Artificial Intelligence to Improve Healthcare Outcomes of Underrepresented and Indigenous Populations*

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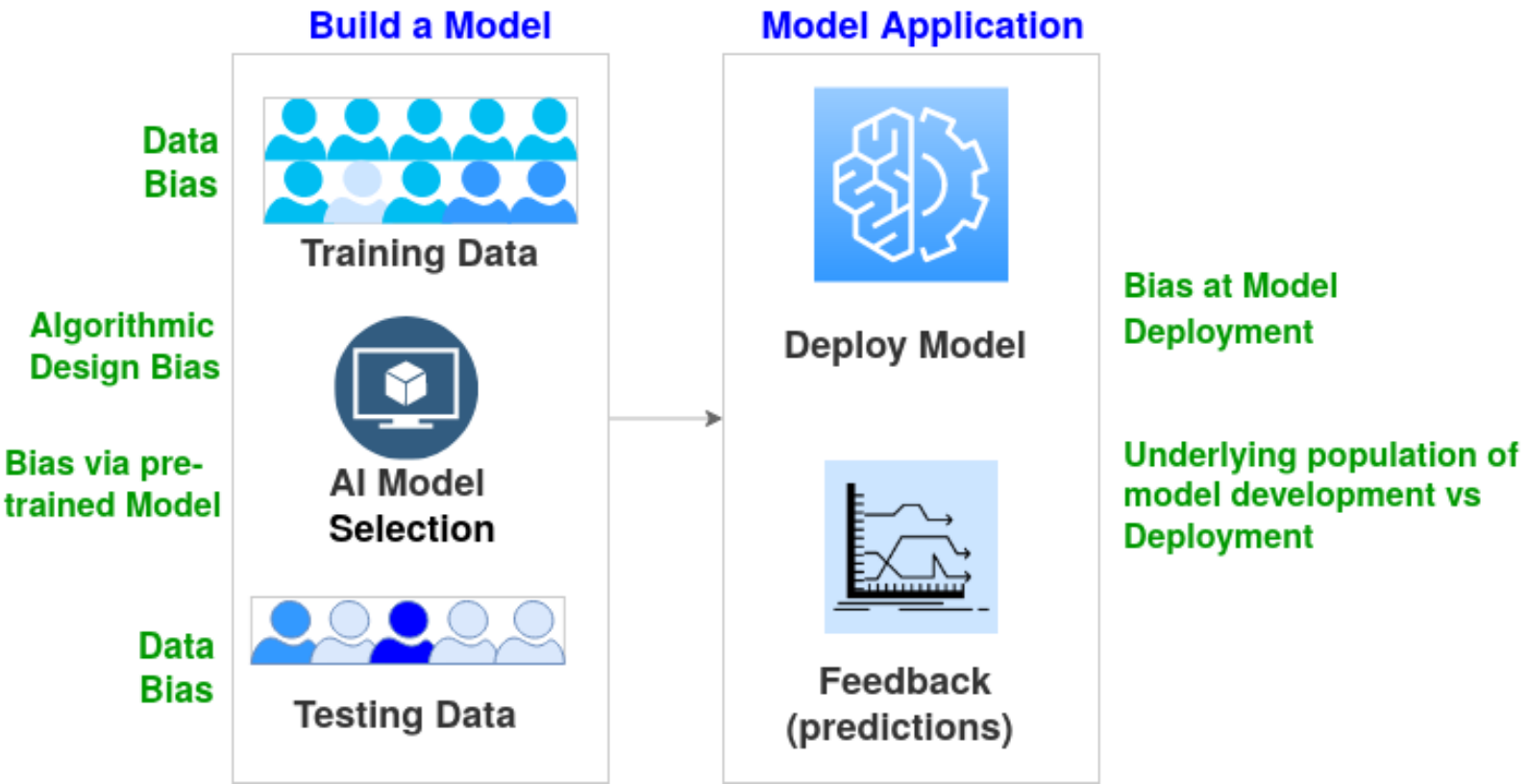
Overview

- Developments in AI are adopted widely in healthcare.
- Examples include:
  - Risk prediction and intervention
  - Population health management
  - Medical advice and triage
  - Diagnostics
  - Clinical decision making
- However, the use of AI comes with its own biases and disparities.

Basic Stages of AI/ML Life Cycle



Initial Study for Aotearoa New Zealand

Vithya Yogarajan [1], Gillian Dobbie [1], Sharon Leitch [2], Te Taka Keegan [3], Joshua Bensemann [1], Michael Witbrock [1], Varsha Asrani [4] and David Reith [5] (2022). Data and Model Bias in Artificial Intelligence for Healthcare Applications. Frontiers in Computer Science. (in progress)

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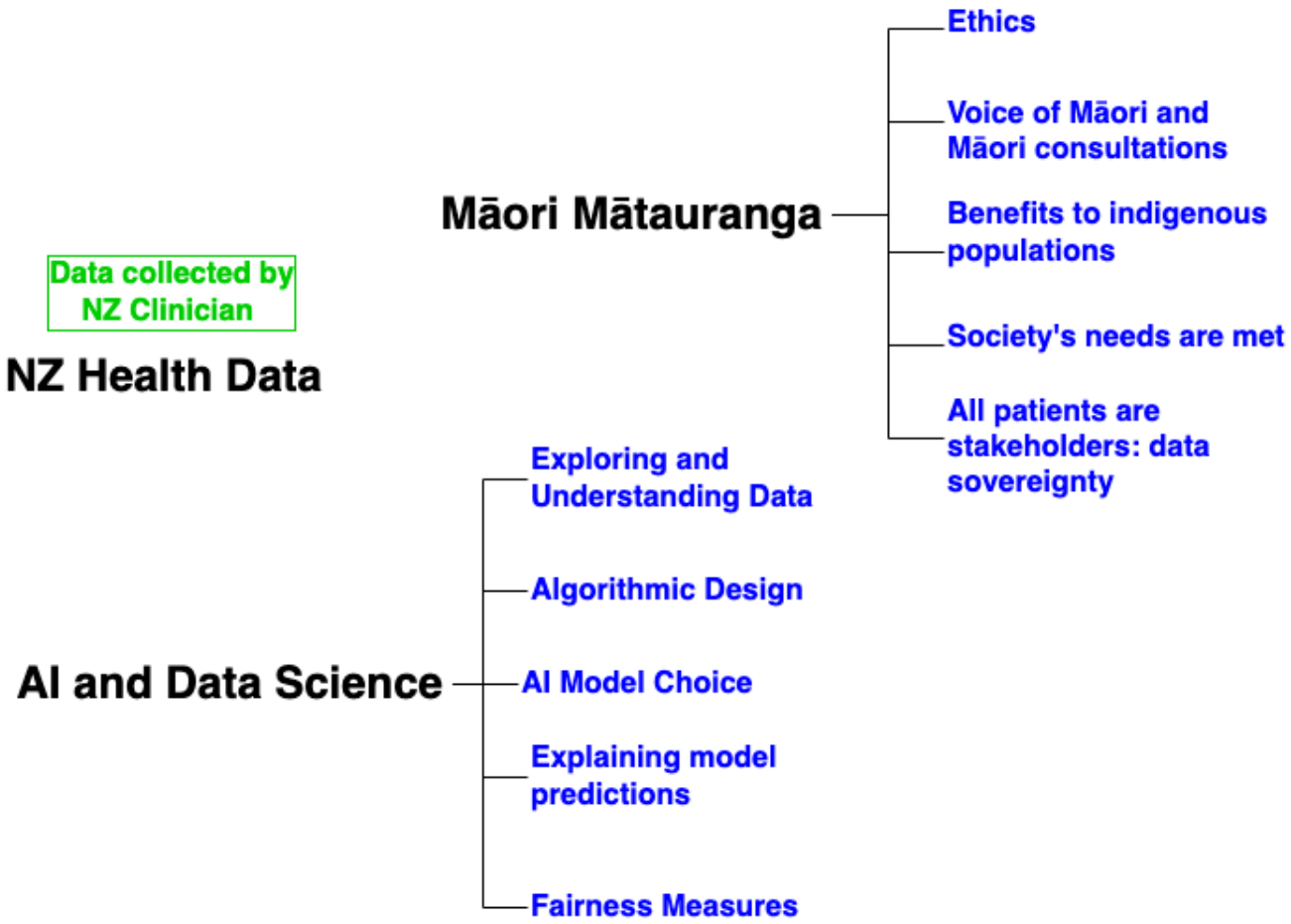
[4] STaR Centre, Department of Surgery, University of Auckland
[5] Office of the Dean, Medical School, University of Otago

Research Components



NZ-GP Data

- New Zealand General Practice (GP) EHRs data.
- Three years' worth of medical records from 44 different GP practices across NZ.
- Collected using a stratified random sampling method to minimise data collection bias.

GP Records: Data Collection

* Primary Health Organization data from the third quarter, 2013.

Bias Measures

Data bias is measured using:

$$DI(Y,S) = \frac{Pr(Y=1|S=0)}{Pr(Y=1|S=1)} \tag{1}$$

Algorithmic bias is measured using:

$$DI(g,X,S) = \frac{Pr(g(X)=1|S=0)}{Pr(g(X)=1|S=1)} \tag{2}$$

* Disparate impact (DI)* score introduced in the US legislation (1971)

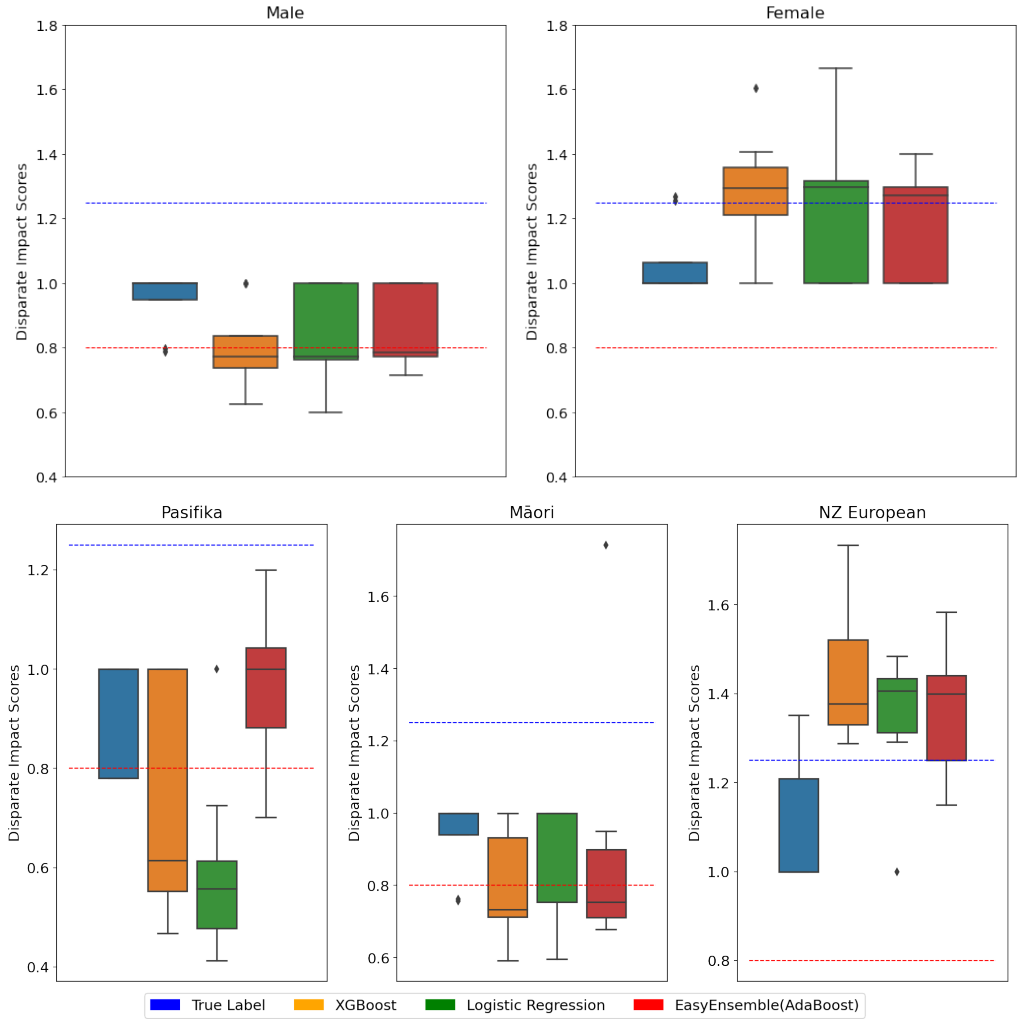
Data Bias

		Task 1		Task 2
Ethnicity				
Māori	14.6%	0.81	12.1%	1.35
NZ European	75.9%	1.36	81.1%	0.78
Pacific	3.50%	0.74	2.60%	1.28
Gender				
Male	54.5%	1.00	42.0%	1.00
Female	45.5%	1.00	58.0%	1.00

- DI scores for two tasks using NZ-GP data (varied subsets)
- DI closer to 1 is better.
- DI < 0.8 – prediction bias against the specific group.
- DI > 1.25 – prediction bias in favour of the specific group.

Protected groups		NZ-GP Data	
Ethnicity	**Gender**	**Task 1**	**Task 2**
Māori	Male	0.72	1.49
	Female	0.89	1.21
NZ European	Male	0.89	0.91
	Female	1.37	0.93
Pacific	Male	0.78	1.80
	Female	0.70	0.69

Algorithmic Bias



Discussions

- An ideal AI/ML cycle should include an in-between stage, where data and model bias needs to be identified and mitigated.
- The modified AI/ML cycle can be:

  Step 1: building a model
  Step 2: identifying and mitigating data and model bias
  Step 3: model application
- Steps 1 and 2 will require multiple iterations.
- Step 2 will require “Humans”, i.e. expertise in AI, NZ clinical context, and te ao Māori.

Future Work

- Development of Policy
- Are changes necessary to adapt these generic measures and thresholds to the New Zealand context?
- Do these models adequately represent Māori data specifically suited for the task?
- If used to guide clinical decision-making or resource allocations, would they entrench systemic or societal biases under the guise of impartiality?

Thanks for your attention!

Are there questions?