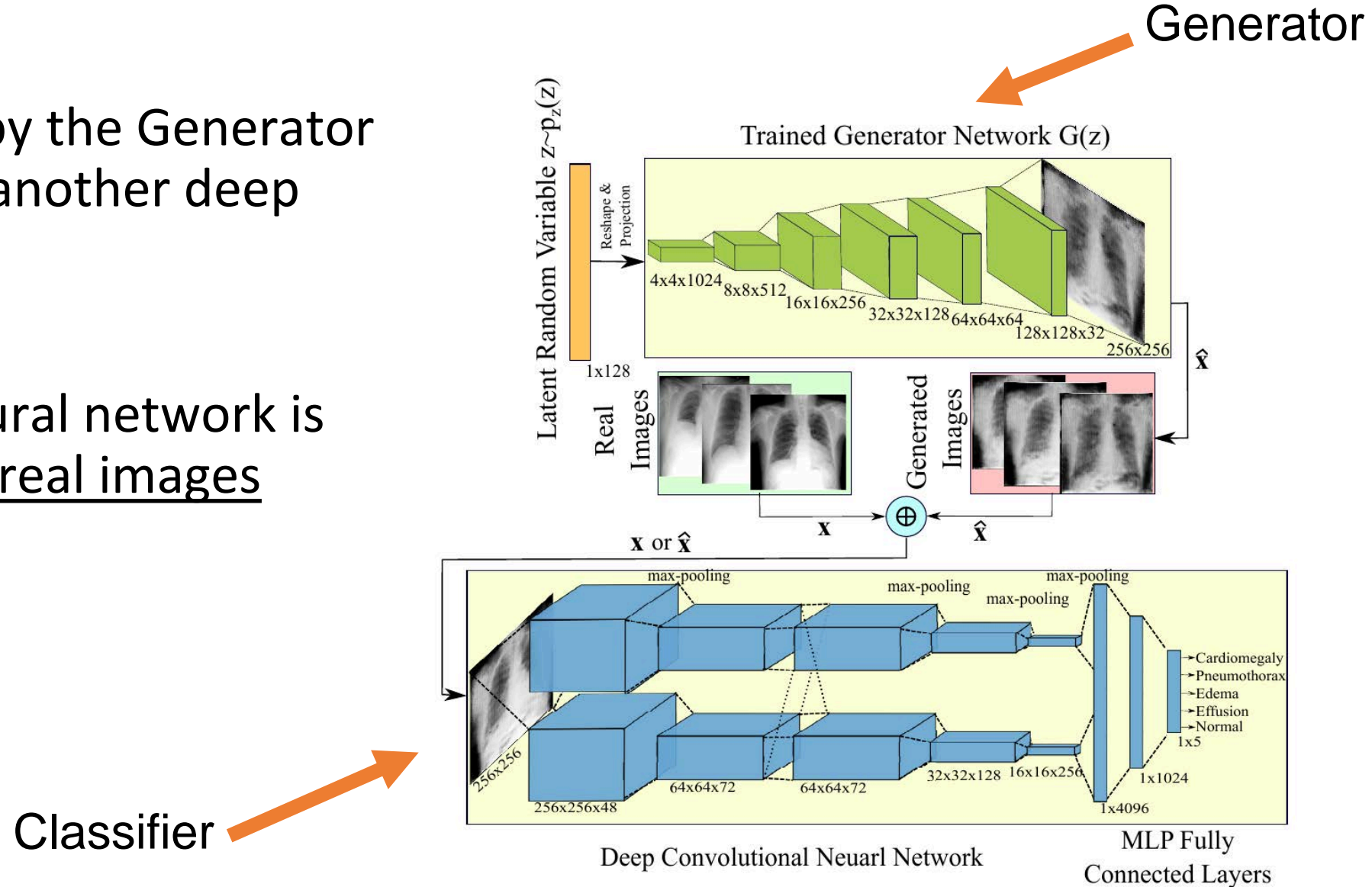
- Generative Adversarial Networks are composed of two parts
  - **Generator Network**
  - **Discriminator Network**
- Generator synthesizes Chest X-rays
- Discriminator classifies inputs images as real or synthesized images
- When Discriminator cannot classify properly, the Generator has been fully trained (Generator can fool the Discriminator)





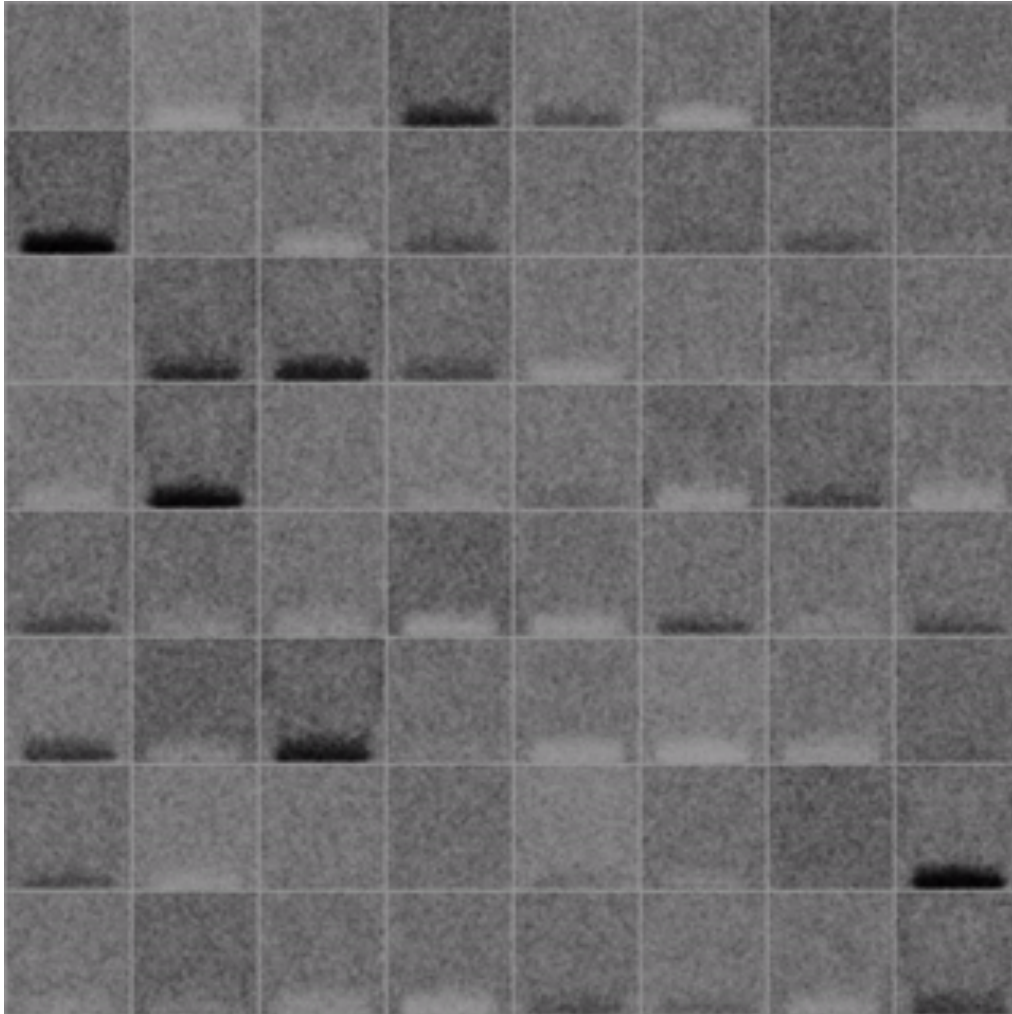
# Using Synthesized Images for Training

- Synthesized images by the Generator can be used to train another deep neural network
- The trained deep neural network is then used to classify real images

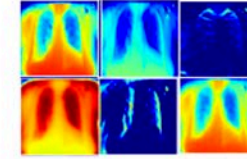




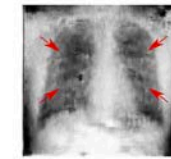
# Generate Chest Radiographs with Generative Adversarial Networks (GAN)



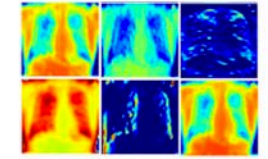
(a) Edema-R



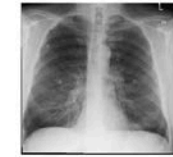
(b) Features after first layer activation function for (a)



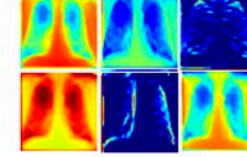
(c) Edema-S



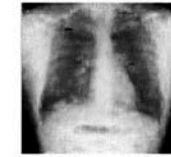
(d) Features after first layer activation function for (c)



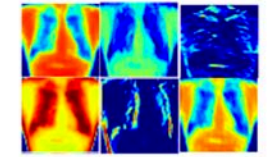
(e) Normal-R



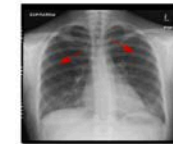
(f) Features after first layer activation function for (e)



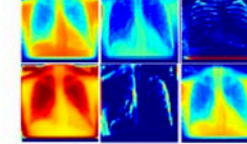
(g) Normal-S



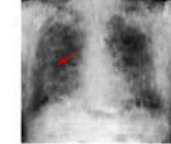
(h) Features after first layer activation function for (g)



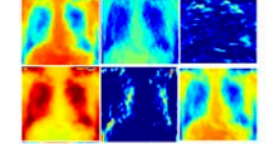
(i) Pneumothorax-R



(j) Features after first layer activation function for (i)



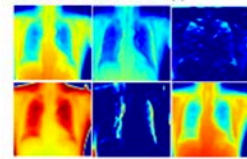
(k) Pneumothorax-S



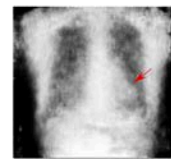
(l) Features after first layer activation function for (k)



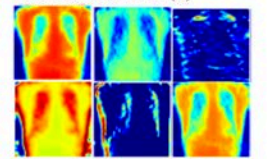
(m) Cardiomegaly-R



(n) Features after first layer activation function for (m)



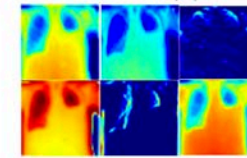
(o) Cardiomegaly-S



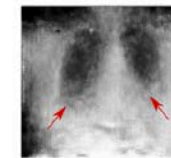
(p) Features after first layer activation function for (o)



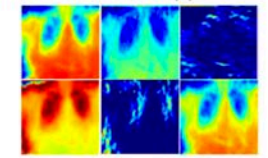
(q) Effusion-R



(r) Features after first layer activation function for (q)

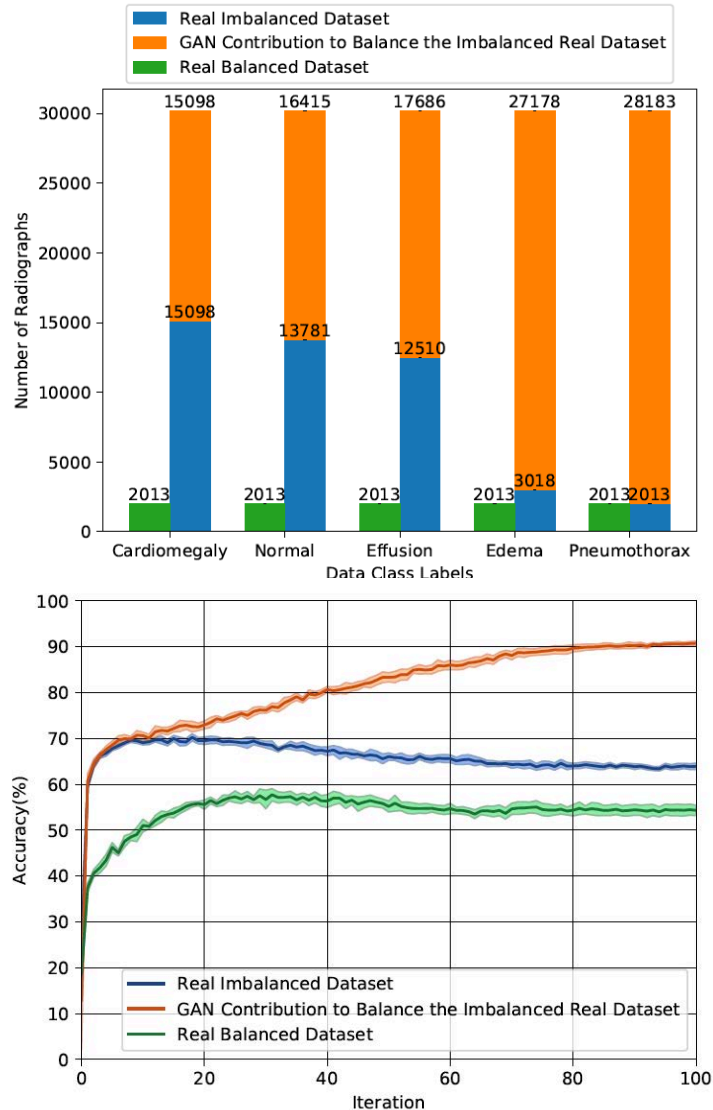


(s) Effusion-S



(t) Features after first layer activation function for (s)

# Chest Pathology with Generated Radiographs



- DS1: Real unbalanced dataset
- DS2: Real + Synthesized dataset
- DS3: Real balanced dataset

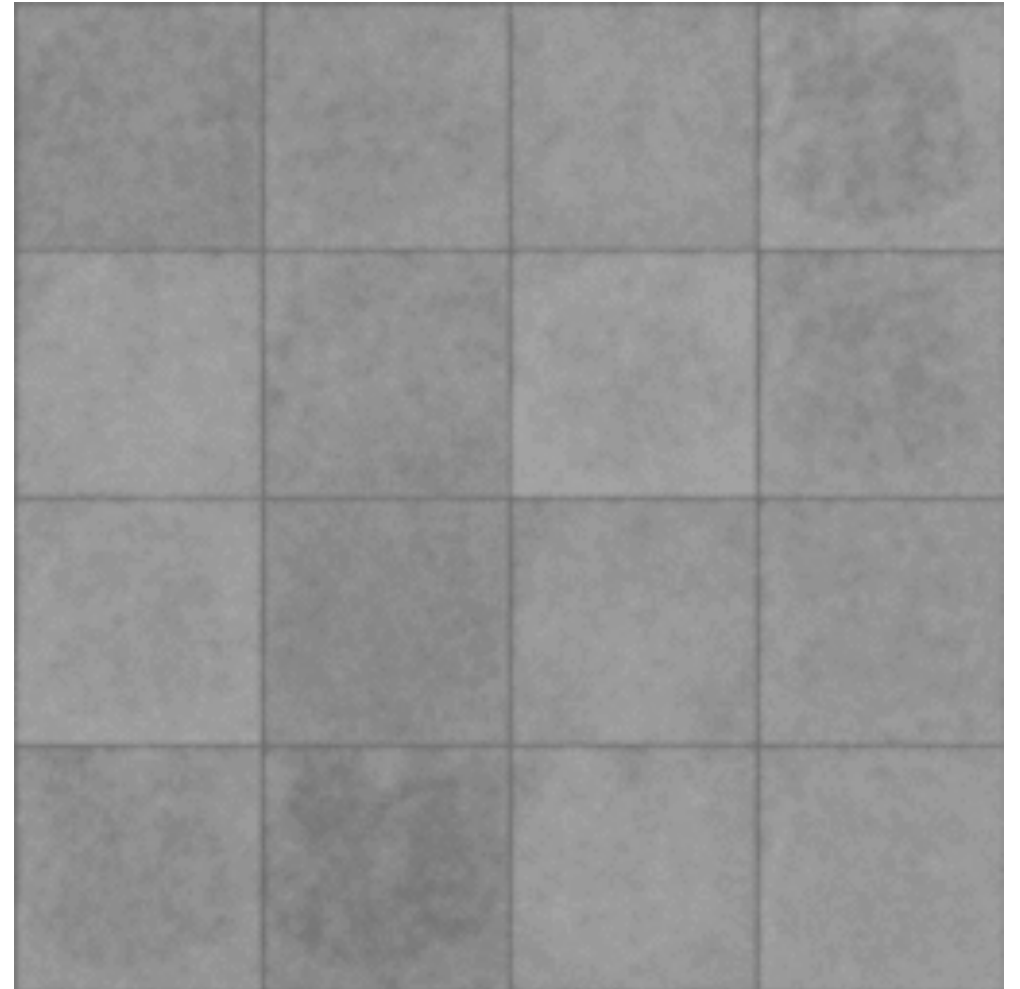
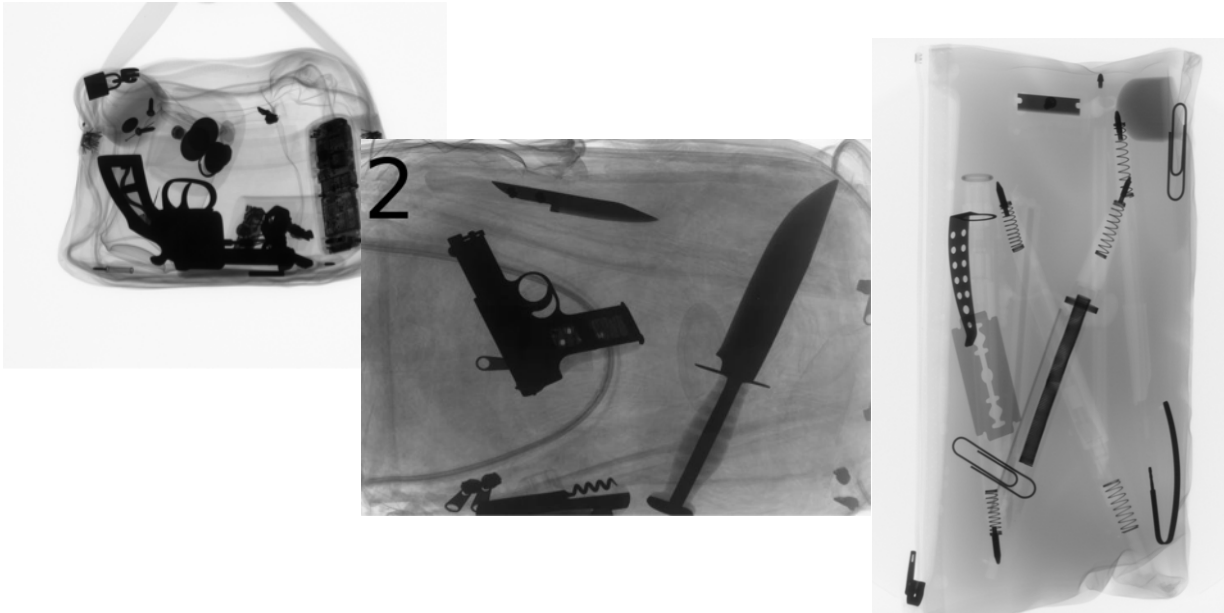
Model	Dataset	Per-Class Accuracy (%)					Accuracy (%)
		Cardiomegaly	Normal	Effusion	Edema	Pneumothorax	
AlexNet	DS1	79.15	77.75	73.64	65.86	57.99	70.87±0.47
	DS2	95.31	95.02	91.19	89.68	88.84	92.10±0.41
	DS3	71.73	72.53	51.23	50.12	48.92	58.90±0.48
GoogLeNet	DS1	80.64	59.57	74.07	68.93	59.57	71.72±0.62
	DS2	96.64	89.39	94.75	90.62	89.39	<b>93.35±0.52</b>
	DS3	75.49	48.19	53.00	44.65	48.19	59.72±0.84

# Privacy Preserving

- Hospitals are bound by privacy of patients
- X-rays cannot be easily moved to outside hospital servers
  - There exist strict codes on how data can be utilized for research purposes
- Synthesized images do not belong to any human being
- Synthesized images can be easily ported without privacy concerns

# Luggage Screening

- Anomalous data for screening application is limited.
- We can generate data using adversarial networks





# Summary

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- Machine Learning can help physicians to better diagnose diseases
  - Cannot replace physicians yet
- Neural Networks are a class of machine learning methods that show very high accuracy
- Deep Neural Networks need a large number of data samples for training
- In the absence of data, generative adversarial networks can synthesize data that can then be for training deep neural networks
- Application of synthesized data for network training results in a very high classification accuracy