Building a Prediction Model for Left-Ventricular Ejection Fraction

Jacob Albers | Shashin Chokshi

Inspiration

Eric Topol @EricTopol · 3m

The FDA approvals for #AI in medicine are accelerating.
@US_FDA @aidocmed @ZebraMedVision @baylabsinc @NeuralAnalytics @icometrix @Viz_AI @ArterysInc @maximumqai @AliveCor imagen.ai eyediagnosis.net
now ≥ 1/month; 10/13 scans, 1 eye disease, 1 neuro,1 heart

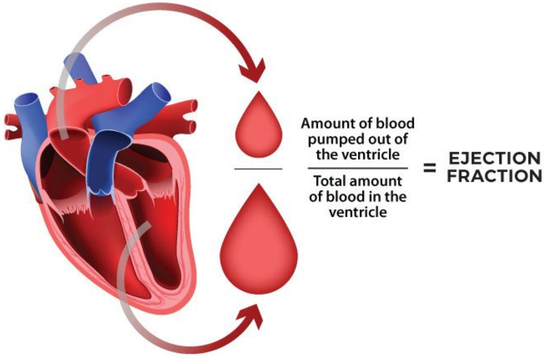
Company	FDA Approval	Indication
Aidoc	August 2018	CT Brain bleed diagnosis
iCAD	August 2018	Breast density via mammography
Zebra Medical	July 2018	Coronary calcium scoring
Bay Labs	June 2018	Echocardiogram EF determination
Neural Analytics	May 2018	Device for paramedic stroke diagnosis
IDx	April 2018	Diabetic retinopathy diagnosis
Icometrix	April 2018	MRI brain interpretation
Imagen	March 2018	X-ray wrist fracture diagnosis
Viz.ai	February 2018	CT Stroke diagnosis
Arterys	February 2018	Liver and lung cancer (MRI,CT) diagnosis
MaxQ-AI	January 2018	CT Brain bleed diagnosis
Alivecor	November 2017	Atrial fibrillation detection via Apple Watch
Arterys	January 2017	MRI heart interpretation

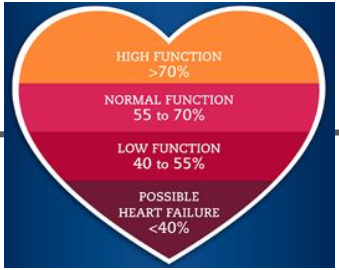
Eric Topol @EricTopol · Aug 12

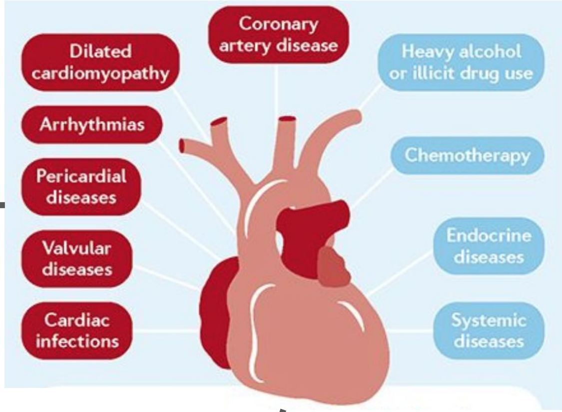
Here's the list of peer-reviewed AI medical publications for image recognition so far, which bears little resemblance to the FDA approval list (and not using the company algorithms).
+ some major papers are due out soon.

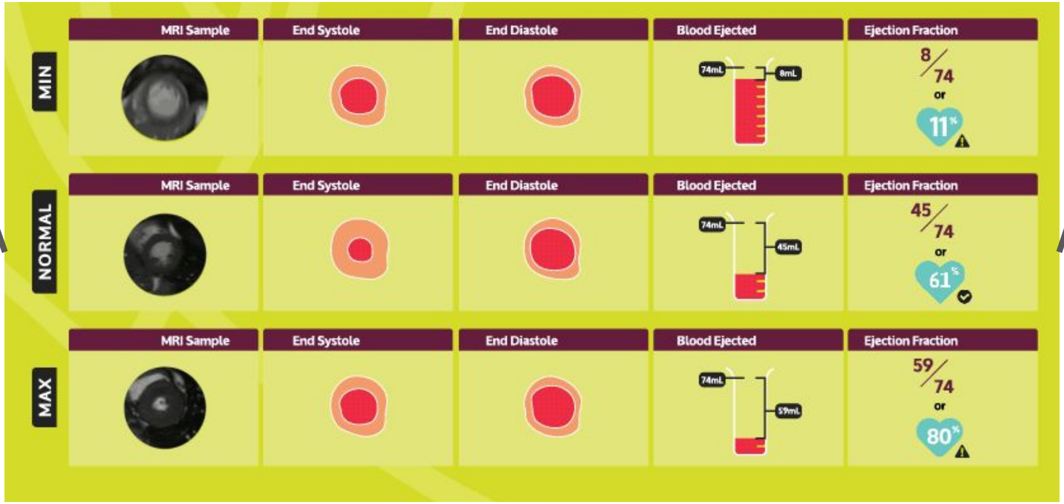
Specialty	Images	Publication
Radiology	CT head for brain hemorrhage	Arbabshirani, NPJ (Nature) Digital Medicine, 2018
Pathology	Breast cancer	Bejnordi, JAMA, 2017
	Brain tumors (+ methylation)	Capper, Nature, 2018
Dermatology	Skin cancers	Esteva, Nature, 2017
	Melanoma	Haenssle, Annals of Oncology, 2018
Ophthalmology	Diabetic retinopathy	Gulshan, JAMA, 2016
	Congenital cataracts	Long, Nature Biomedical Engineering, 2017
	Macular degeneration	Burlina, JAMA Ophthalmology, 2018
	Retinopathy of Prematurity	Brown, JAMA Ophthalmology, 2018
	AMD and diabetic retinopathy	Kermany, Cell, 2018
Cardiology	Echocardiography	Madani, NPJ (Nature) Digital Medicine, 2018

LEFT VENTRICULAR EJECTION FRACTION (LVEF)

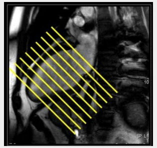




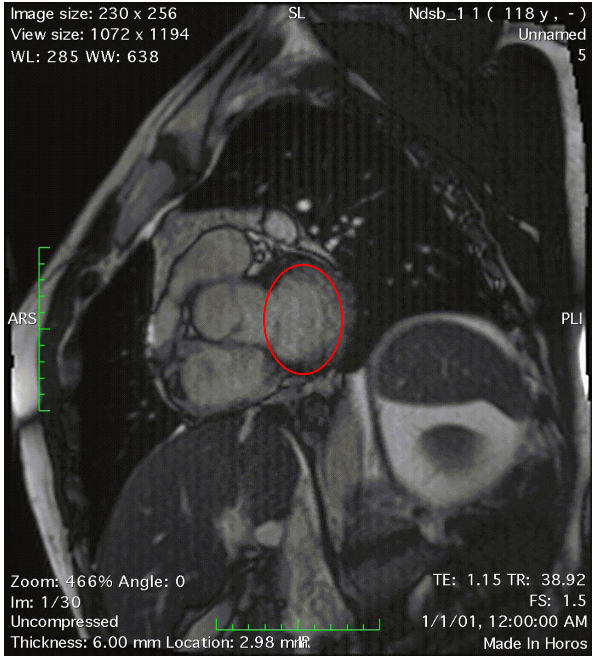




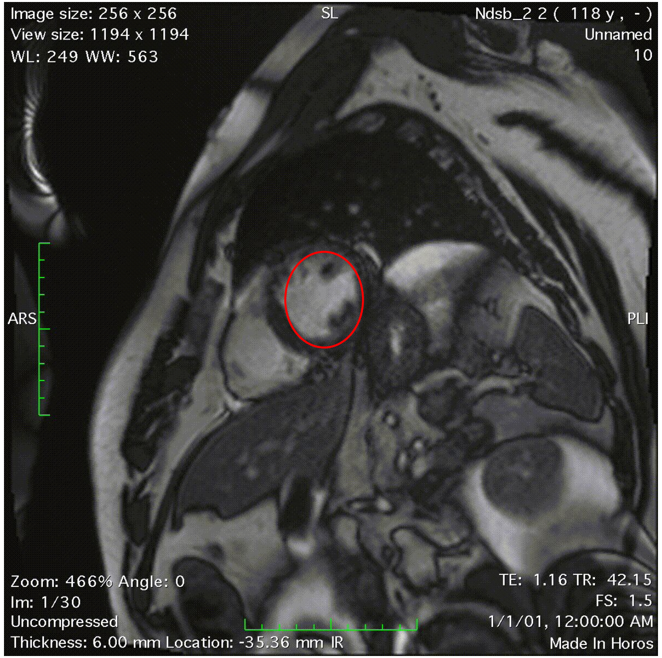
Raw Cardiac MRIs (DICOM)



Short Axis View



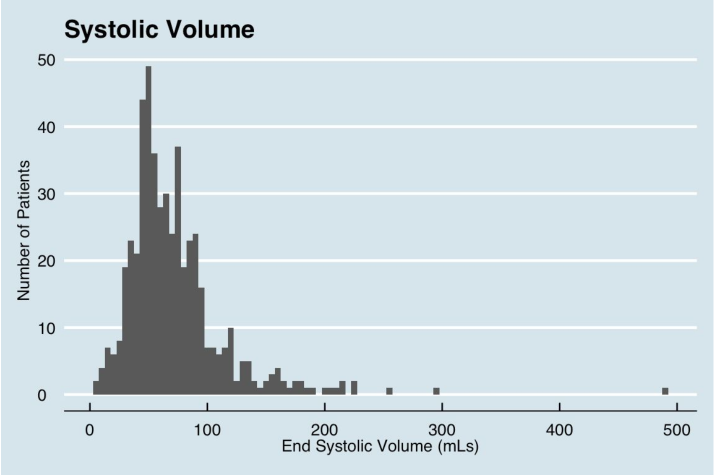
Patient 1 | Slice 5

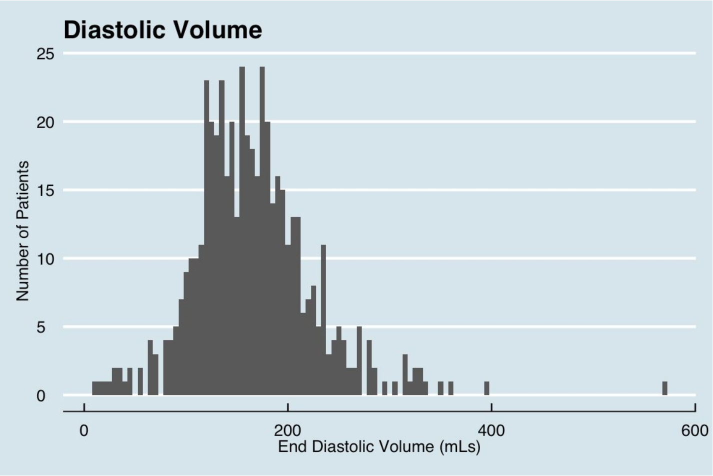


Patient 2 | Slice 10

Table 1 Summary

	level	Overall
n		500
patient_id (mean (sd))		250.50 (144.48)
rows (mean (sd))		299.24 (107.76)
columns (mean (sd))		253.92 (88.94)
spacing (mean (sd))		1.26 (0.34)
slice_thickness (mean (sd))		7.75 (0.70)
plane (%)	COL	98 (19.6)
	ROW	402 (80.4)
slice_count (mean (sd))		10.80 (1.82)
up_down_agg (mean (sd))		9.18 (1.41)
age_years (mean (sd))		42.78 (20.40)
sex (%)	F	208 (41.6)
	M	292 (58.4)
small_slice_count (mean (sd))		0.37 (1.33)
normal_slice_count (mean (sd))		10.43 (1.19)
angle (mean (sd))		56.25 (10.02)
Systole (mean (sd))		71.96 (43.29)
Diastole (mean (sd))		165.87 (59.34)
ejection_fraction (mean (sd))		58.45 (10.91)





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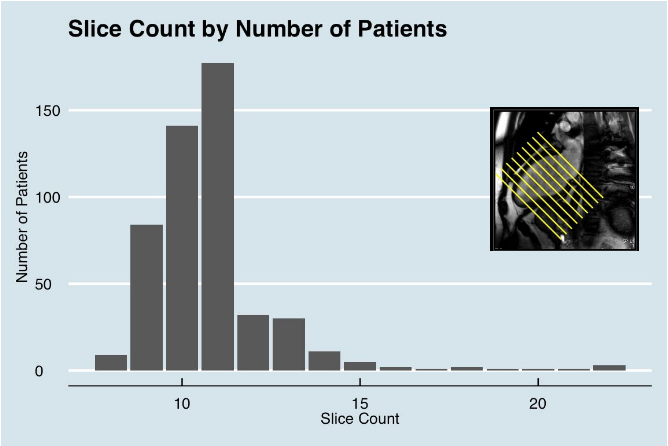
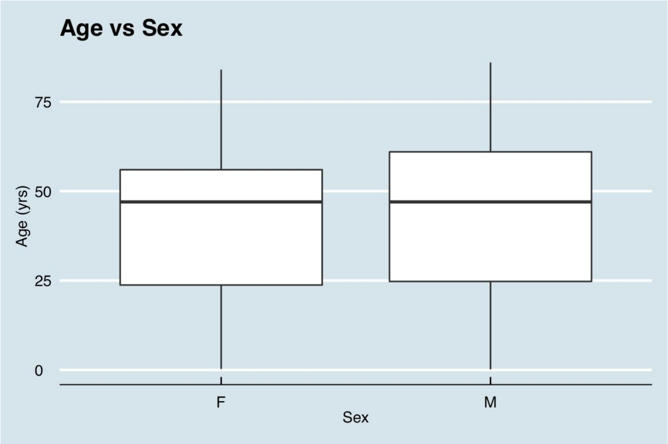
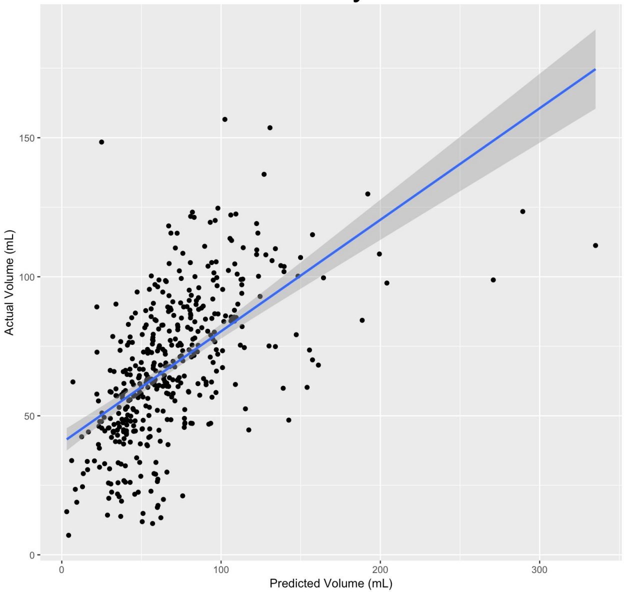


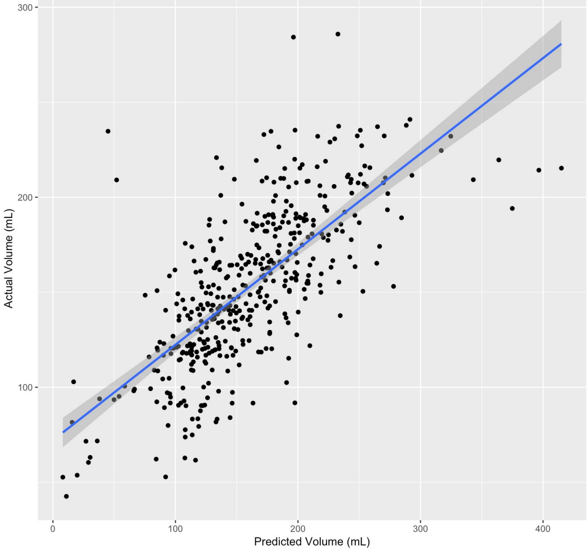


Results of Linear Regression using DICOM Metadata

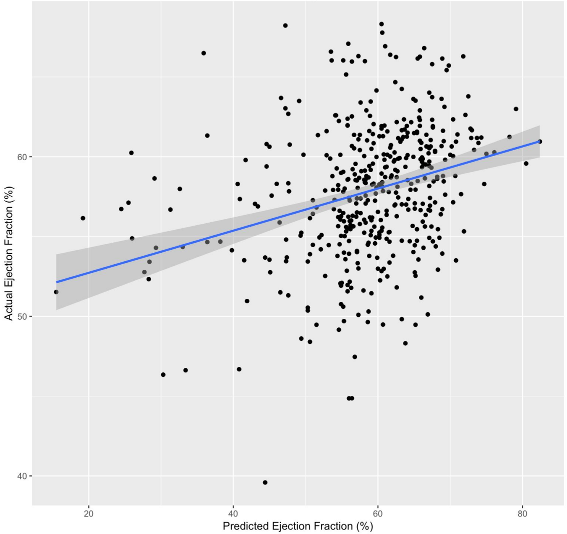
Predicted vs Actual Systolic Volume



Predicted vs Actual Diastolic Volume



Predicted vs Actual Ejection Fraction



Correlation = .5797133
RMSE = 654.8027

Correlation = 0.7052103
RMSE = 881.9993

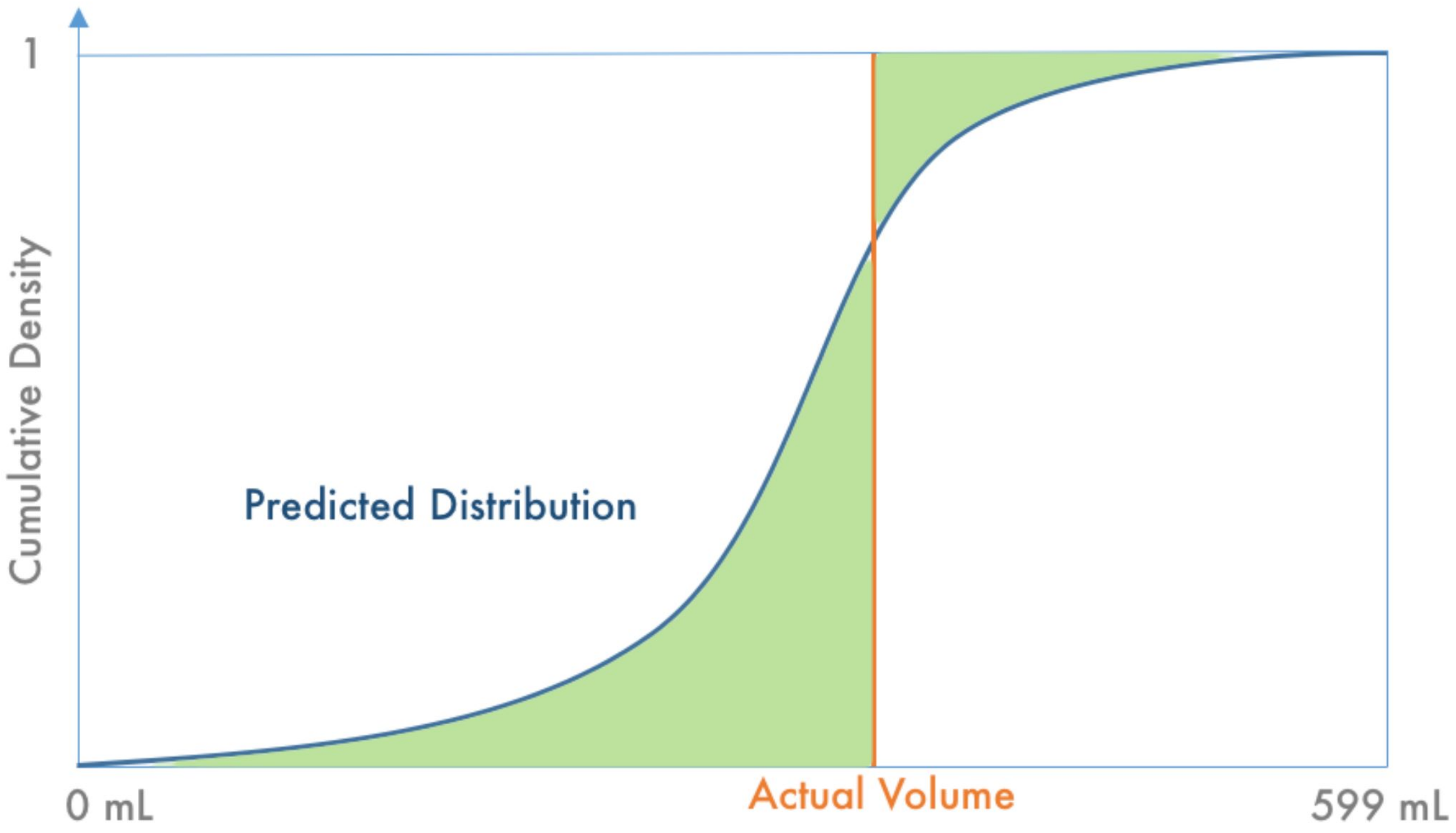
Correlation = 0.2996
RMSE = 194.6957

Since ROC curves are designed point estimates - and we are trying to estimate a distribution - we need a different accuracy metric

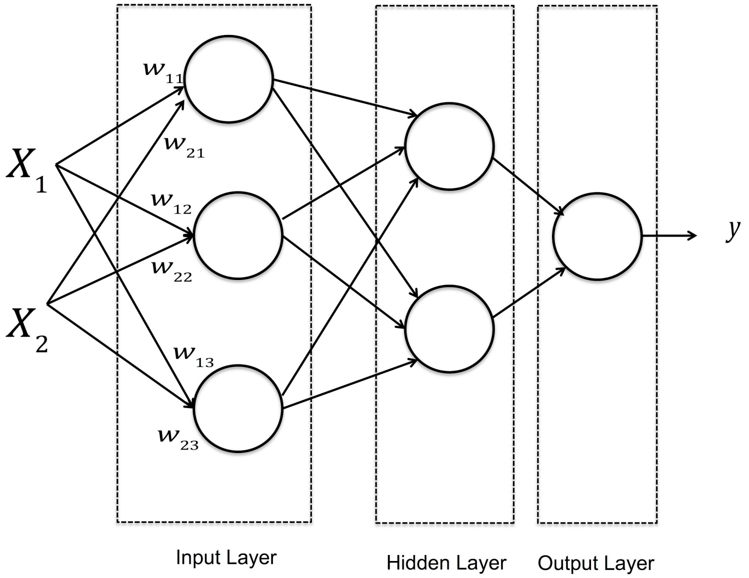
CONTINUOUS RANKED PROBABILITY SCORE

$$C = \frac{1}{600N} \sum_{m=1}^{N} \sum_{n=0}^{599} (P(y \leq n) - H(n - V_m))^2,$$

- Steps through the predicted and aggregates an average distance from real volumes
- *P* is the predicted distribution
- *N* is the number of rows in the test set
- *V* is the actual volume
- *H(x)* is the heaviside function: *H(x)* = 1 for x ≥ 0, *H(x)* = 0

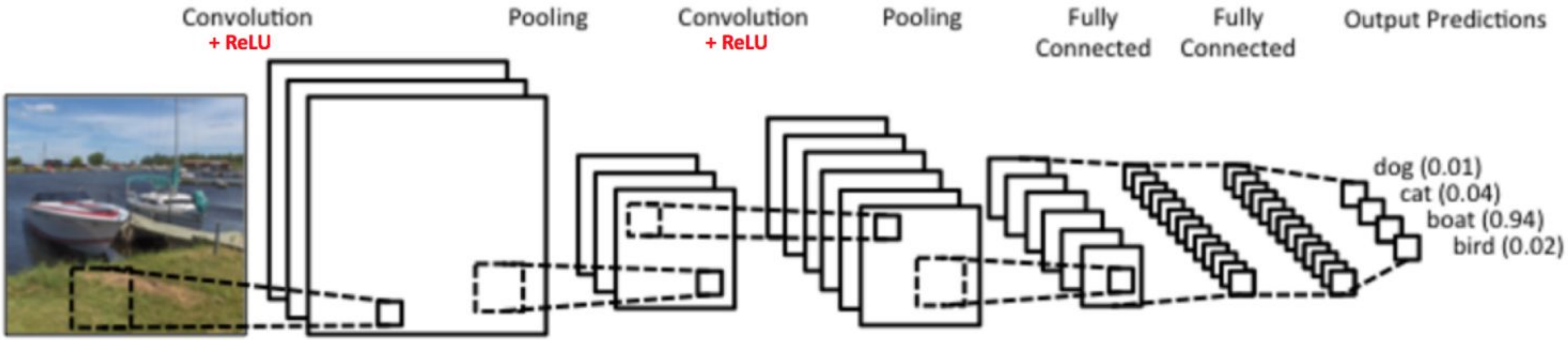

1
Cumulative Density
Predicted Distribution
0 mL
Actual Volume
599 mL

First option: our old friend, the Multilayer Perceptron



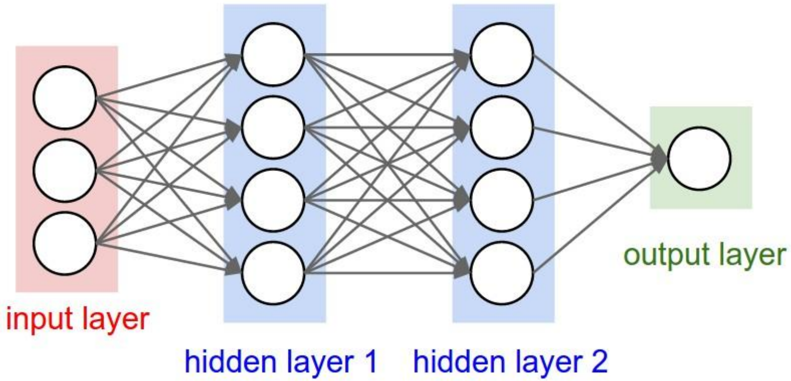
- Convert image to a 64x64 matrix (csv) of calculated distances
- Input is a 3-dimensional data shape (height, width, and frame numbers)
- Run separate networks to estimate both systolic and diastolic volumes
- Utilizing the mxnet python library package!

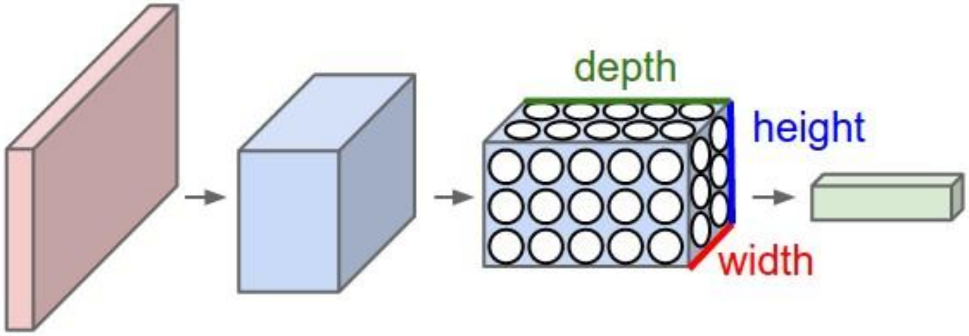
Resulting CRPS score: **0.2415** (not very good)



Other option, particularly good for image data: **a convolutional neural network**

- The dense connections between MLP layers makes this solution difficult to scale to image analysis
- CNNs provide a more effective way of pinpointing specific feature in an image





Main differences between MLP & CNN:

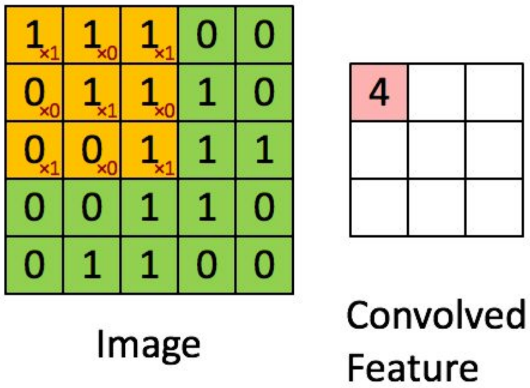
- CNNs have 3 dimensional layers (height, width and depth) that enable weights to be distributed along a depth parameter
- Each neuron in a CNN will only be connected to a small number of neurons on the preceding layer (not the fully connected layers of an MLP)

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

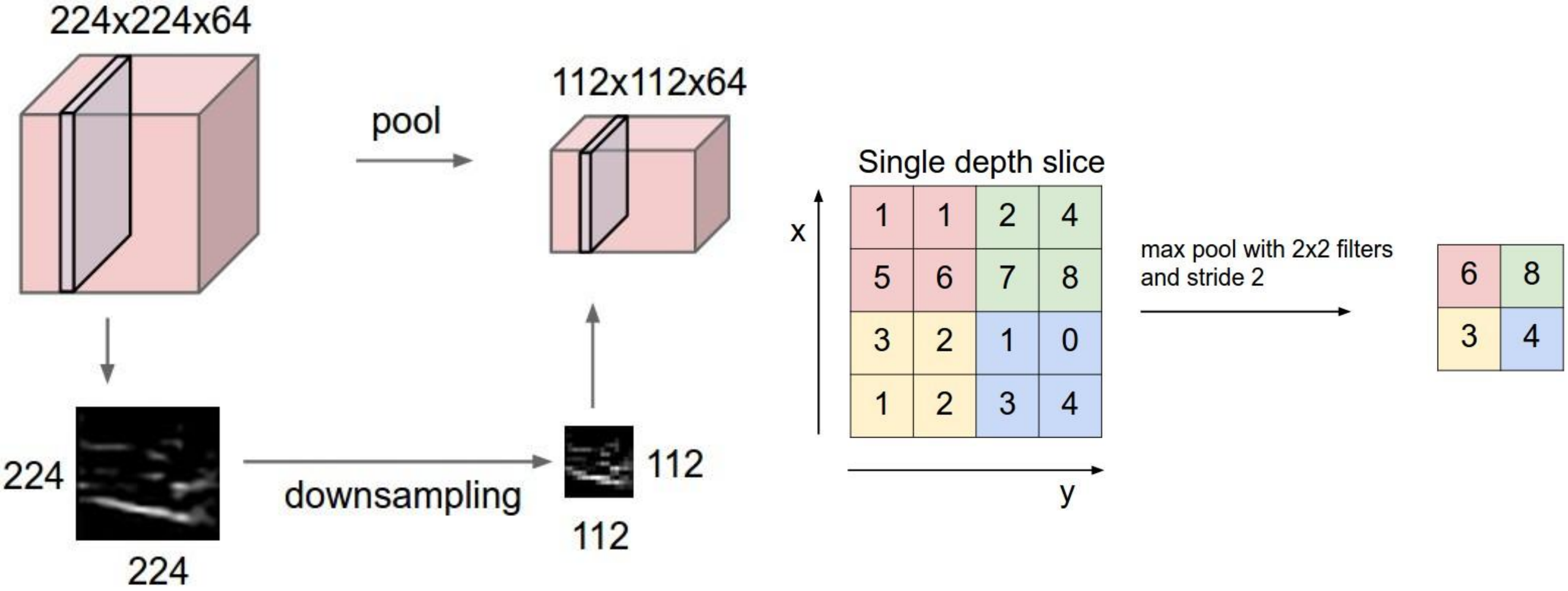
Data

1	0	1
0	1	0
1	0	1

Kernel (Filter)



Each convolution layer utilizes a filter to calculate the dot product of adjacent cells (across all channels) and aggregate the results into a convolved feature matrix.



Since convolution layers will still create relatively large resulting matrices, a “pooling layer” downsamples the amount of data reduces the chance of overfitting the model

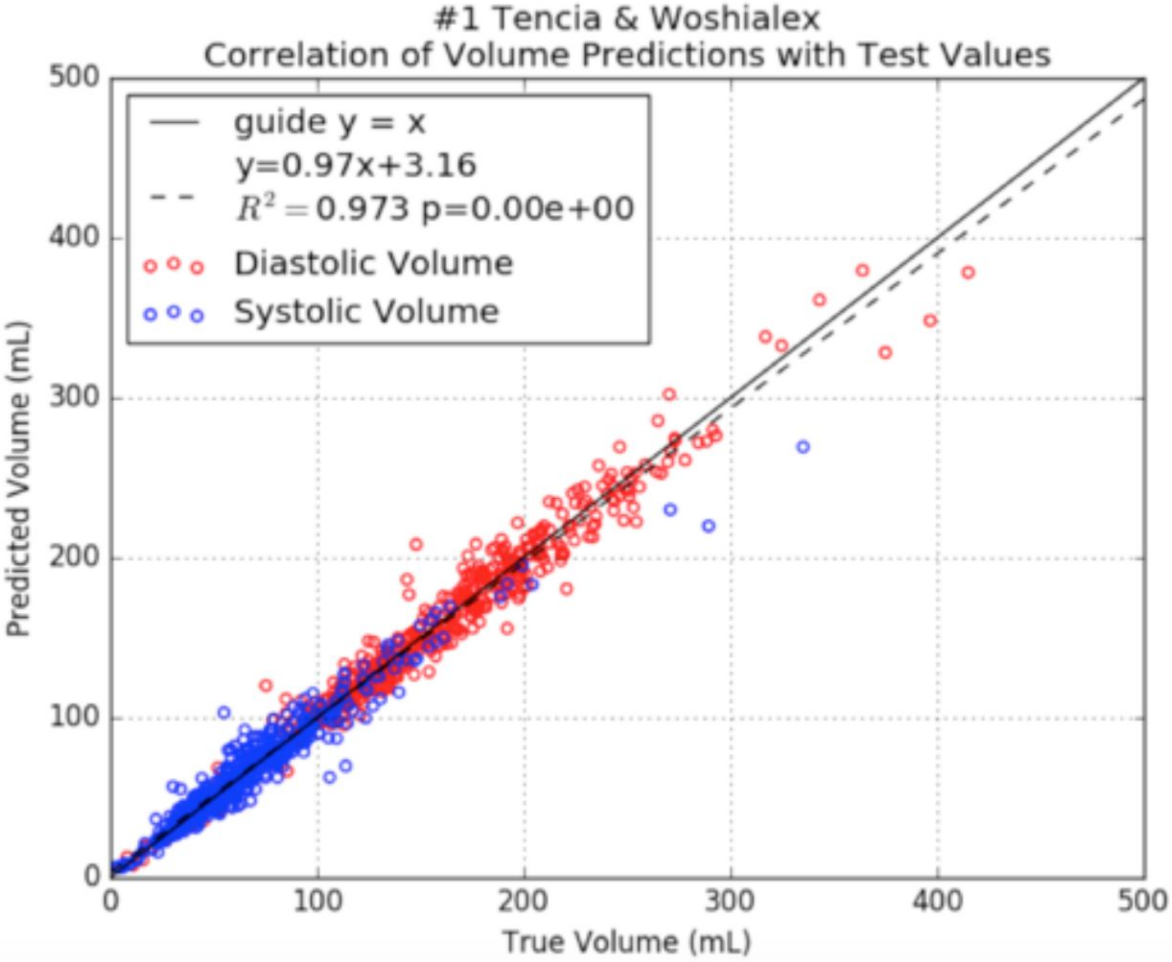
Our Scores:

Neural Network	Systole CRPS	Diastole CRPS
MLP	0.237614	0.238631
LeNet	0.038950	0.056660
AlexNet	**0.034336**	**0.054229**
GoogLeNet	0.115578	0.145879

Top Kaggle Scores: (We would rank 180/773)

In the money   Gold   Silver   Bronze

#	△pub	Team Name	Kernel	Team Members	Score	Entries	Last
1	▲ 4	Tencia & Woshialex			0.009485	4	2y
2	▲ 22	kunsthart			0.010123	3	2y
3	▲ 13	Julian de Wit			0.010139	2	2y


#1 Tencia & Woshialex
Correlation of Volume Predictions with Test Values
guide y = x
y=0.97x+3.16
$R^2 = $0.973 p=0.00e+00
Diastolic Volume
Systolic Volume
Predicted Volume (mL)
True Volume (mL)
0
100
200
300
400
500
0
100
200
300
400
500