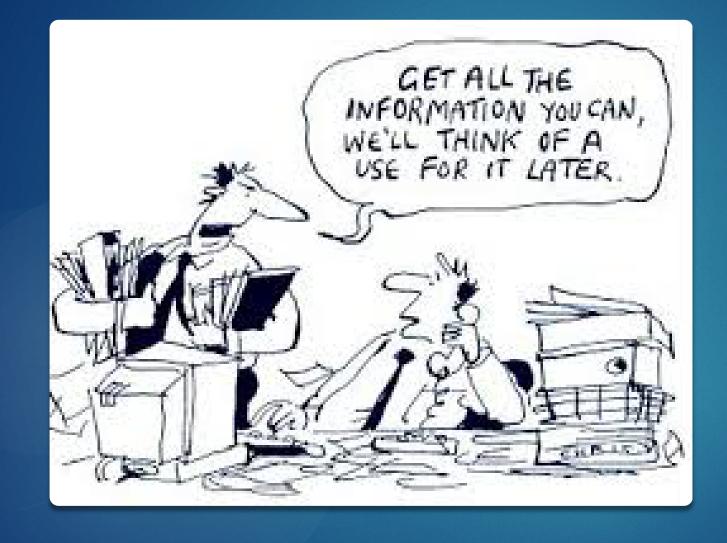


# Deep Learning in a Clinical Context: School of Medicine & Health Sci Regional Downscaling of Climate Data Using Deep Learning and Applications for prought (Rainfall' Forecasting



NATHAN RUSSELL (1<sup>ST</sup> YEAR PHD STUDENT)



Clinical Data Overload

## "Big Data" keeps getting "Bigger"

- "Big data" is a dataset with a large number of attributes
- Clinical data is a major source of "Big data"
- ▶ The amount of collected information is continuing to grow.

#### If this data isn't utilised, then it is being collected and stored at an unnecessary cost.

### Machine Learning in 60secs (Sorry no robots here)

"The Four Ingredients of Machine Learning"

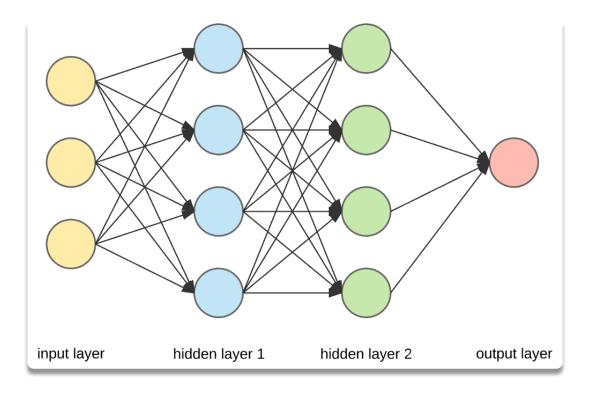
- T) A task to solve
- M) A performance metric
- P) A computer program
- E) A source of experience



### Deep Learning: Neural Networks are Onions?

### WELL NO... BUT THEY BOTH HAVE LAYERS!



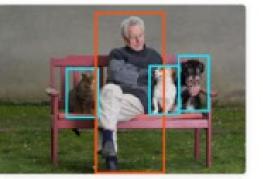


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#### PERSON, CAT, DOG



(A) Classification



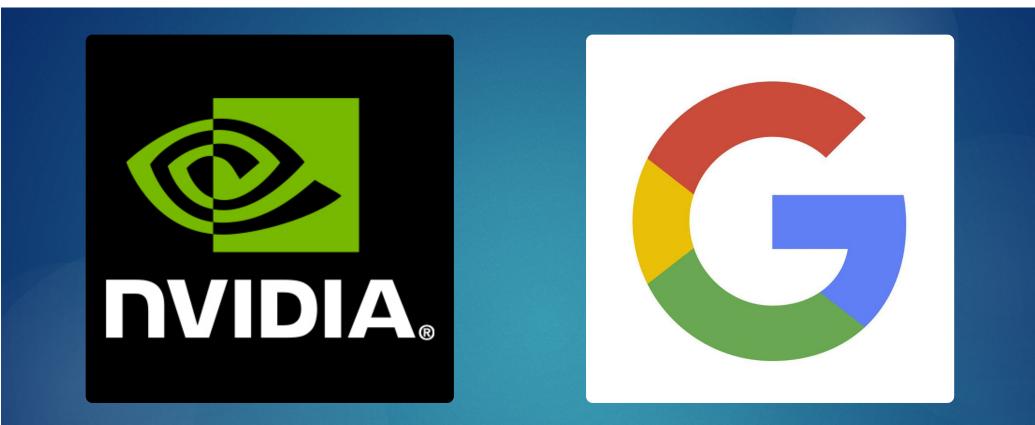
(B) Detection



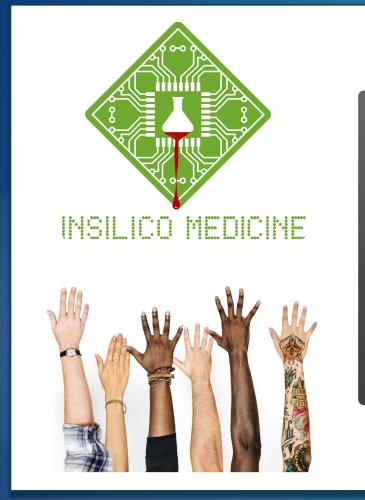
(C) Segmention

# Image Segmentation

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# Deep Learning in Healthcare





Deep Learning Models and Diverse Populations

### PhD Aims



To aid the development of tools and pipelines that facilitate improved data processing and analysis.



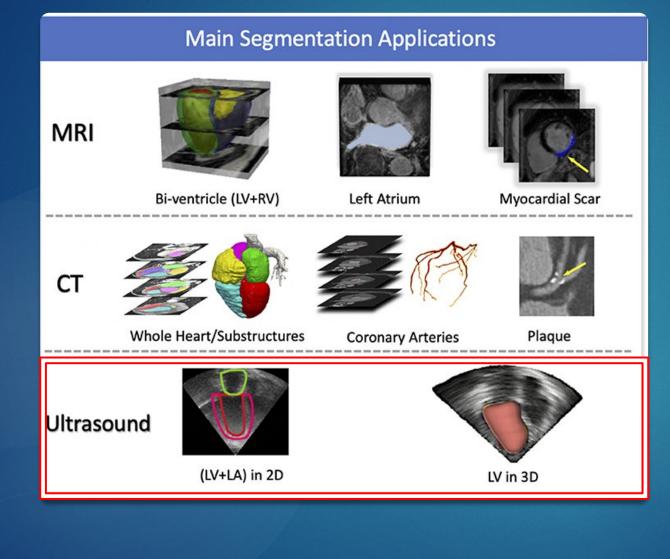
To develop tools interfaces for data exploration and visualisation, for integration in a medical decision-making framework.



Ensure developed tools are accessibly designed and clinician friendly as possible whilst maintaining research capabilities.



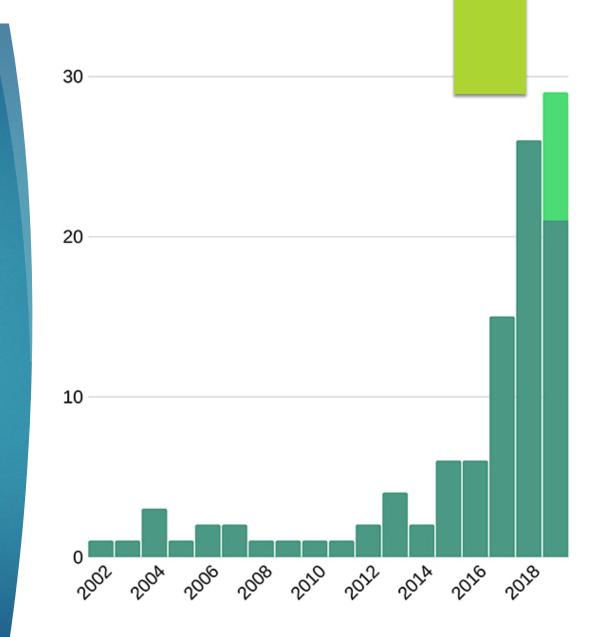
Improving the Clinical Decision-Making Process Through implementation of Deep Learning Tools for "Big Data" Integration, Analysis and Visualisation



Our Starting Point

### Cardiac Imaging and Machine Learning in Publication

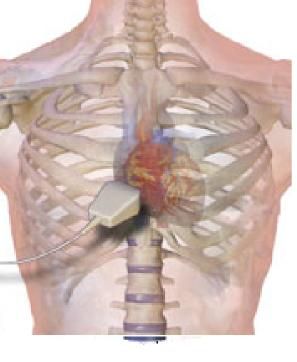
The number of publications on machine learning and cardiac imaging per year.

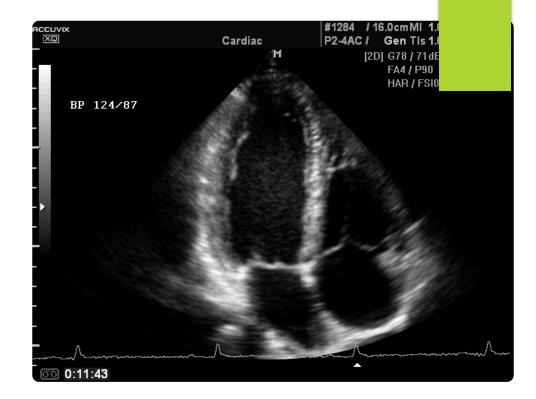


#### Echocardiogram

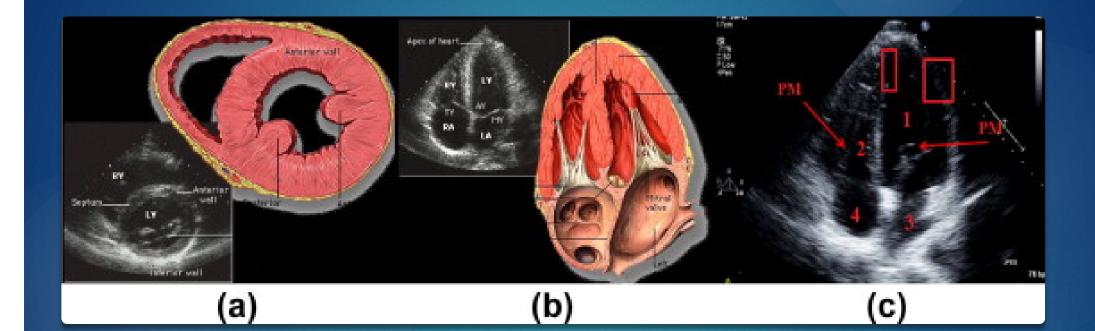


An echocardiogram uses sound waves to produce an image of the heart





# Echocardiogram 101



# Echocardiogram 101

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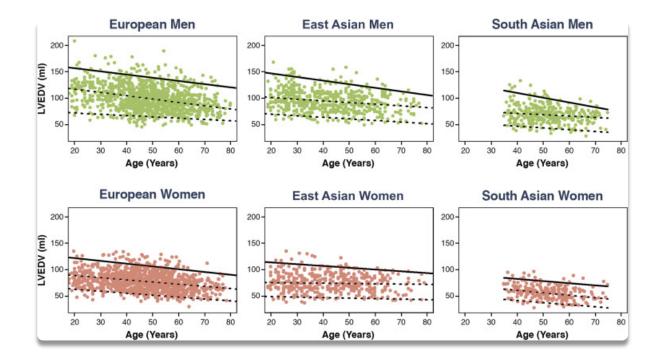
## Existing Models

#### View classification

- Madani, A., Arnaout, R., Mofrad, M. et al. Fast and accurate view classification of echocardiograms using deep learning. npj Digital Med 1, 6 (2018).
- Pathology identification
  - Madani, A., Ong, J.R., Tibrewal, A. et al. Deep echocardiography: data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease. npj Digital Med 1, 59 (2018).
- Risk prediction
  - Kwon, Joon-myoung, et al. "Deep learning for predicting in- mortality among heart disease patients hospitalbased on echocardiography." Echocardiography 36.2 (2019): 213-218.

#### Evidence of Ethnic Variation in Heart Parameters

## The ECHOnormal Study (2015)



	Caucasian	African	Hispanic	Asian	Native	р
	n=17,342	American n=1,676	n=156	n=720	American n=64	
Demographics						
Age	50.5±15.5	44.0±15.2*	44.4±13.8*	46.5±14.5*	48.1±13.6*	< 0.001
Female gender	55.6%	65.4%*	75.6%*	57.8%	56.3%	< 0.001
3SA (m2)	1.9±0.3*	2.0±0.3*	1.8±0.2*	1.7±0.2*	2.0±0.3	< 0.001
Dimensions (mm	n) or Mass (gr	n)				
LV End- Diastolic Diameter	46.9±5.5	46.4±5.5*	45.7±5.1	44.7±4.7*	48.0±6.4	<0.001
.V End-Systolic Diameter	30.1±5.2	29.6±5.2*	28.8±4.6*	28.5±4.6*	30.2±6.0	<0.001
nterventricular Septum	9.2±2.3	9.7±2.5*	8.7±1.6	8.5±1.8*	9.7±2.0	<0.001
Posterior Wall	9.0±1.7	9.5±2.0*	8.8±1.6	8.3±1.4*	9.3±1.8	< 0.001
V Mass	147.9±51.8	156.0±58.2*	133.3±42.8*	121.7±37.8*	163.6±62.0	< 0.001
eft Atrial Diameter	36.8±6.7	36.0±6.1	35.2±6.3*	33.8±5.6*	38.1±8.0	<0.001
Dimensions (mm	n/m2) or Mas	s (gm/m2) ind	exed to BSA			
.V End- Diastolic Diameter/BSA	24.6±3.3	23.8±3.3*	25.4±3.0*	26.2±3.3*	24.8±3.2	<0.001
V End-Systolic Diameter/BSA	15.8±2.9	15.2±2.9*	16.0±2.7	16.7±3.0*	15.6±2.7	<0.001
nterventricular Septum/BSA	4.8±1.1	5.0±1.3*	4.8±0.8	5.0±1.0*	5.0±1.0	<0.001
Posterior Wall/BSA	4.7±0.9	4.9±1.0*	4.9±0.8	4.9±0.9*	4.85±0.9	<0.001
V Mass/BSA	75.9±22.3	78.8±25.6*	73.0±19.4	70.5±19.5*	82.9±26.3	< 0.001
eft Atrial Diameter/BSA	19.2±3.1	18.4±3.0*	19.4±3.1	19.8±3.2*	19.6±4.0	<0.001
hannetery bar						

Evidence of Ethnic Variation in Heart Parameters

\*p<0.05 vs. Caucasian race. BSA, body surface area; LV, left ventricle.

Ethnicity is Associated With Differences in Left Heart Dimensions on Echocardiography. (2018)

## Our Project

We propose the development of suitable convolutional neural network architecture from current models in order to allow for identification of ethnicity specific features within echocardiograms

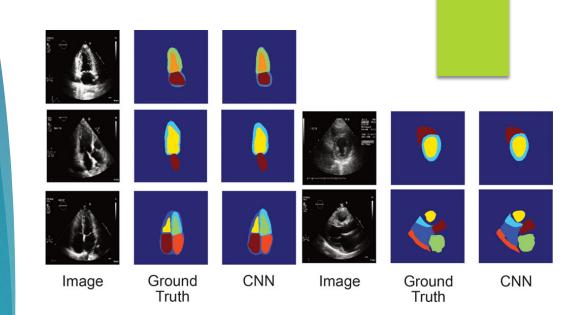
- Data from Wellington Hospital Cardiology Dept.
- A model representative of New Zealand's ethnic diversity
- Research is lacking in the area of variation in echocardiograms of people of a pacific island ethnicity

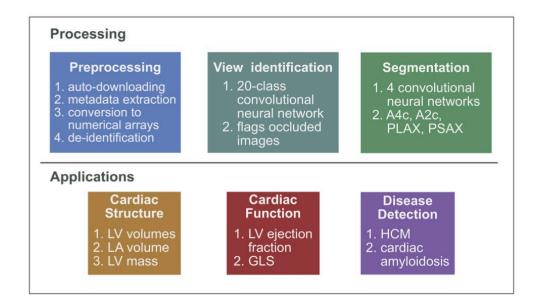


## Our Progress: EchoCV (adapting)

"EchoCV": A Web-Based Fully Automated Echocardiogram Interpretation System (2017)

- Deep Learning group UCSF
  - Uses VGG Neural Network
    Architecture for image classification
  - A CNN based on the U-net architecture for image segmentation
  - View classification, segmentation and disease detection.
  - Written using Python 2.7

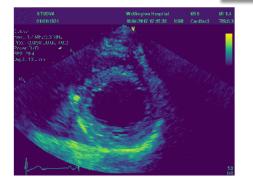




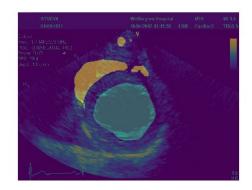
### Our Progress: EchoCV:

#### NeSI consultancy

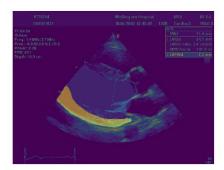
- Successfully enabled GPU recognition
- Using Nesi Mahuika GPUs: P100s
- Added additional customization options for segmentation and classification
- Begun analysis on images from Wellington hospital
  - Implementing a preprocessing pipeline

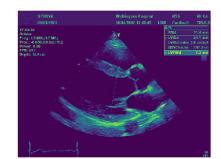


#### **PSAX View**

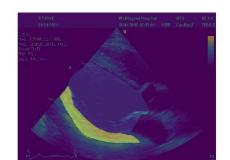


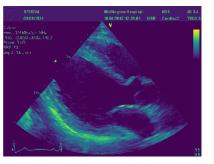
## An Example of Our Images (PLAX)











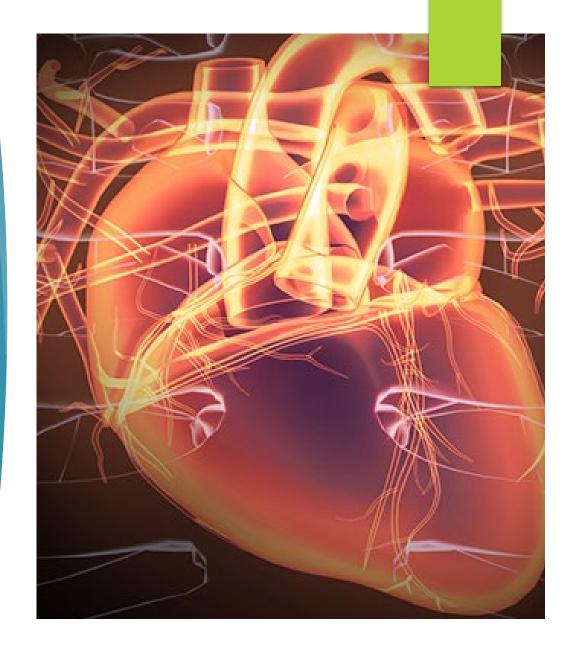


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### Precision Medicine (The Future)

- The ambition of precision medicine is to design and optimize the pathway for diagnosis, therapeutic intervention, and prognosis.
- This offers clinicians the opportunity to more carefully tailor early interventions.

Taking advantage of high performance computer capabilities, using deep learning models and embracing diversity in these models allows for a individualised course of care.



### Acknowledgements

#### Supervisory Team:

- Associate Professor Mik Black (University of Otago)
- Dr Miles Benton (ESR)
- Associate Professor Peter Larsen (University of Otago & Wellington Hospital)
- Advisory Role:
  - Dr Donia Macarteny-Coxson (ESR)
- NeSI Consultancy:
  - Maxime Rio
  - Dinindu Senanayake

# **E**/**S**/**R** Science for Communities







# Thank You

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