Use of AI to improve the early detection of upper GI cancers from routine blood tests

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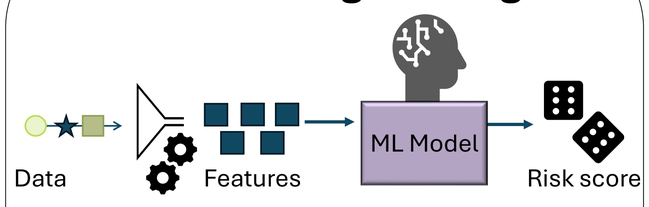
Introduction

- Upper gastrointestinal (GI) cancers are characterised by late diagnosis and **poor survival rates**.
- Upper GI cancers are **difficult to diagnose**, largely due to late-presenting, vague symptoms.
- Changes in blood tests over time may show signs of cancer **earlier** than current diagnostic criteria.
- Models using longitudinal data for cancer prediction often fall under two approaches: feature engineering or sequential input. The two approaches are **rarely compared**[1].

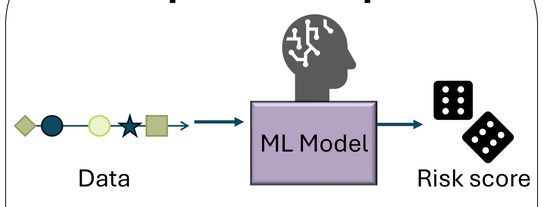
AIM: Develop predictive models to detect upper GI cancers from primary care blood tests, comparing feature engineering and sequential approaches

Feature engineering

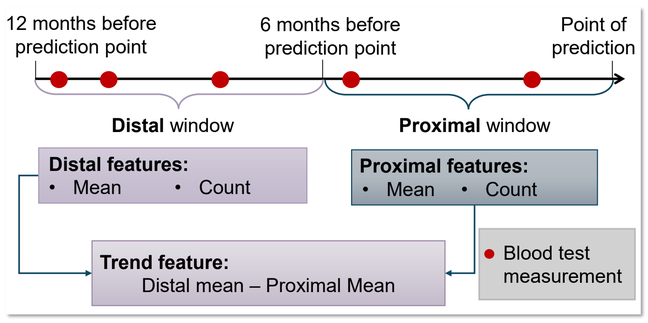


+ Interpretable, can be used alongside simpler classification algorithms
− Requires expert knowledge to craft features, may miss complex patterns

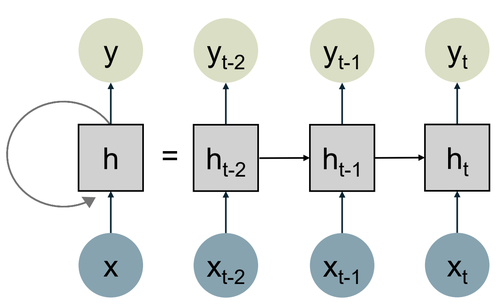
Sequential input



+ Can potentially capture more complex, novel patterns
− Computationally expensive, 'black box' models

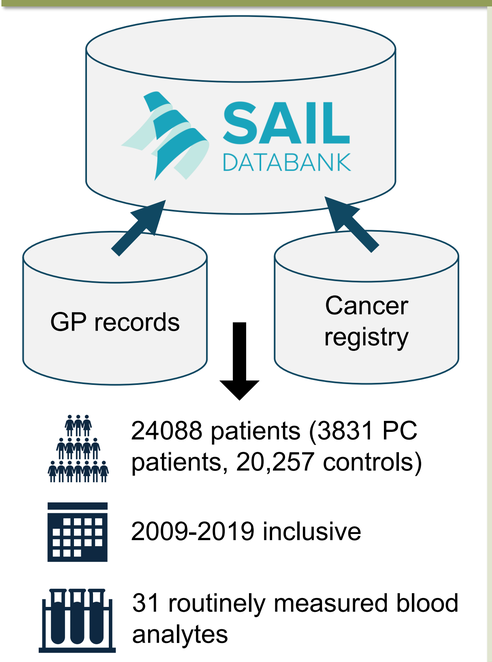


Feature engineering approach



Unfolded representation of an RNN model

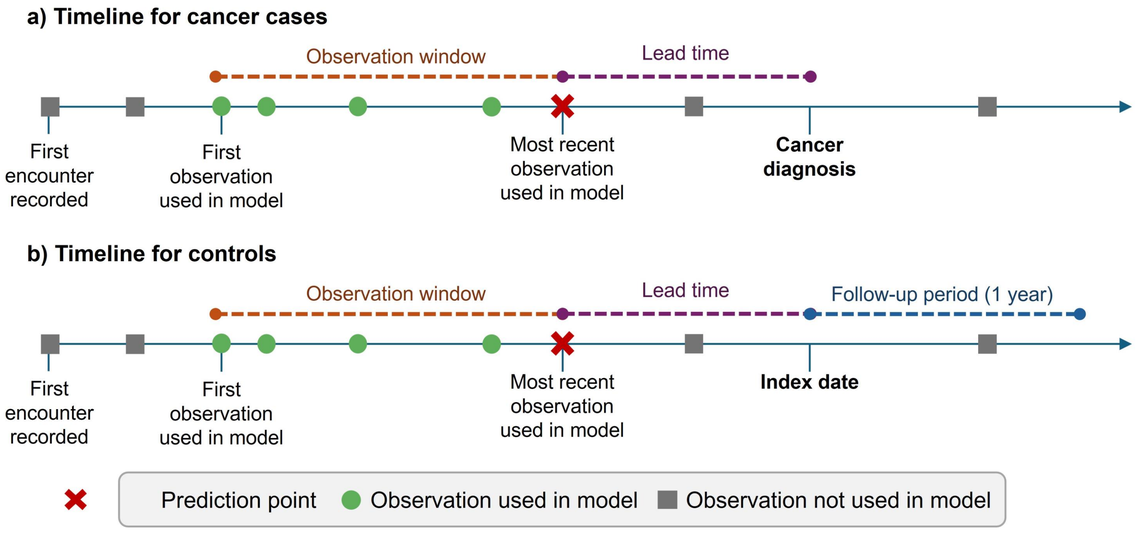
Data



- **S**ecure **A**nonymised **I**nformation **L**inkage (SAIL) databank[2]
  - Linked GP records and cancer registry data for Wales, covering 2.8 million patients
- **Case-control** dataset matched 1:4 on age and sex at each lead time. Index date was date of diagnosis for PC patients; for controls, a random index date was chosen within their trajectories.

Methodology

- Models were trained and evaluated at different **lead times** before diagnosis
- 5-fold cross-validation
- Feature engineering + Logistic Regression (best performing in prior work)
- Sequential input models were LSTM, GRU, & GRU-D[3]



Acknowledgments
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References
[1] V. Moglia *et al., BMC Med Res Methodol*, vol. 25, no. 1, p. 24, 2025.
[2] R. A. Lyons *et al.*, *BMC Medical Informatics and Decision Making*, vol. 9, no. 1, p. 3, Jan. 2009
[3] Z. Che *et al.,* Sci Rep, vol. 8, no. 1, p. 6085, 2018

Findings

- **Trend features improve performance** compared to traditional machine learning models using a single timepoint:

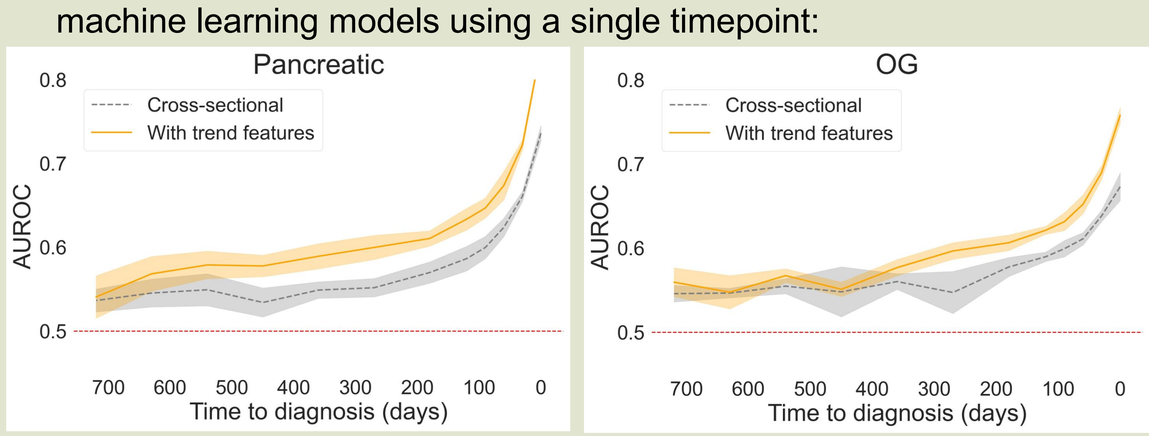

Figure 1: Performance of logistic regression models with and without trend features when predicting pancreatic and oesophageal cancer. The red dotted line is random classification.

- **Deep learning models** did not improve upon logistic regression with engineered features

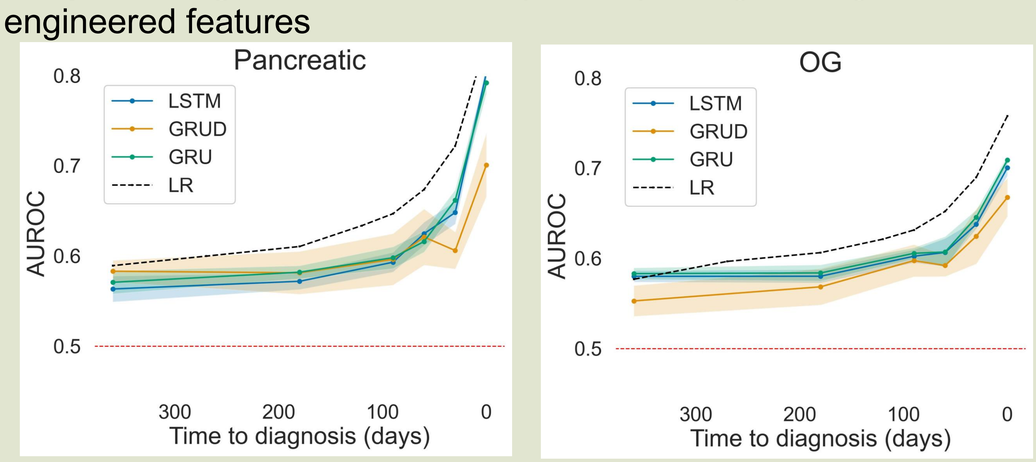

Figure 2: Performance of deep learning models with logistic regression (LR) for comparison, shown with a black dotted line.

Note: higher AUROC means a **model is better** at differentiating between a cancer patient and a non-cancer patient

In real numbers…

At **2 months before diagnosis**, the pancreatic cancer model has an AUROC of **0.67**. At the optimal threshold, if we applied the model to 100 patients, of whom 20 have cancer:

- ⊕ Correctly identify 12 cancer patients.
- ⊕ 30 false positives.
- ⊖ Miss 8 cancers.
- ⊖ 50 true negatives.

Takeaways

- Pre-cancer signals in blood tests are **difficult to detect**, but some differences **can be detected months** before diagnosis
- Blood test **trends** could be used to **improve** prediction models
- **More complex models don't necessarily mean better performance**