Deploying Machine Learning Algorithms in Healthcare: Challenges

Machine Learning for Healthcare and Diabetes Workshop

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CYBORG

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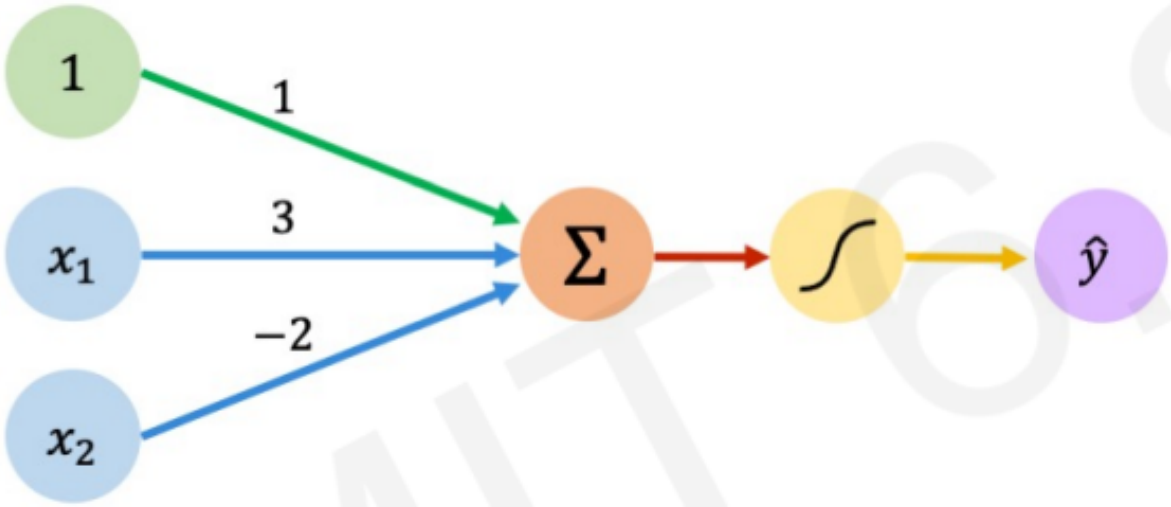

Figure 1: Perceptron [Amini, 2021]

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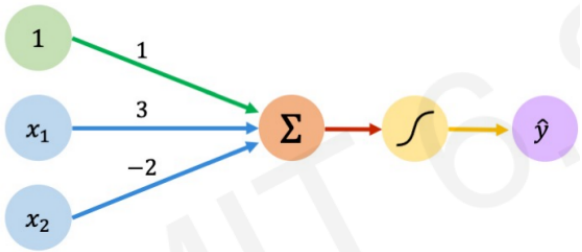

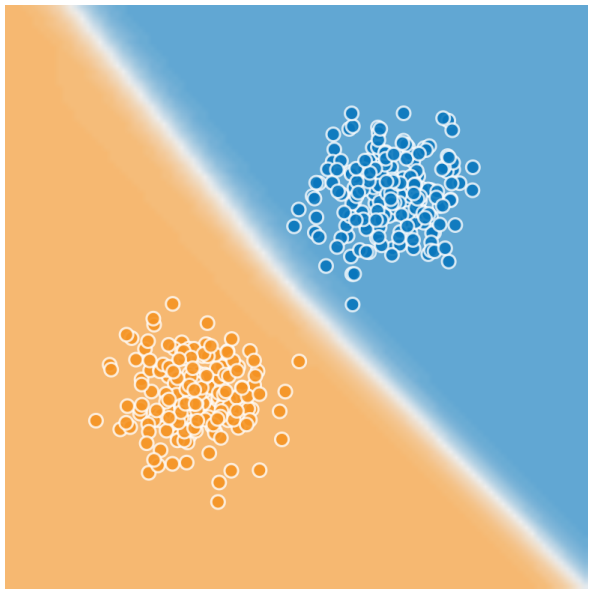

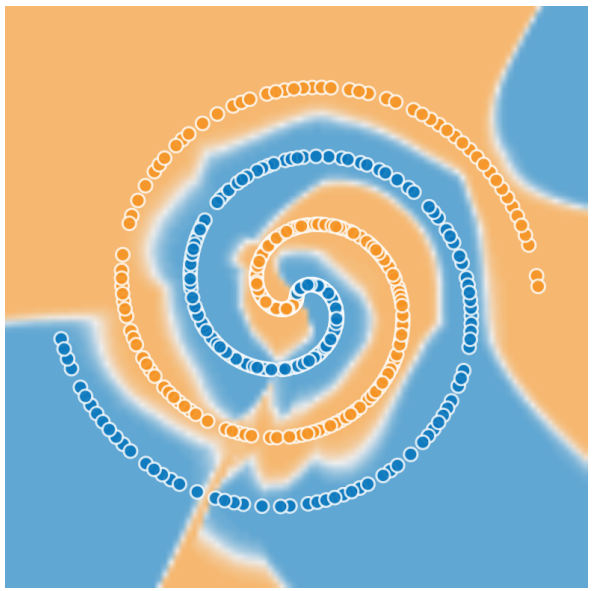

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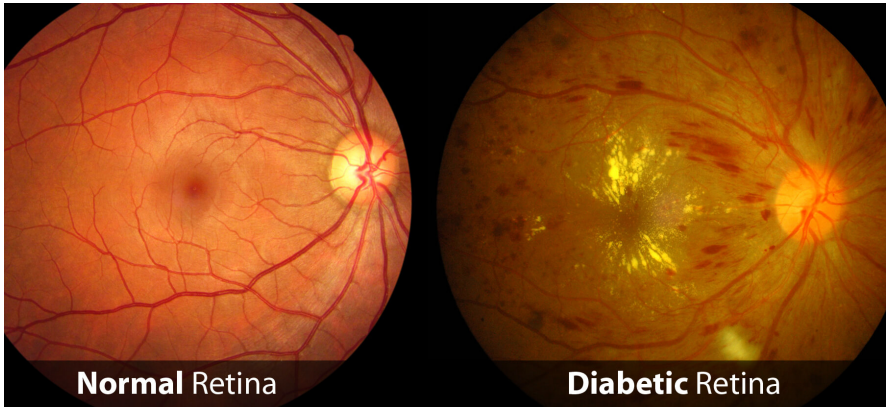
- deploying AI in a sensitive area such as healthcare necessitates a careful revisiting of every minor detail, leading to foundational innovations in the field itself

A Success Story: Diabetic Retinopathy and Macular Edema [Gulshan et al., 2016]

- regular screening by an ophthalmologist



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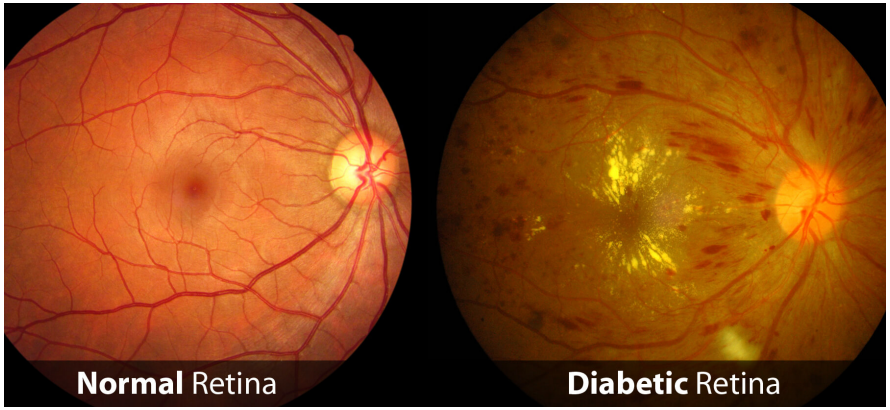

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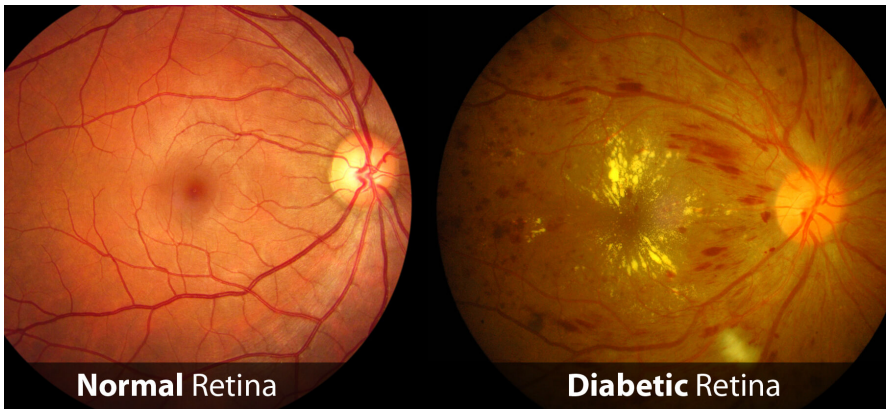

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- **specificity focused**: 90.3% sensitivity, 98.5% specificity

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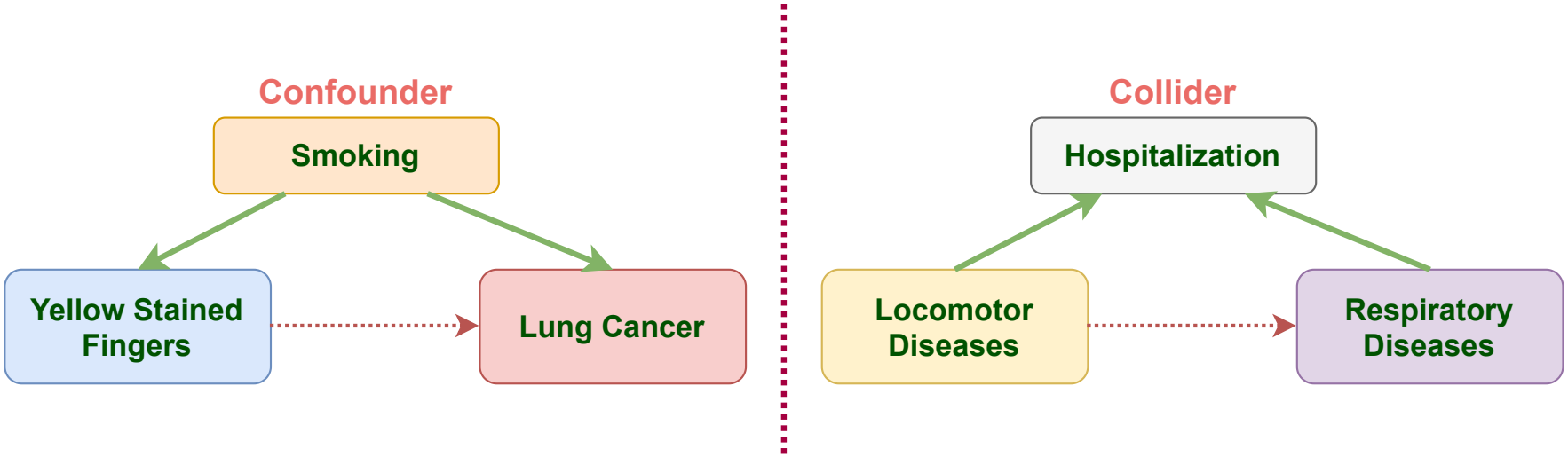

Figure 3: Confounder Bias and Collider Bias [Prosperi et al., 2020]

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- especially if we use AI for discovery in the fields where we do not have sufficient domain knowledge

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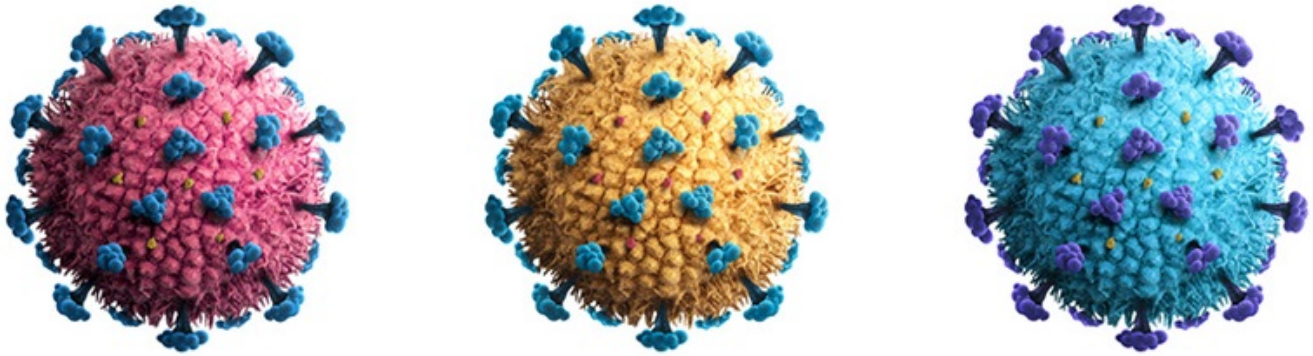

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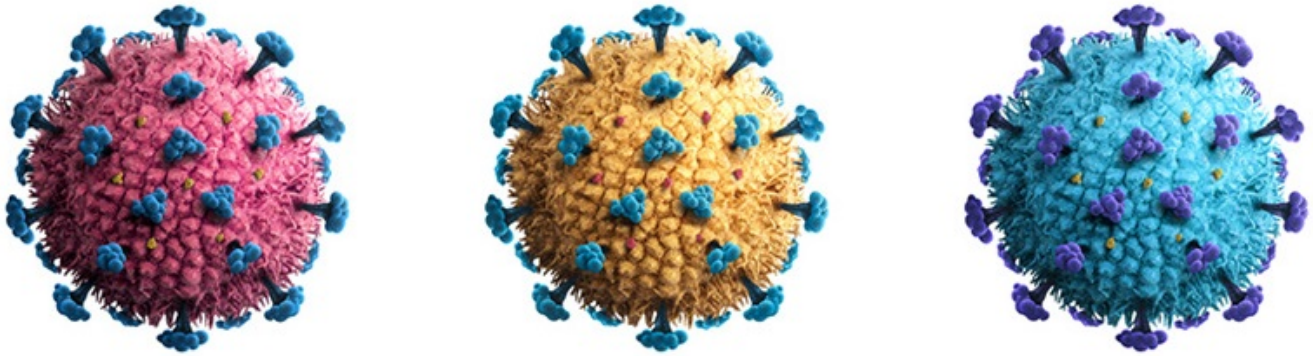

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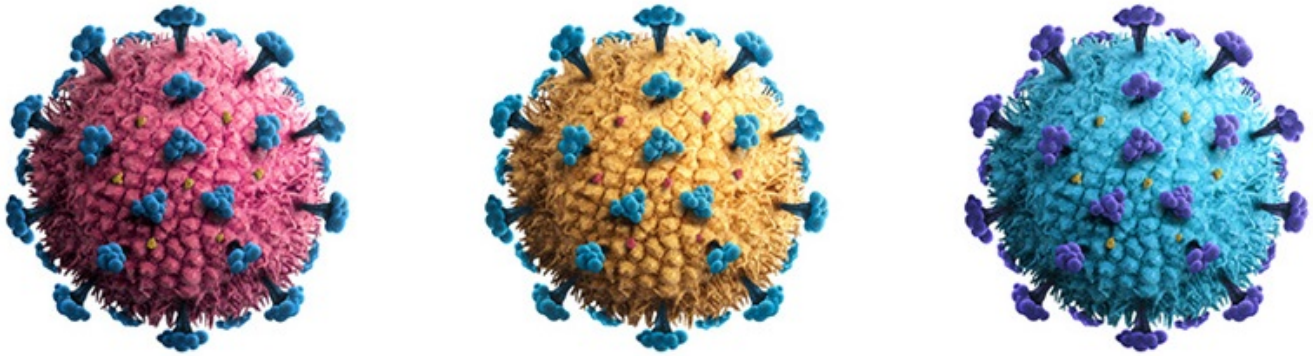

- a clinical decision-making assistance algorithm can alter the clinicians' practice...
- ...leading to **previously unattended** patient states for which the **model may not be representative anymore**

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- medical datasets are heterogenous with lots of missing entries [Ghassemi et al., 2020]
- sometimes we can resort to: **transfer learning**
  - leveraging another model's expertise on some different task
  - generally used in vision domain

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- evaluation of the patient's medical history, examination by a diabetic foot specialist, supplementary tests such as MRI, X-Ray, CT...
- can AI help in early diagnosis?

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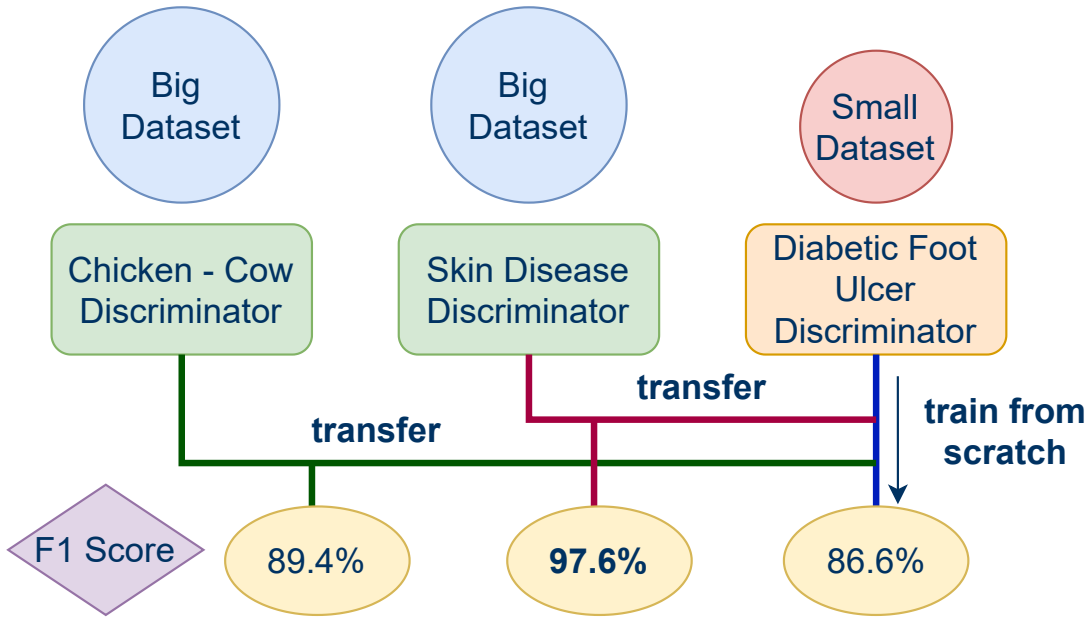

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- **wrong modeling of missing data** may lead to false predictions
  - troponin-T is measured when myocardial infarction is thought to be probable
  - if an imputer assumes troponin-T are MCAR rather than MAR, then the resulting model would overpredict the risk of myocardial infarction

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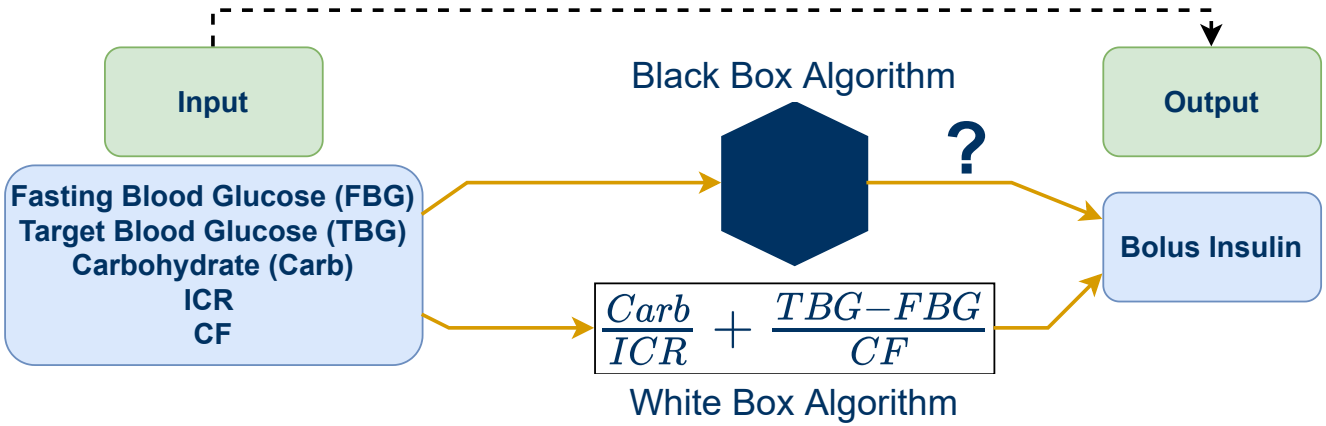

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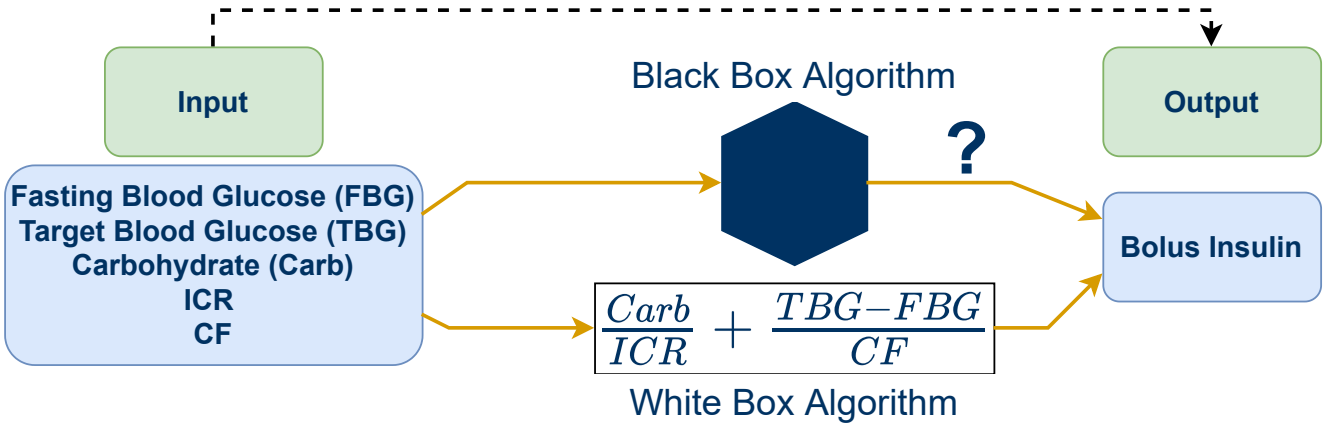

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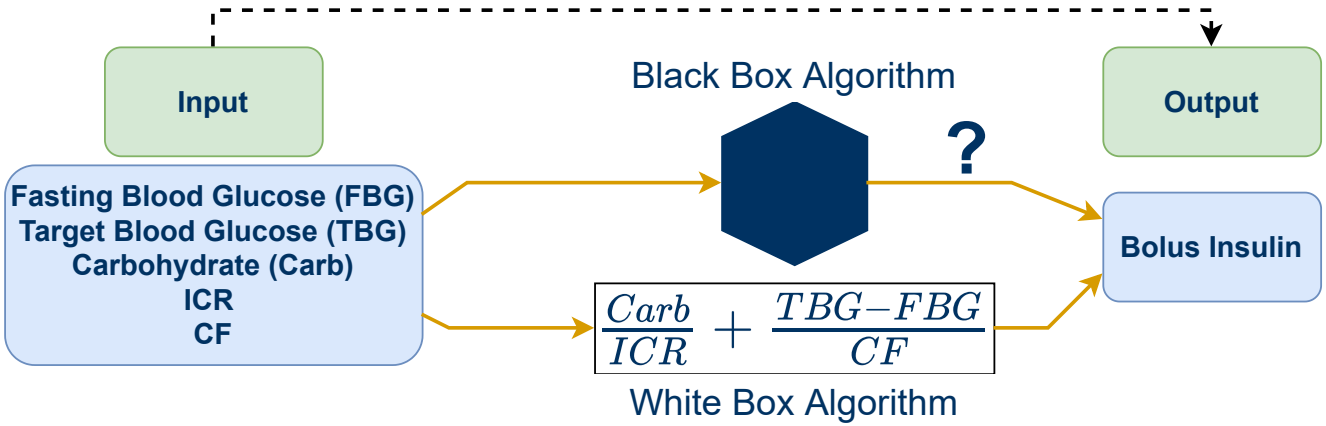

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- a (currently) safer reference: **thorough external validation**

Ethical Aspect

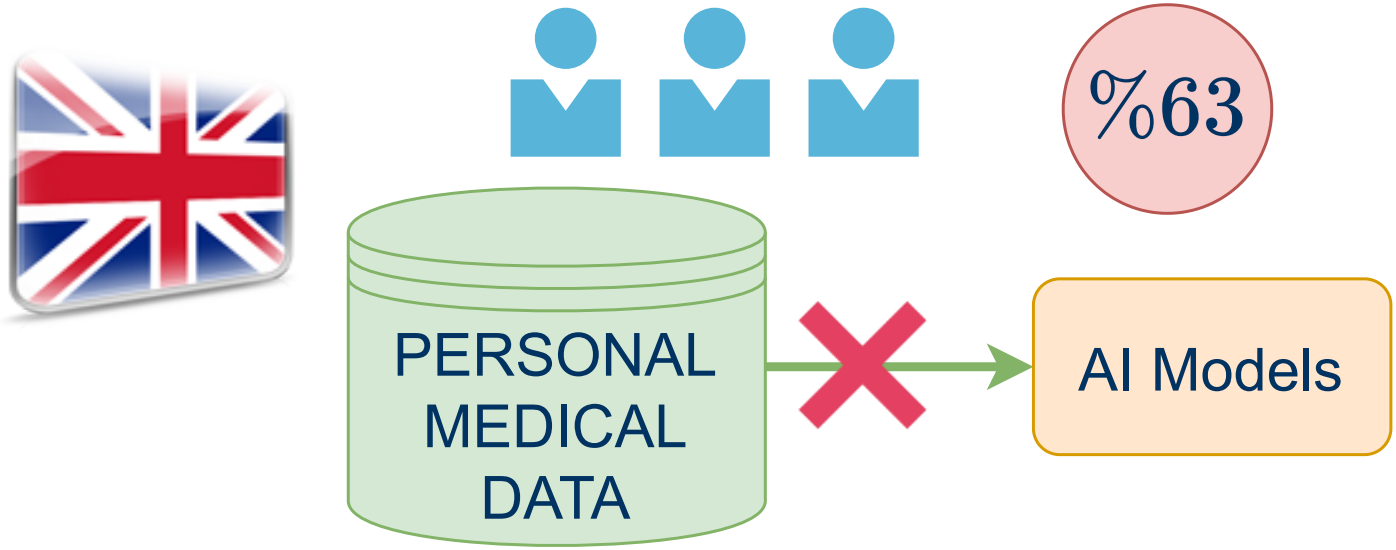

Figure 5: [Vayena et al., 2018]

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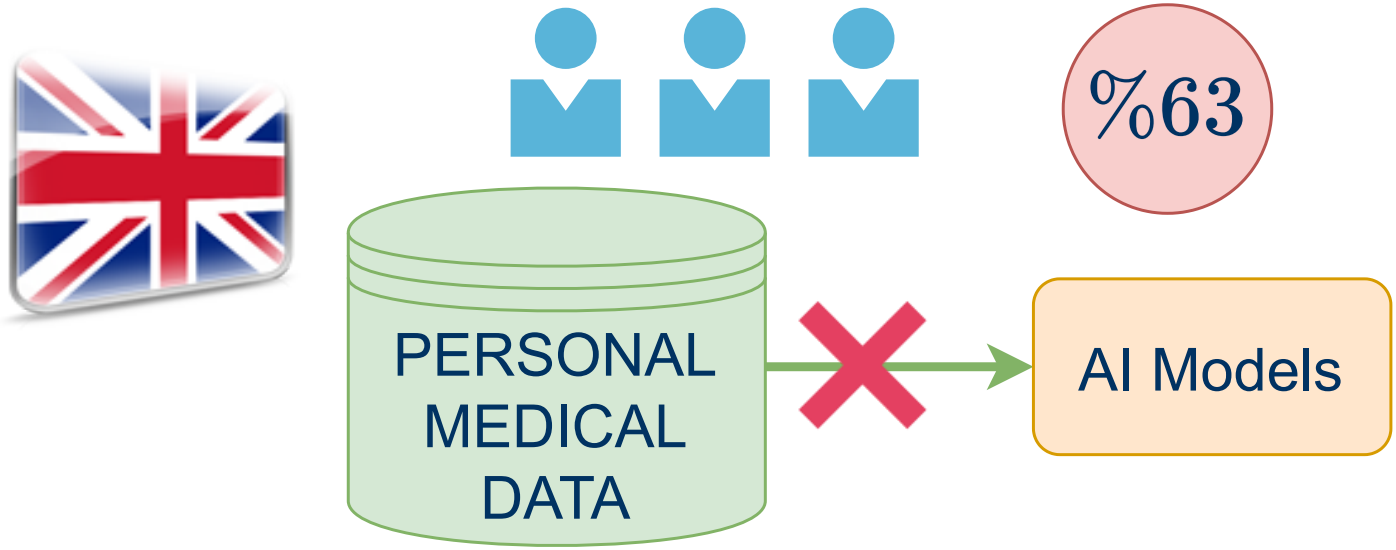

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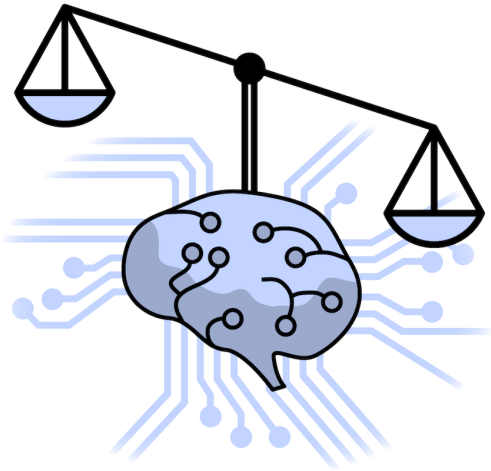
- if a patient did not share her smoking status or HIV status...
- should we use imputation methods to impute them? [Wiens et al., 2019]

Fairness



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- what could "fairness" mean in the context of AI and healthcare?

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- another interesting bias: **healthy volunteer bias**
- 23andMe genotype dataset, 2399 people: **2,098 (87%) European**, **58 (2%) Asian**, and **50 (2%) African** [Mehrabi et al., 2021]

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- an exome analysis study to predict hypertrophic cardiomyopathy [Manrai et al., 2016]
  - benign variant classified as pathogenic for people with African ancestry...
  - ...which would not occur should more people with African ancestry were included during training

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