Deep Learning at Lilly

Automatic Diabetic Retinopathy Detection

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Acknowledgments

- Haoda Fu (Supervisor, RDSA)
- Xuanyao He (GSS, DBU)
- Jeffery Kriske (IT)
- Lilly HPC
- GSS and Internship program

Highlights

- Expanded Lilly capabilities in Deep Learning technology
- Explored state-of-the-art computer vision research
- Engineered an automatic Diabetic Retinopathy grading algorithm
- Developed an tutorial and best-practices guideline

Background

- **Why** Deep Learning?
- **What** can Deep Learning do?
- **How** does Deep Learning work?
- **How** to apply Deep Learning?

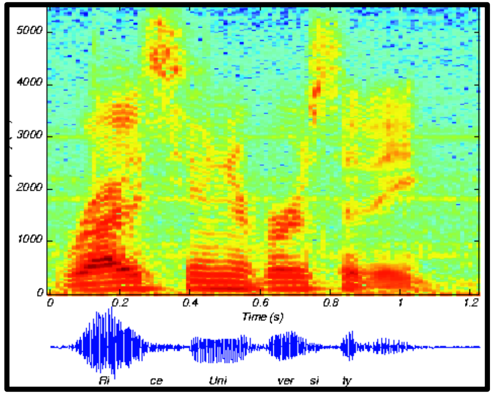
Deep Learning

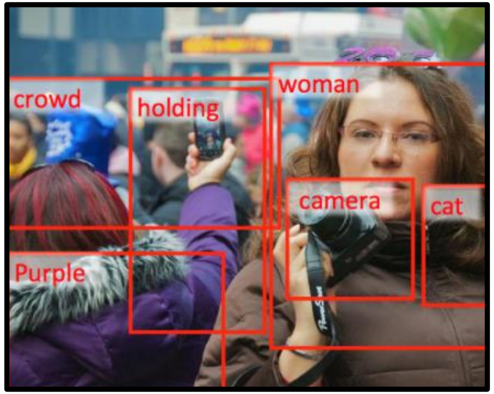
- Branch of machine learning
- Concerned with learning from data
- Study of artificial neural networks
- Related to Artificial Intelligence (AI)

Why Deep Learning?

- Broadly and commercially applicable
- Rapidly growing field
- Engagement in community
- Burgeoning open-source tools

What Can Deep Learning Do?





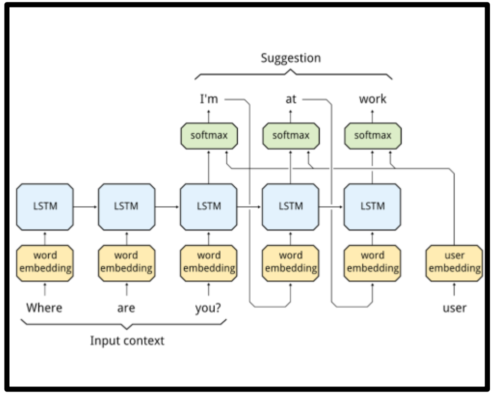
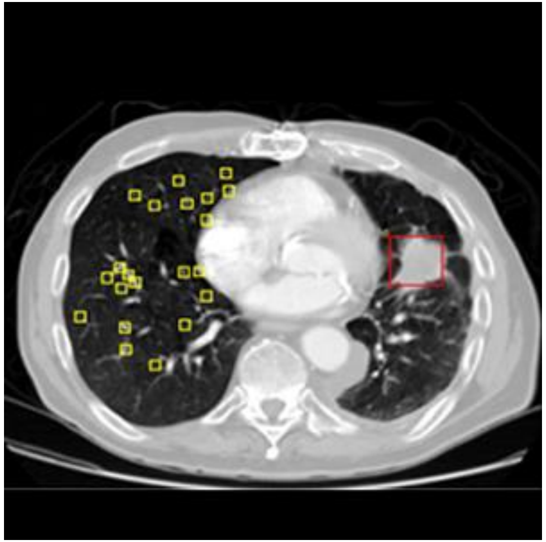


Image Source: *Google Images*

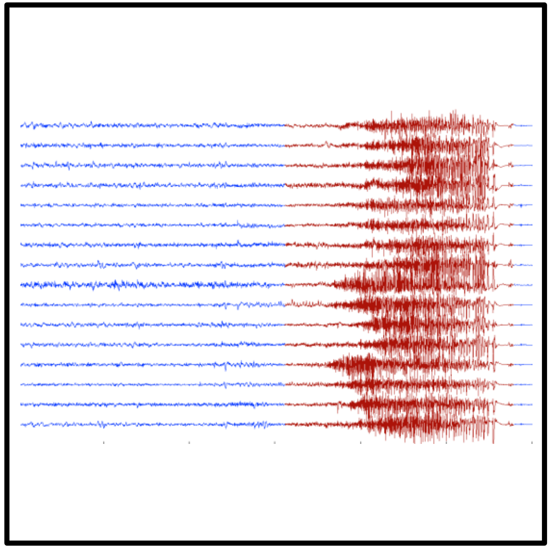
Deep Learning in Medicine

- Data-rich and data-driven field
- Wealth of problems to solve
- Potential to improve patient well-being
- Growing interest in applying new technologies

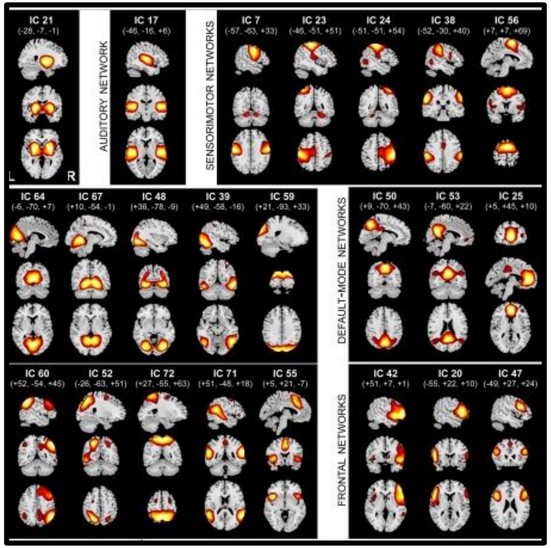
Medical Diagnostics



Source: *Kaggle, Data Science Bowl 2017*



Source: *Kaggle, Seizure Prediction*

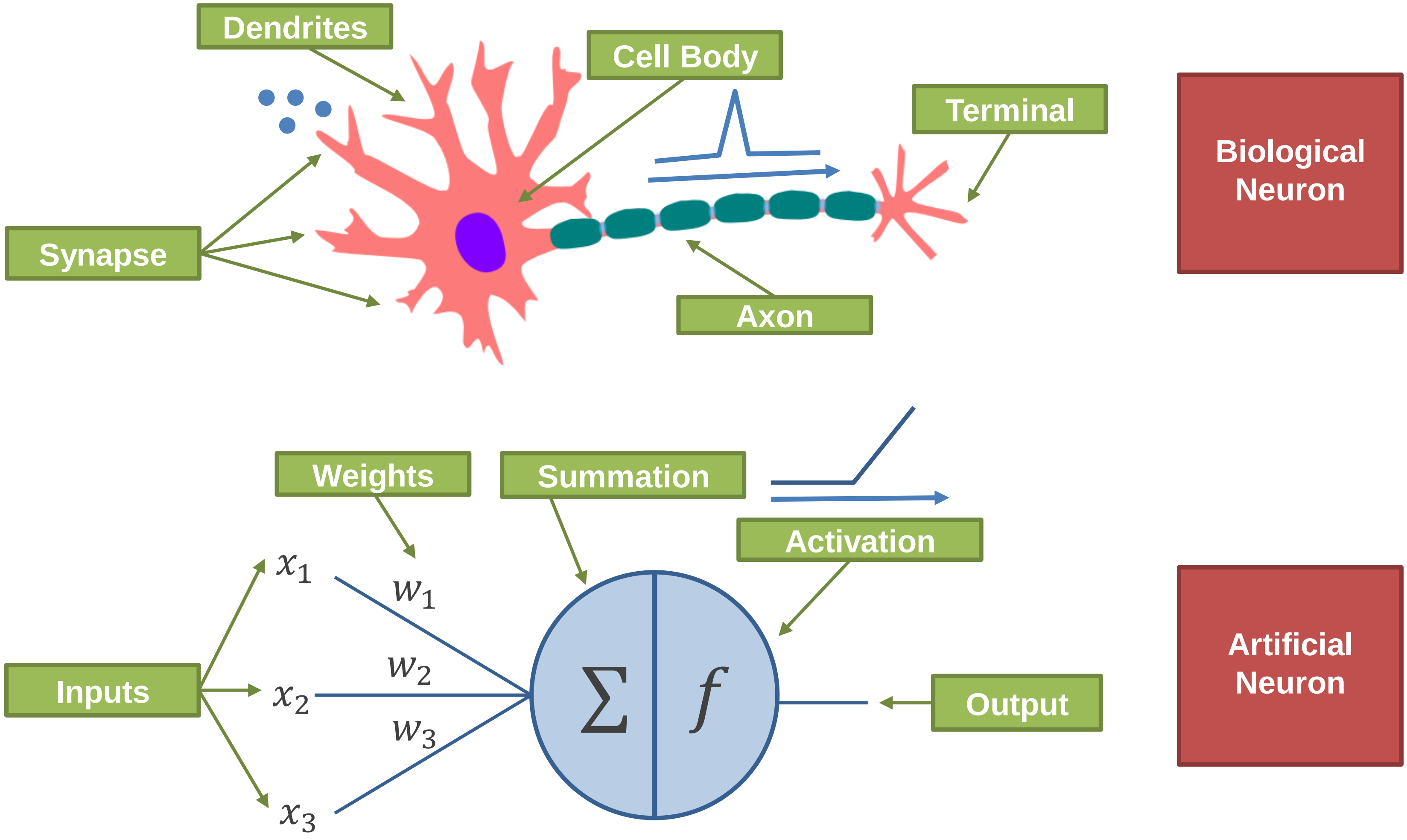


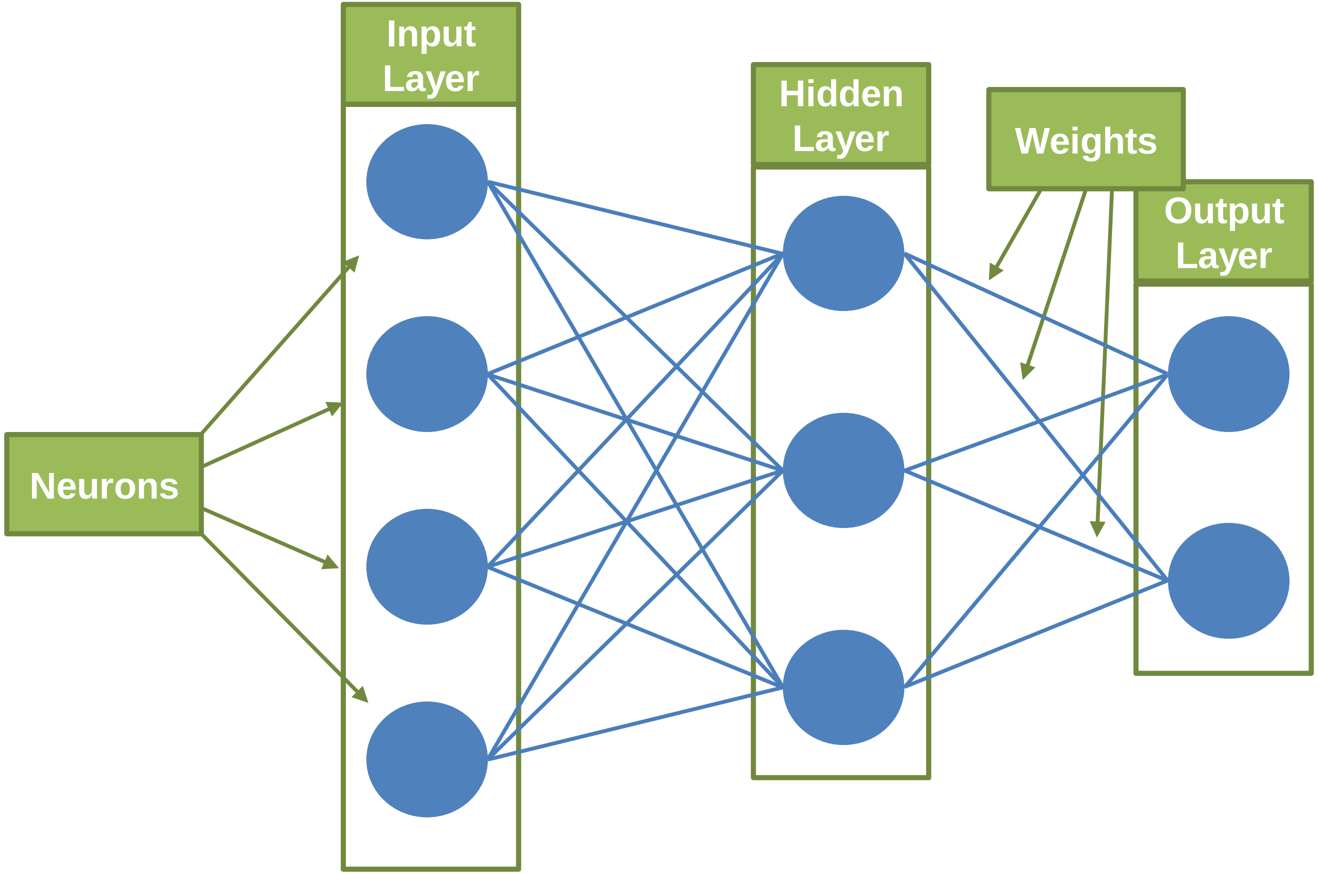
Source: *Kaggle, Schizophrenia Prediction*

kaggle

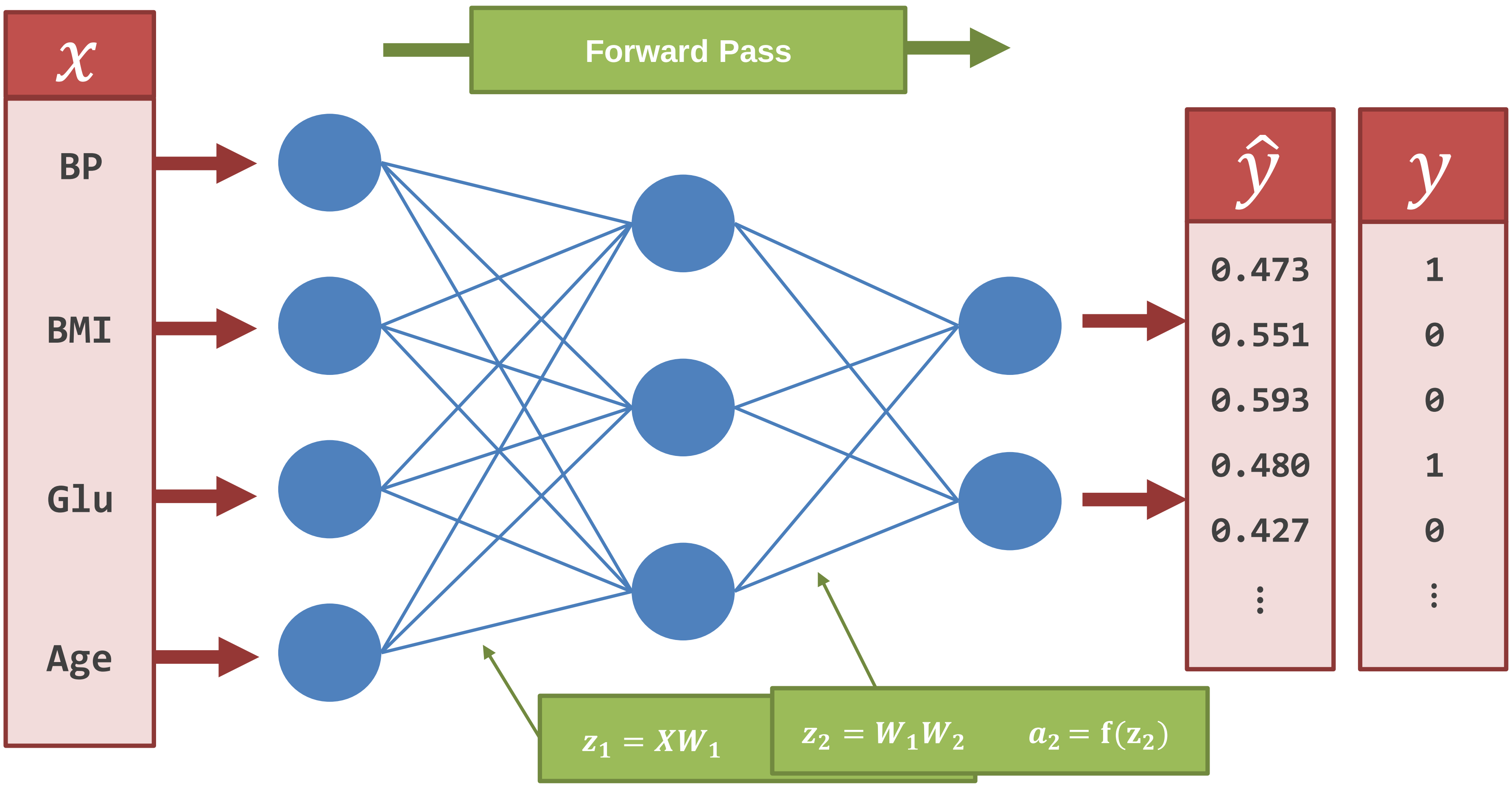
How does Deep Learning Work?

- Artificial Neurons
- Feed Forward Neural Networks
- Training (Back Propagation)
- Convolutional Neural Networks

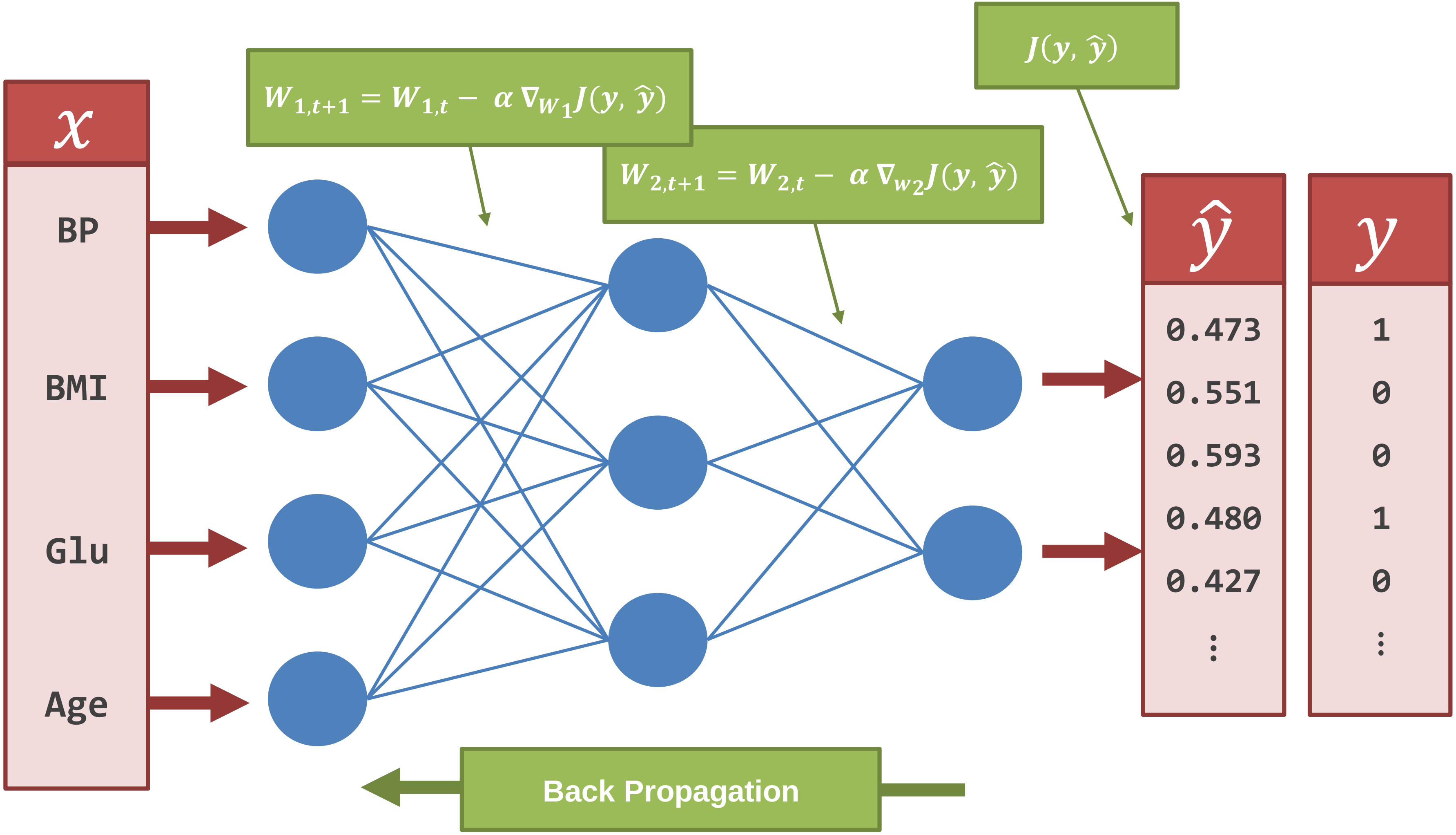

Dendrites
Cell Body
Terminal
Biological Neuron
Synapse
Axon
Weights
Summation
Activation
x_1
w_1
w_2
x_2
w_3
x_3
Inputs
Σ
f
Output
Artificial Neuron

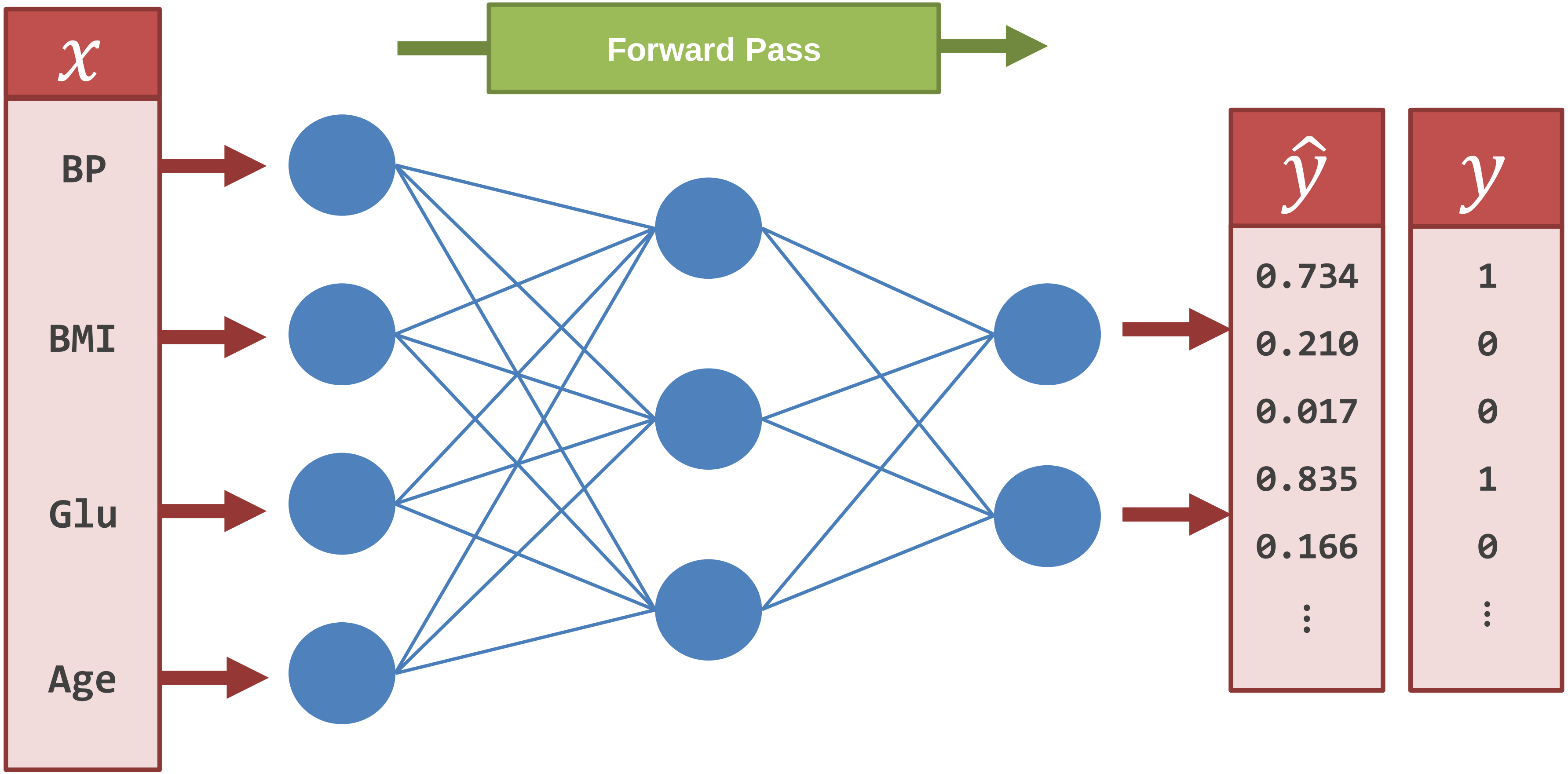


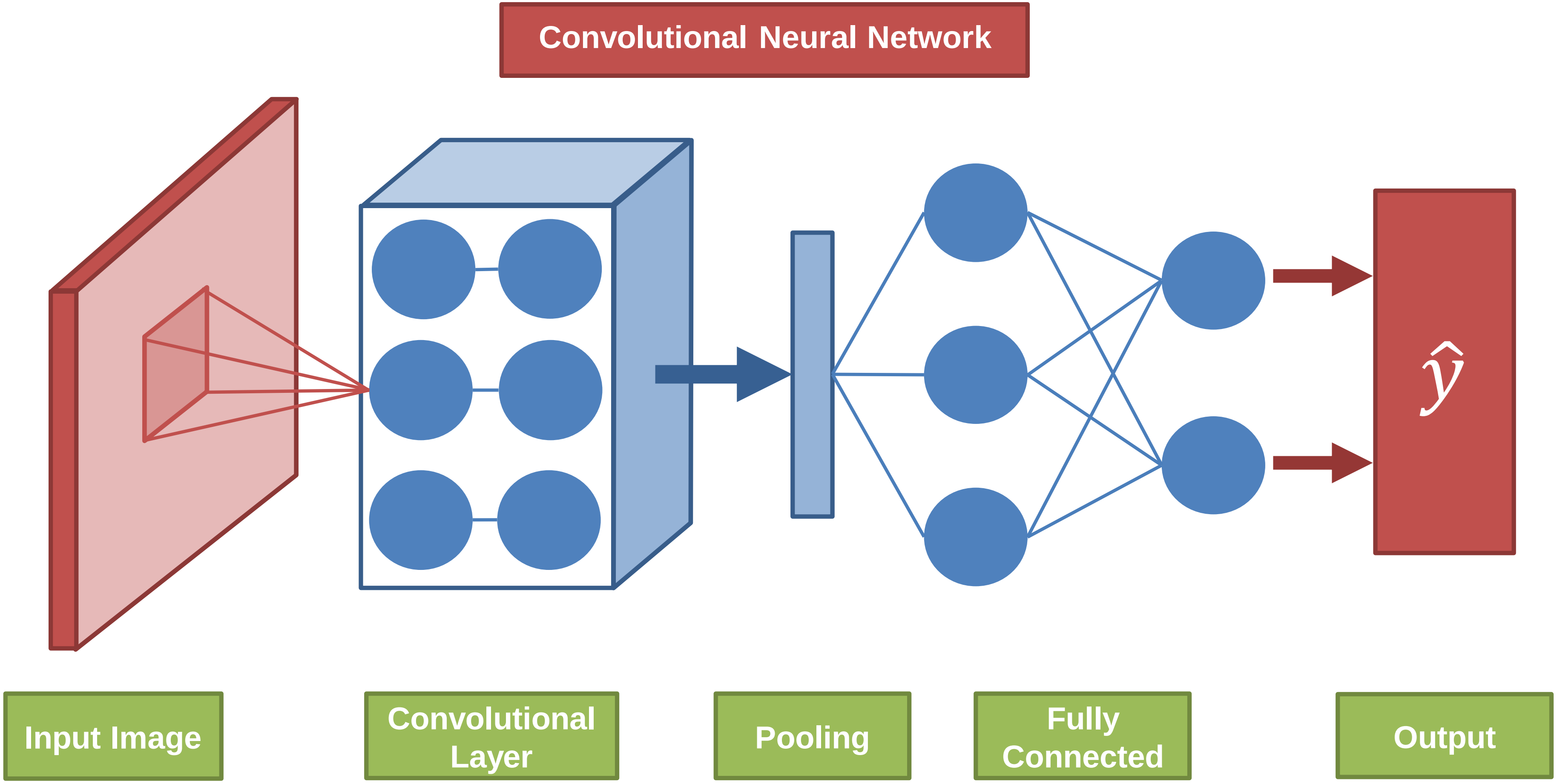
Artificial Neural Network



x
BP
BMI
Glu
Age
Forward Pass
$\hat{y}$
0.473
0.551
0.593
0.480
0.427
⋮
y
1
0
0
1
0
⋮
$z_1 = XW_1$
$z_2 = W_1W_2$
$a_2 = \mathrm{f}(z_2)$


x
BP
BMI
Glu
Age
$W_{1,t+1} = W_{1,t} - \alpha \nabla_{W_1} J(y, \hat{y})$
$W_{2,t+1} = W_{2,t} - \alpha \nabla_{W_2} J(y, \hat{y})$
$J(y, \hat{y})$
$\hat{y}$
0.473
0.551
0.593
0.480
0.427
⋮
y
1
0
0
1
0
⋮
Back Propagation


x
BP
BMI
Glu
Age
Forward Pass
$\hat{y}$
0.734
0.210
0.017
0.835
0.166
⋮
y
1
0
0
1
0
⋮



Convolutional Neural Network
$\hat{y}$
Input Image
Convolutional Layer
Pooling
Fully Connected
Output

Deep Learning Tools

TensorFlow

Keras

Python

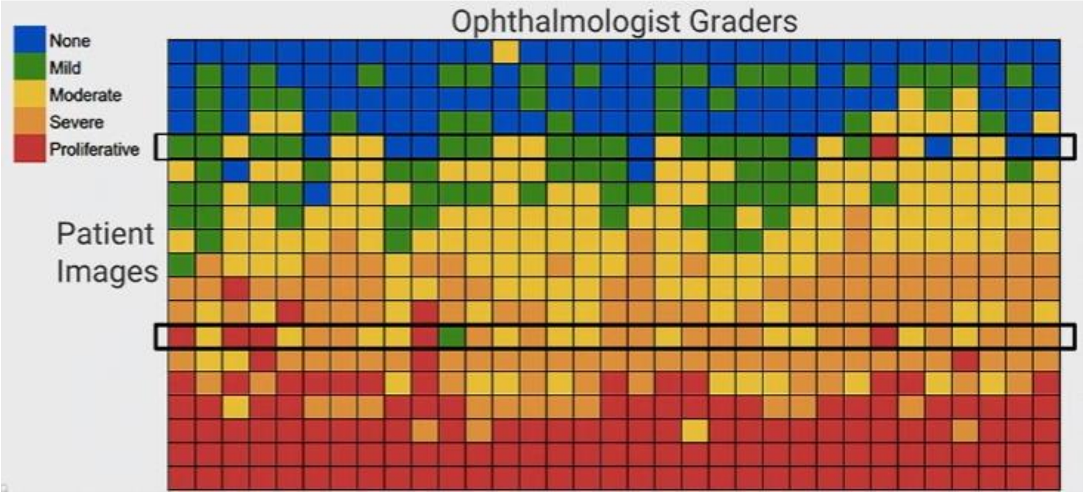
Image Source: *Wikimedia Commons*

Diabetic Retinopathy

- Eye disease of diabetes suffers
- Leading cause of blindness
- Regular screening is recommended
- Shortage of trained professionals
- High variability

Manual Grading

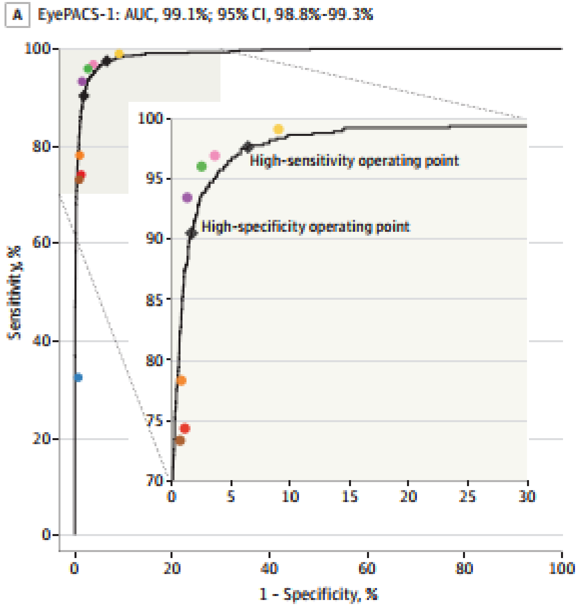
- Five classes
- Consistency
  - 65% Intergrader
  - 60% Intragrader



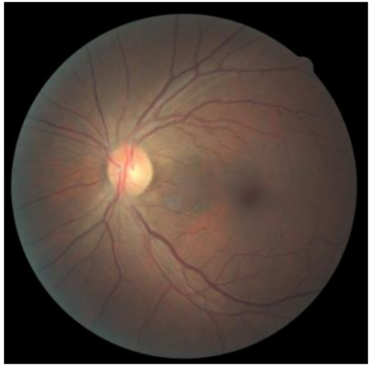
Source: *TensorFlow in Medicine - Retinal Imaging (TensorFlow Dev Summit 2017)*

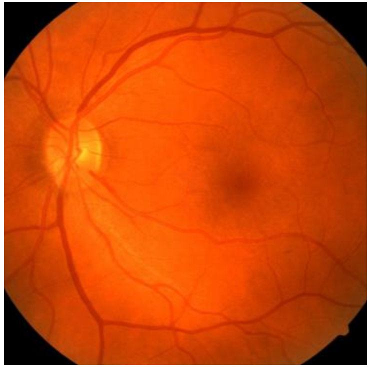
Deep Learning for Automatic Grading

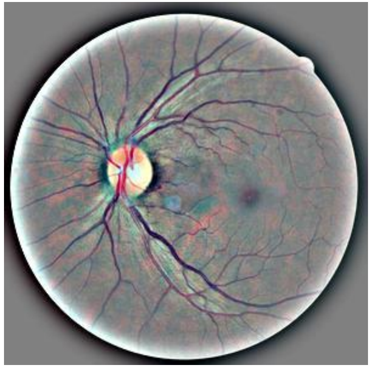
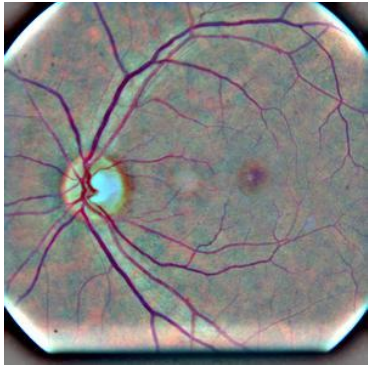
- Glushan, Peng, et. al (JAMA 2016)
- Achieved human level performance
- Inception model
  - Over 20 million parameters
  - Several weeks to train on high-end hardware



Data Transformation

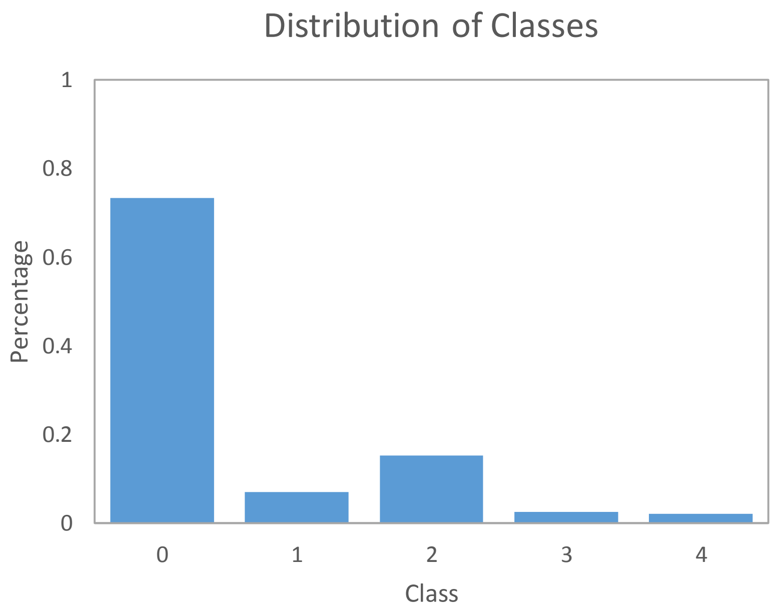





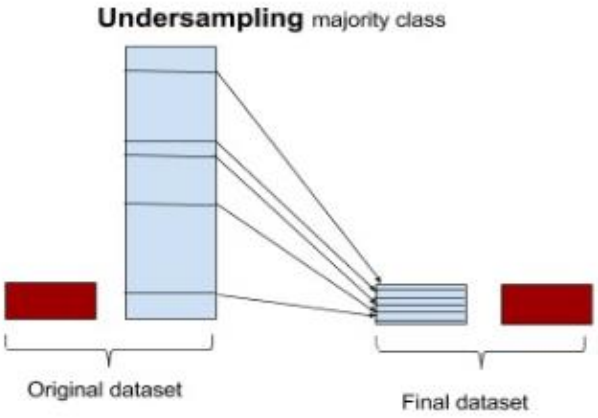

Unbalanced Data

- Models not learning
- Label imbalance issues
- Multiple methods to remedy



Unbalanced Data

Resampling



Weighted Loss

$$Loss = J(y, \hat{y})$$

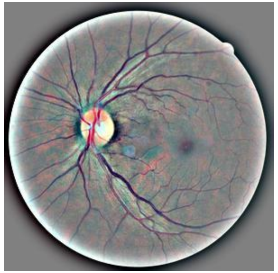
$$Weighted\ Loss = \sum^{k} C_k\, J(y_k, \hat{y})$$

$$C_k = \frac{n_k}{\sum n_k}$$

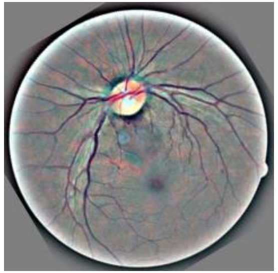
Source: *https://svds.com/learning-imbalanced-classes/*

Overfitting

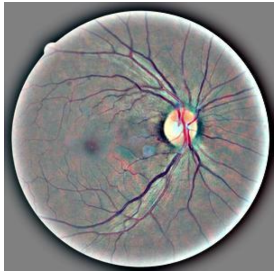
- Occurs when model fails to generalize
- Problem when resampling data
- Data augmentation helps



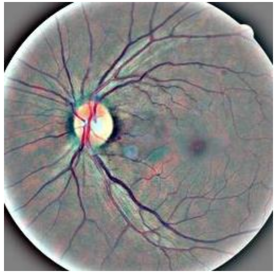
original



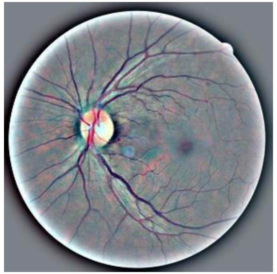
rotation



reflection



zoom



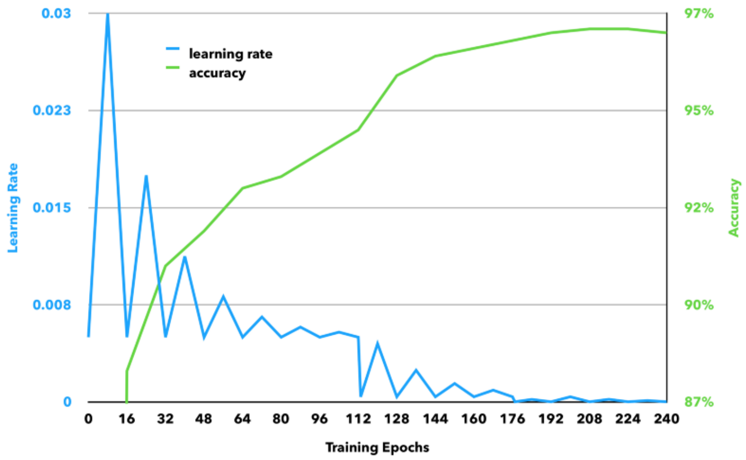
tint

MobileNet

- Smaller network (optimized for mobile devices)
- Good performance but faster to train
- Keras implementation out-of-the-box
- Trained using cyclic learning rate schedule

Cyclic Learning Rate

- Learning rate cycles
- Automatic schedule
- Training in three cycles
- About 20 hours training time



Source: https://arxiv.org/abs/1506.01186
Image Source :https://hackernoon.com

Results

	Naïve	Resampled	Weighted	MobileNet
Accuracy	0.738	0.489	0.754	0.801
Kappa	0	0.403	0.529	0.668
Precision	-	0.685	0.693	0.734
F1 Score	-	0.555	0.720	0.764

Interactive App

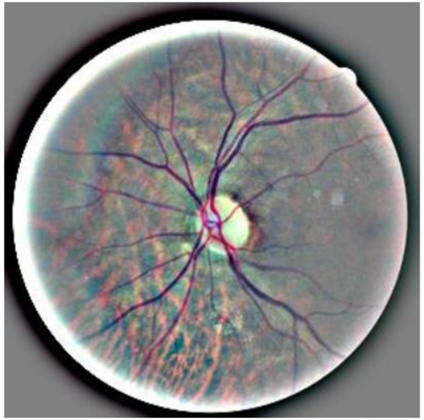
Diabetic Retinopathy Detection with Keras

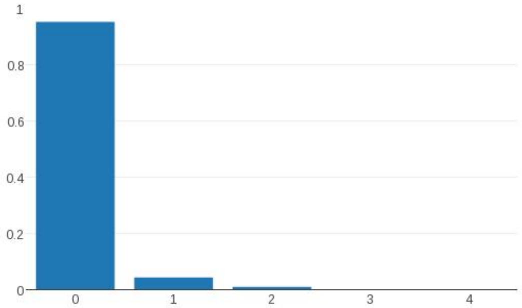
Diabetic retinopathy is an eye disease affecting diabetes suffers. It has few early-warning signs and left untreated it can cause blindness. Regular screening is recommended for at risk patients. The current standard is manual grading of retinal fundus images.
Automating detection of diabetic retinopathy could have benefits increasing diagnotic availability to patients, decreasing human variability in outcomes, and lowering the time for diagnotic analysis. We apply the task of automating diabetic retinopathy grading using a neural network model.
Neural networks are powerful models that can be trained to perform a wide variety of tasks. They are well suited to learning from large amounts of data like images. This network is based on a convolutional neural network architecture and trained on over 30,000 hand-labeled images.

Choose an image below and see the predicted severity level on the right. The scale goes from 0 (no disease) to 4 (severe disease). The height of the bar represents how confident the model is of a given grading.

10_left

undo





Further Work

- Investigate custom loss and activation functions
- Utilize batch normalization
- Use different learning rate policies
- Try different data pre-processing schemes
- Iterate on different models

Challenges

Strengths

- Powerful and flexible
- Handles big data
- Composible
- SOTA predictive power
- Solves non-convex losses
- Rich community support

Weaknesses

- Prone to overfitting
- Slow to train
- Hard to choose models
- Less interpretable
- Sensitive to initial conditions
- Evolving best practices

Deep Learning is not trivial!

Closing Thoughts

“We are going through what many people call a fourth Industrial Revolution and I have absolutely no doubt AI is the biggest driving force changing how humans live and work”

- Fei Fei Li

Image Source: Google Images
Quote Source: Startup Grind 2017

Resources

- TensorFlow
- Keras
- Python
- Stanford CS231
- Lilly HPC

- **Lilly Deep Learning White Paper**

Getting Started with Deep Learning at Lilly

Faustine Li
Haoda Fu

Lilly

Thanks!

Faustine Li