

Improvements in Fault Prediction Capabilities for Radiotherapy Machines

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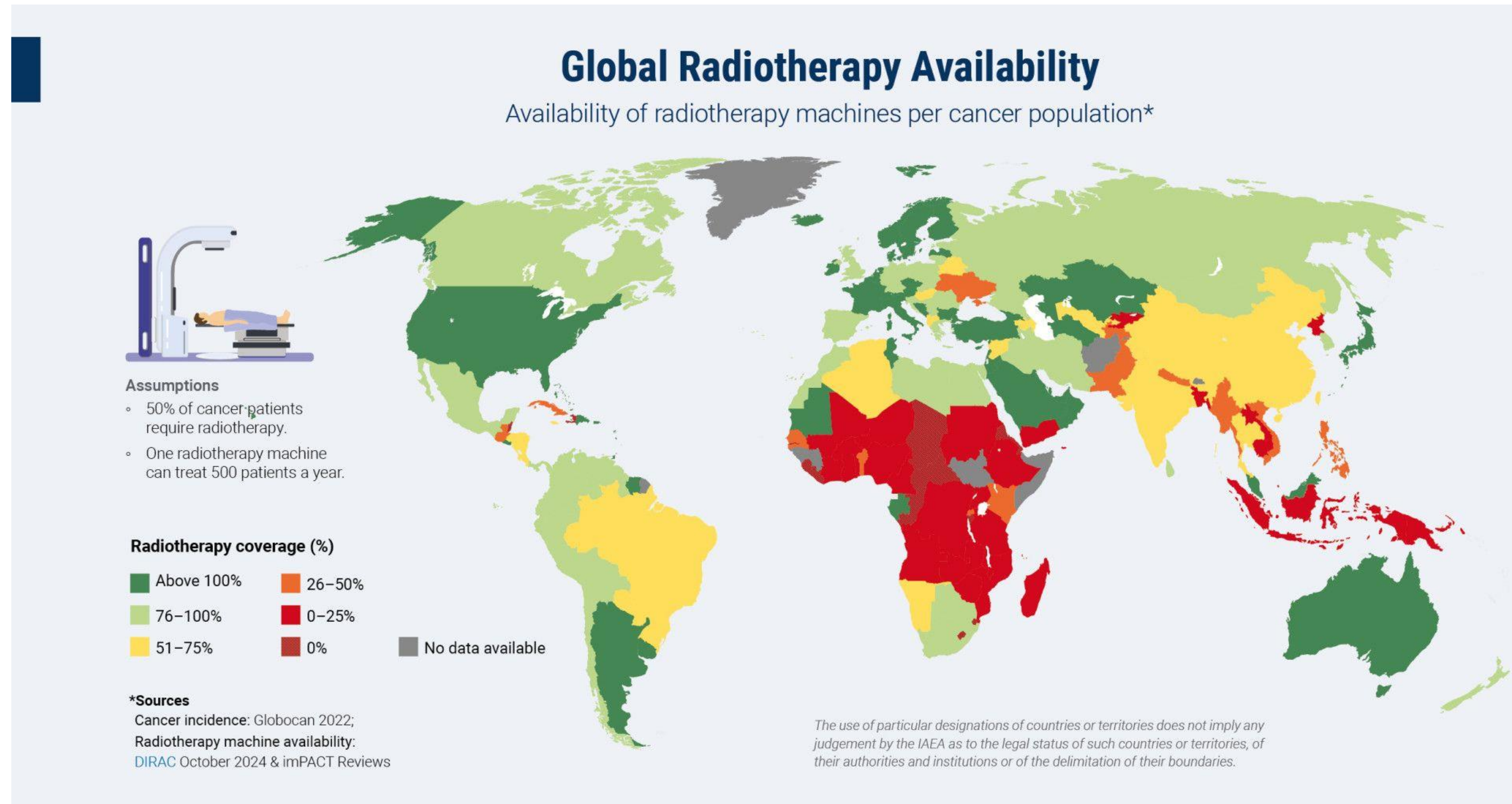


STELLA

SMART TECHNOLOGY
TO EXTEND LIVES WITH
LINEAR ACCELERATORS

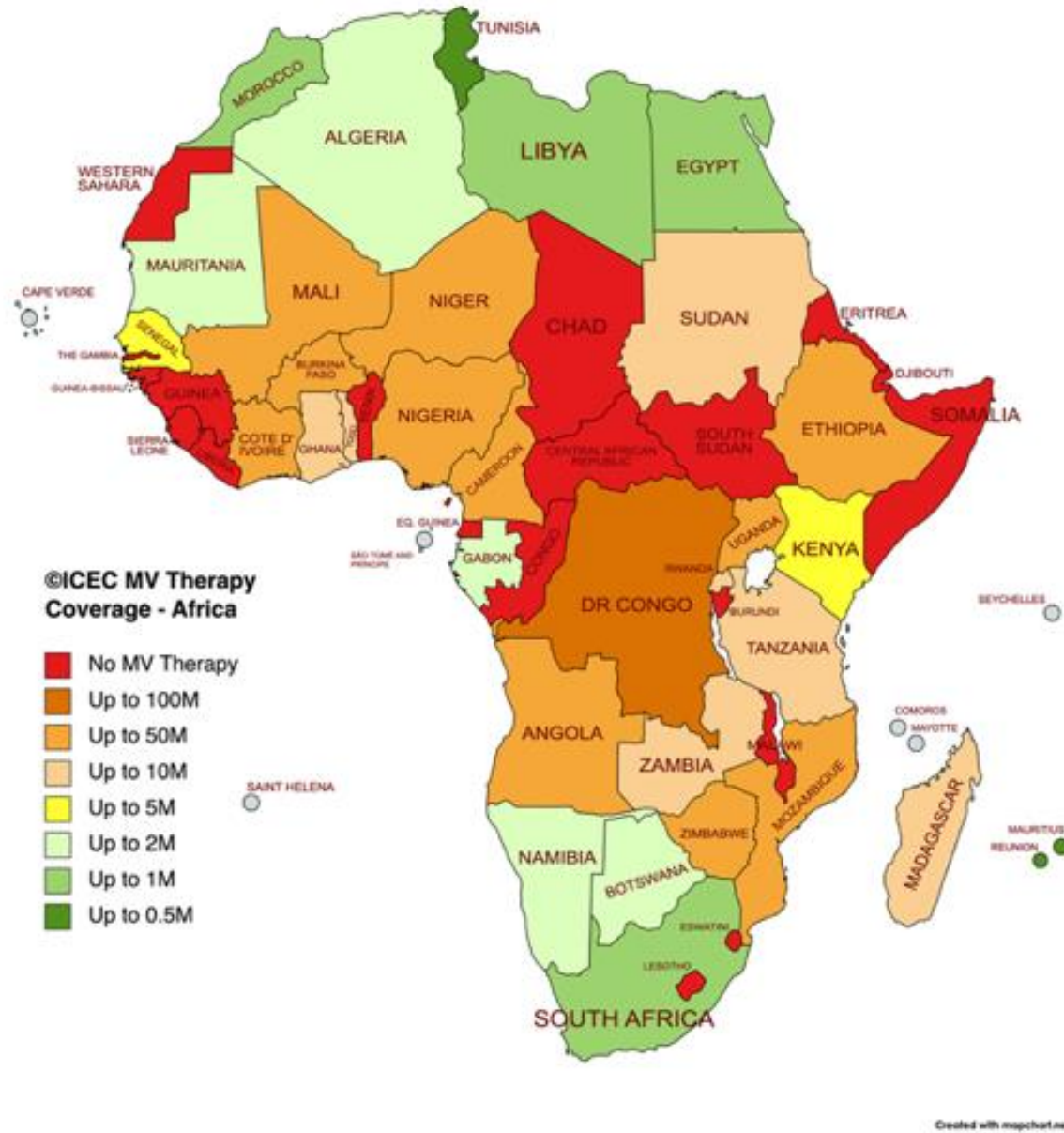


Background

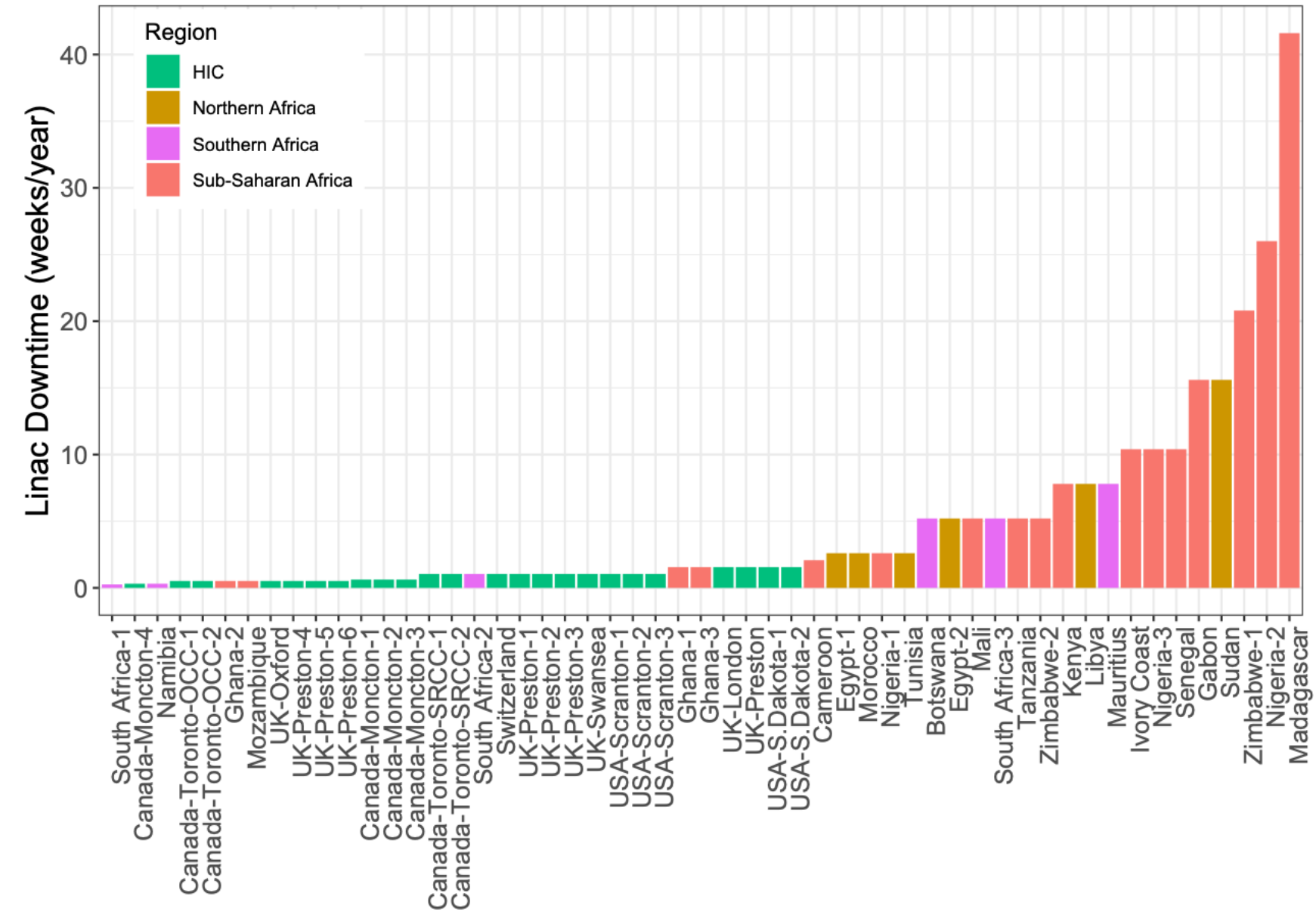


M. Dosanjh, 2025. "Towards Implementing Project STELLA on radiotherapy powered by AI", GHC Summit. MIT, Boston, 19/09/25.

Background



Number of linacs per country in Africa. *Credit: ICEC*



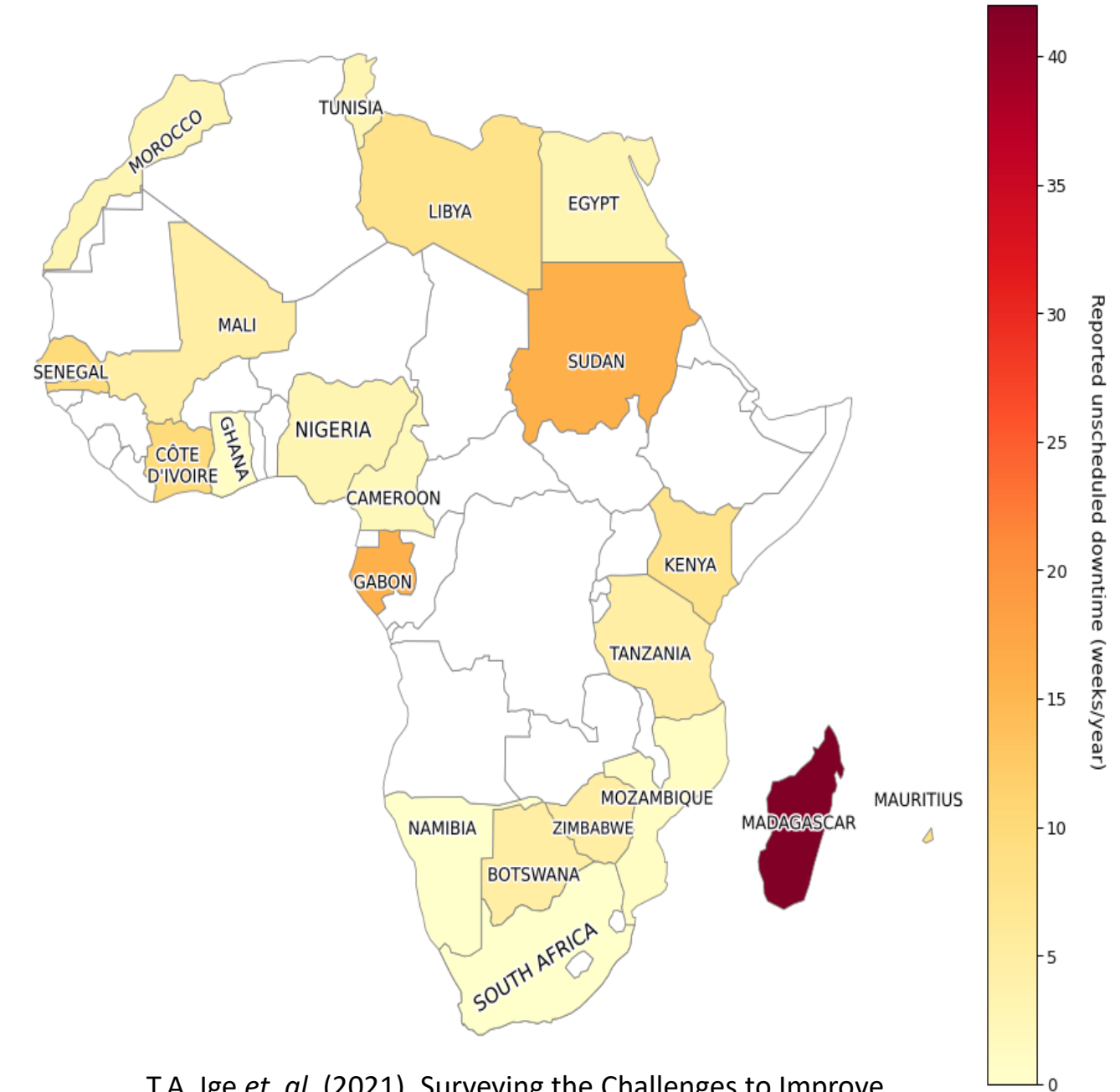
Machine downtime in countries in Africa compared with that in Canada, UK and US.

Project STELLA

- Established 2016 with the goal of increasing global radiotherapy access.
- Global multidisciplinary NGO collaboration under the umbrella of ICEC.
 - Oxford, Cambridge, Lancaster, CERN, African partners
- Increase access to radiotherapy in LMICs and rural areas.
 - New LINAC design, more robust, cheaper, same treatment capabilities
 - Improved training for RT engineers to operate and troubleshoot RT LINACs
 - Reduce downtime in existing RT centres using advanced computing techniques

Motivation

- Access to RT in LMICs (such as in Africa) is highly limited by available machines.
- Of the few available machines, many experience significant downtime, far more than in HICs.
- Machines are pushed harder to compensate for lower availability.
- Ability to predict machine downtime in advance allows for repair preparation & preventative maintenance.



T.A. Ige *et. al.* (2021). Surveying the Challenges to Improve Linear Accelerator-based Radiation Therapy in Africa

RT Machine Log Files

- Automatically recorded onto RT LINACS (Varian TrueBeam), no patient identifiable data.
- Contains information on the exact state of the machine at any point in time.
- “Interlocks” – reduction in the state of treatment readiness for the RT LINAC
- Want to predict when specific interlocks are likely to occur.

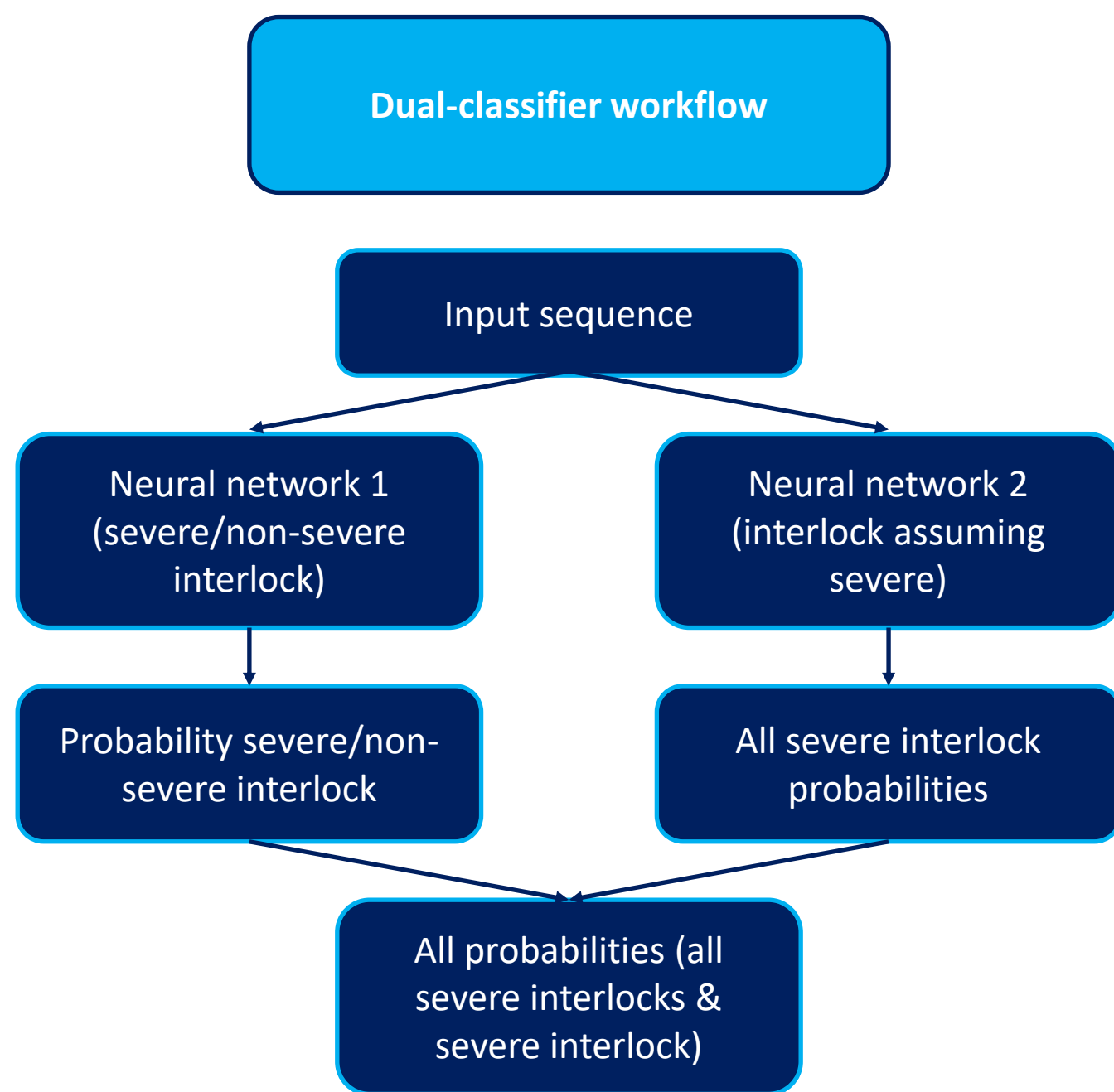
Time & date of interlock code	Interlock code
2024-03-27 07:49:15 Local0Info07:49:15:679SN# 3936COLFaultCMNFault::raise	Fault detected (420302: L B MLC Fiber Op
2024-03-27 07:49:15 Local0Info07:49:15:746SN# 3936BGMFaultCMNFault::raise	Fault detected (214261 L B POS PCB: Cui
2024-03-27 07:49:15 Local0Info07:49:15:746SN# 3936BGMFaultCMNFault::raise	Fault detected (214262 L B POS PCB: Cui
2024-03-27 07:49:15 Local0Info07:49:15:746SN# 3936BGMFaultCMNFault::raise	Fault detected (214268 L B POS PCB: 28)
2024-03-27 07:49:15 Local0Info07:49:15:709SN# 3936COLFaultCMNFault::raise	Fault detected (420400: L B MLC Bank A L
2024-03-27 07:49:15 Local0Info07:49:15:719SN# 3936COLFaultCMNFault::raise	Fault detected (420500: L B MLC Bank A C
2024-03-27 07:49:15 Local0Info07:49:15:730SN# 3936COLFaultCMNFault::raise	Fault detected (420600: L B MLC Bank B L

Example of processed Varian Combined Log file. All interlocks have been extracted but are yet to be filtered.

“Severe” Interlocks & Machine Learning

- “Severe” interlocks are defined as interlocks causing *machine downtime* and reducing patient throughput capability (increasing *clinical downtime*).
- A list of these interlocks has been collated by radiotherapy engineers at Exeter Hospital based on past faults that have caused machine downtime.
- Prediction of severe interlocks is key to allowing preventative maintenance and preparation
 - With so much data, this is a high-dimensional pattern recognition problem that a human would struggle to solve.
 - Machine learning algorithms can recognise long-term relationships and contexts in data and reduce the dimensionality of the problem for interpretation.

Dual-Classifier Variational Autoencoder Approach



- Novel dual- classifier VAE splits classification into two tasks:
 - severe/non-severe interlock
 - most likely severe interlock (assuming interlock is severe)
- Inputs are sets of 100 consecutive interlocks, plus 50 more sampled up to 1 week prior.
 - Training inputs are labelled with the next interlock code.
- Inputs are projected into a low-dimensional latent space:
 - Severe interlocks with similar causes are spatially close in the latent space.
 - Position of an input in latent space allows for probabilistic predictions of proceeding interlocks.

(Aside) Best Model Selection

- Best models are selected by macro-F1 score.
- F1 defined as the harmonic mean of precision and recall
 - Range between 0 (no accurate classification) and 1 (perfect classification)

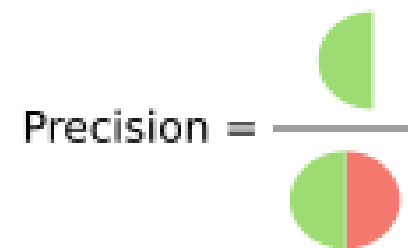
$$F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

$$F_1^{macro} = \sum_{class} F_1^{class}$$

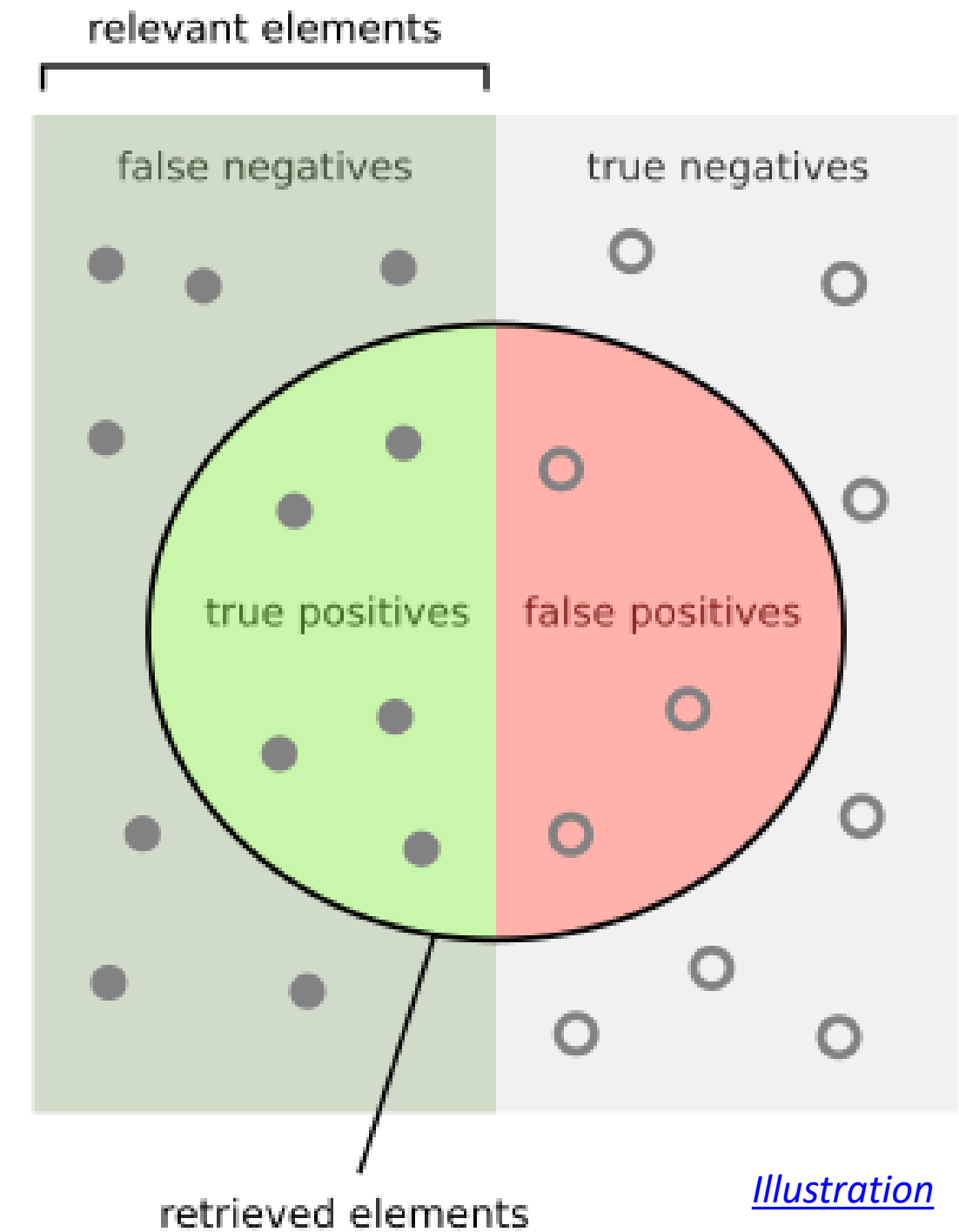
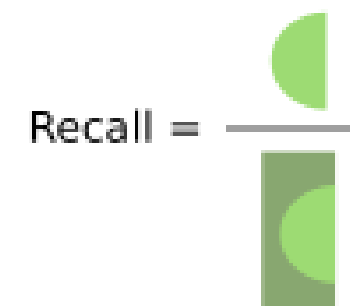
- Accuracy also considered to initially drive learning:

$$\text{Acc} = \frac{\text{correct preds}}{\text{total preds}}$$

How many retrieved items are relevant?

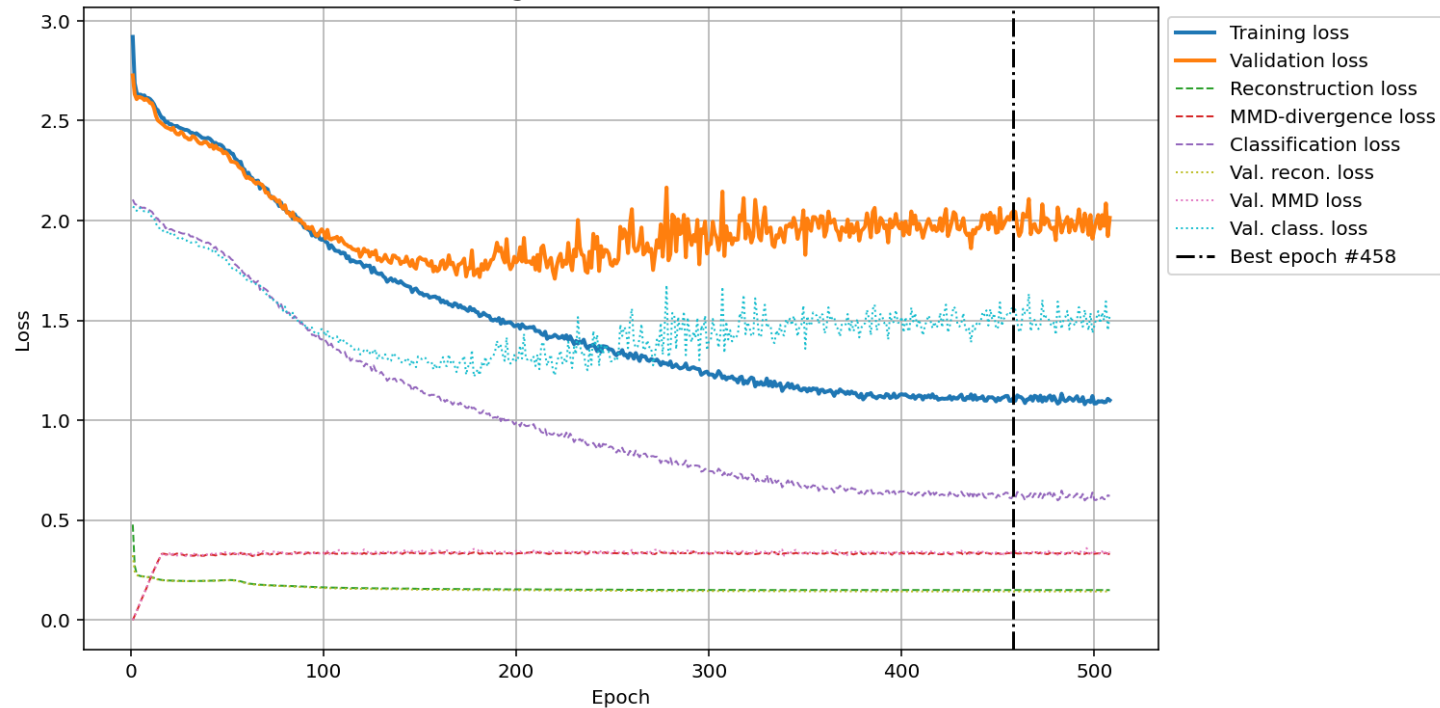


How many relevant items are retrieved?

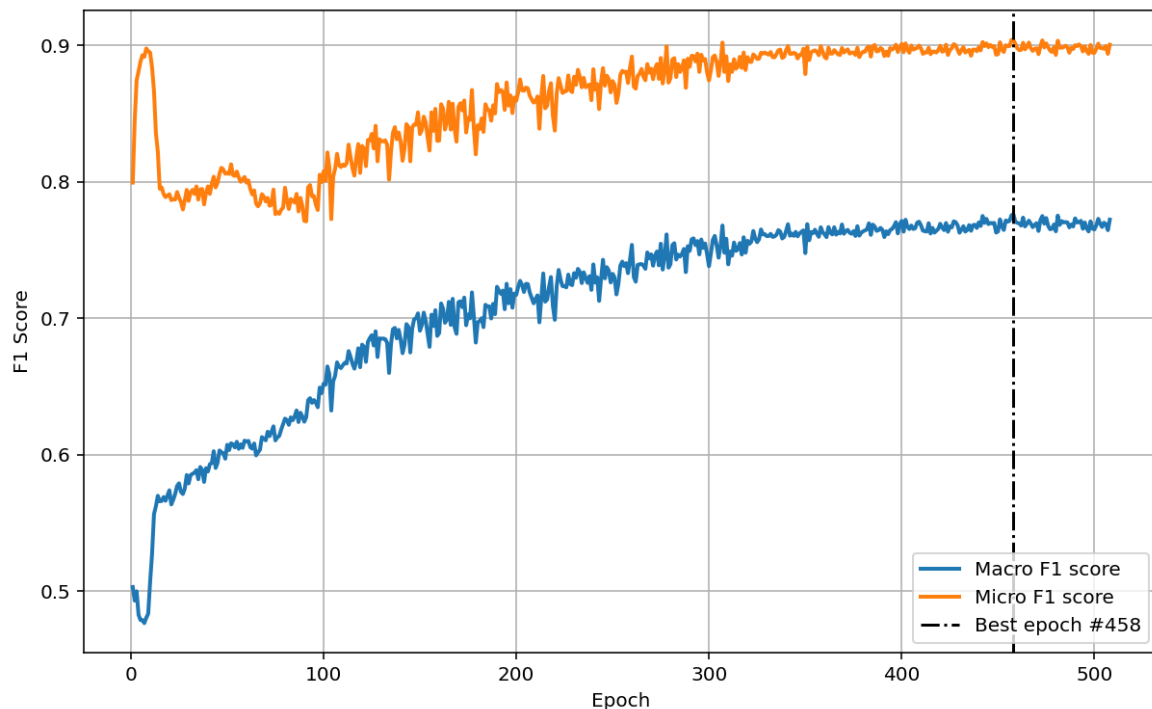


Binary Classifier Performance

Training & validation loss curves



Macro- and Micro-F1 scores



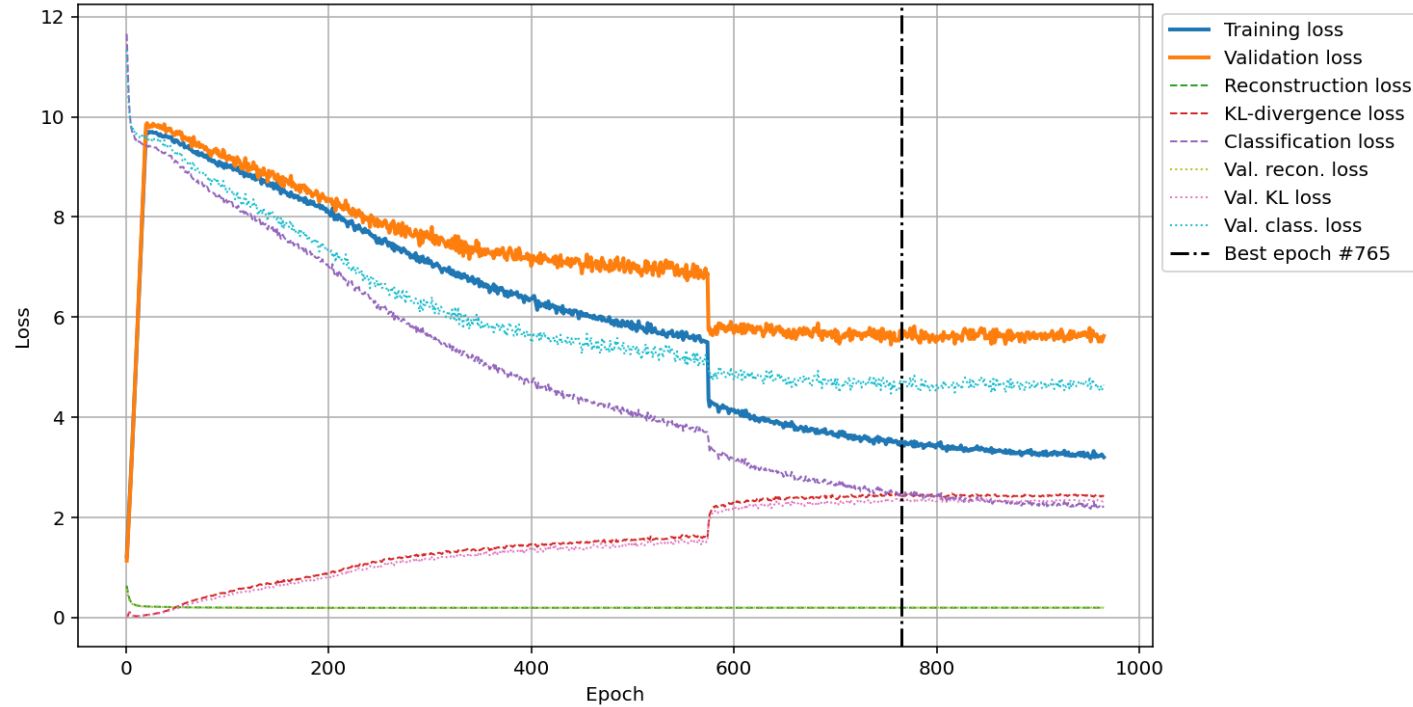
- F1 scores are very strong:

```
Classification accuracy on all samples: 88.81% (1127/1269)
Classification accuracy on severe samples: 70.54% (91/129)
Classification accuracy on non-severe samples: 90.88% (1036/1140)
Val Macro-F1: 0.7488, Micro-F1: 0.8881
```

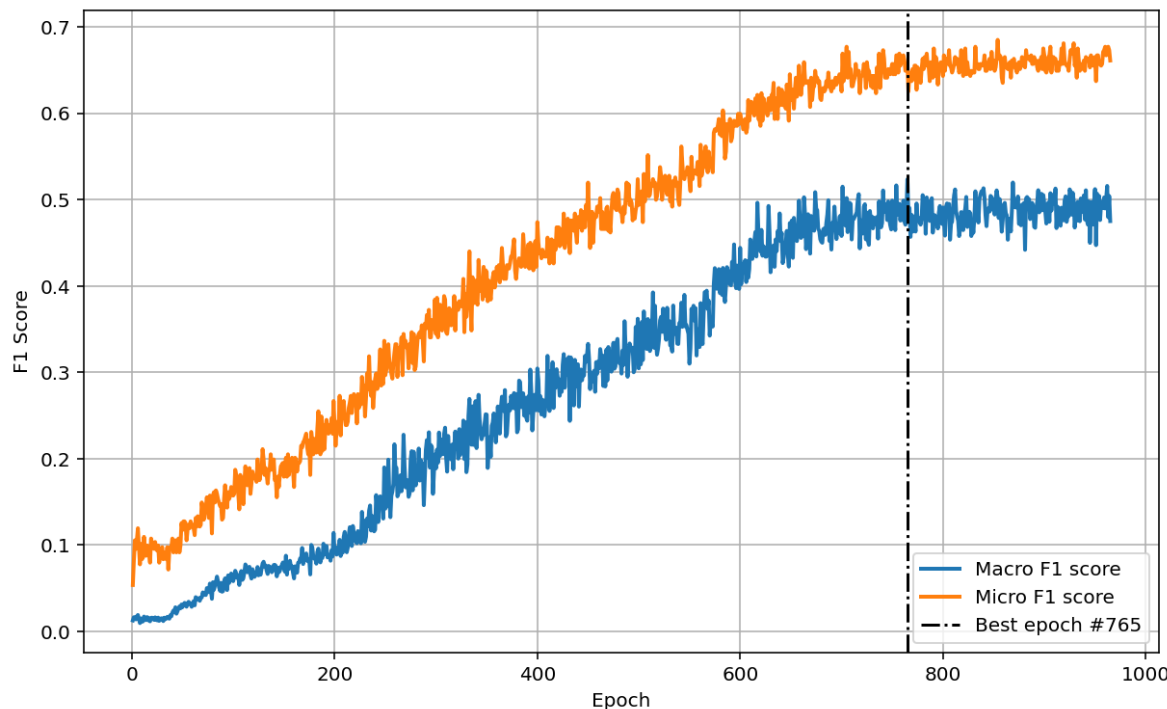
- Model is better at predicting non-severe vs. severe interlocks:
 - Potentially expected due to large class imbalance.
 - Tried several methods e.g. class weighting to improve this with limited success.
 - Improvement will likely require larger volumes of data, specifically with severe interlocks.

Fault Classifier Performance

Training & validation loss curves



Macro- and Micro-F1 scores



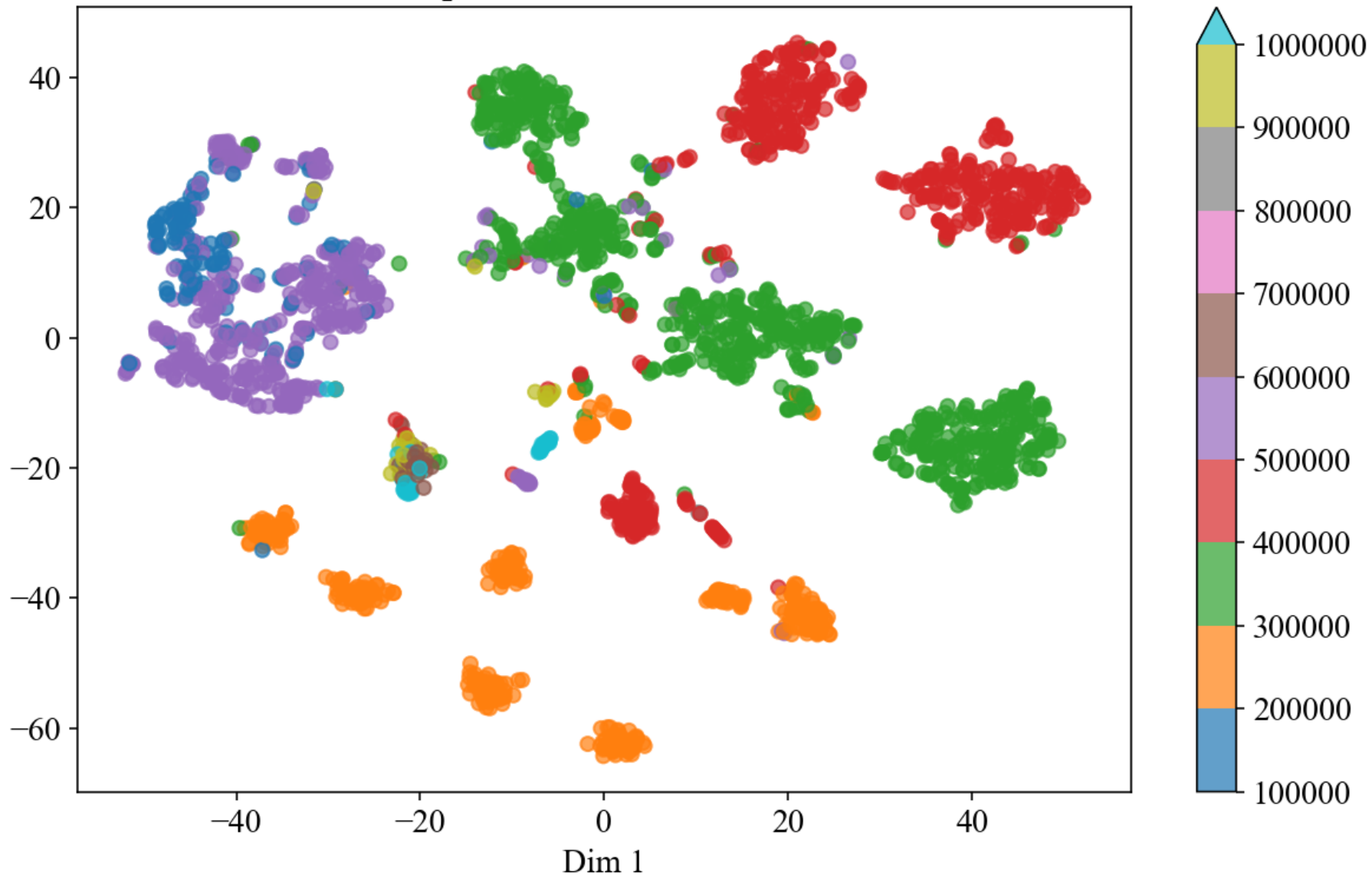
- F1 Scores:

```
Classification accuracy: 65.61% (248/378)
Classification accuracy (top 3): 87.04% (329/378)
Subsystem classification accuracy: 81.48% (308/378)
Val Macro-F1: 0.5438, Micro-F1: 0.6561
```

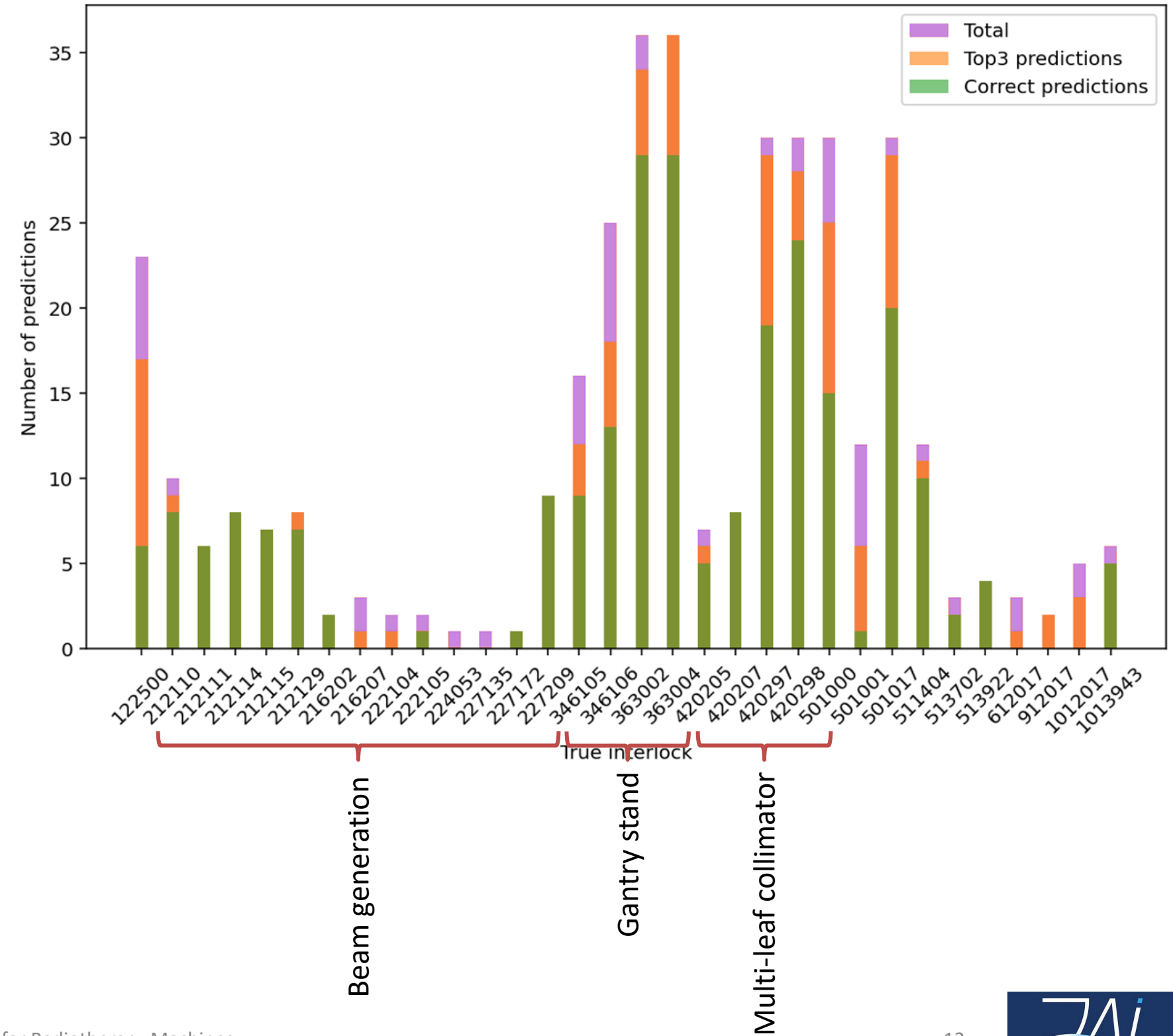
- Model shows significantly better-than-even odds of predicting exactly the correct next severe interlock in series:
 - Top 3 accuracy is approaching 90%.
 - Most of the time all top 3 interlocks are very similar e.g. 212110, 212111, 212114 (Dose less than expected).
- Significant improvement over this is difficult due to the inherently random nature of breakdowns.

Fault Classifier Latent Space

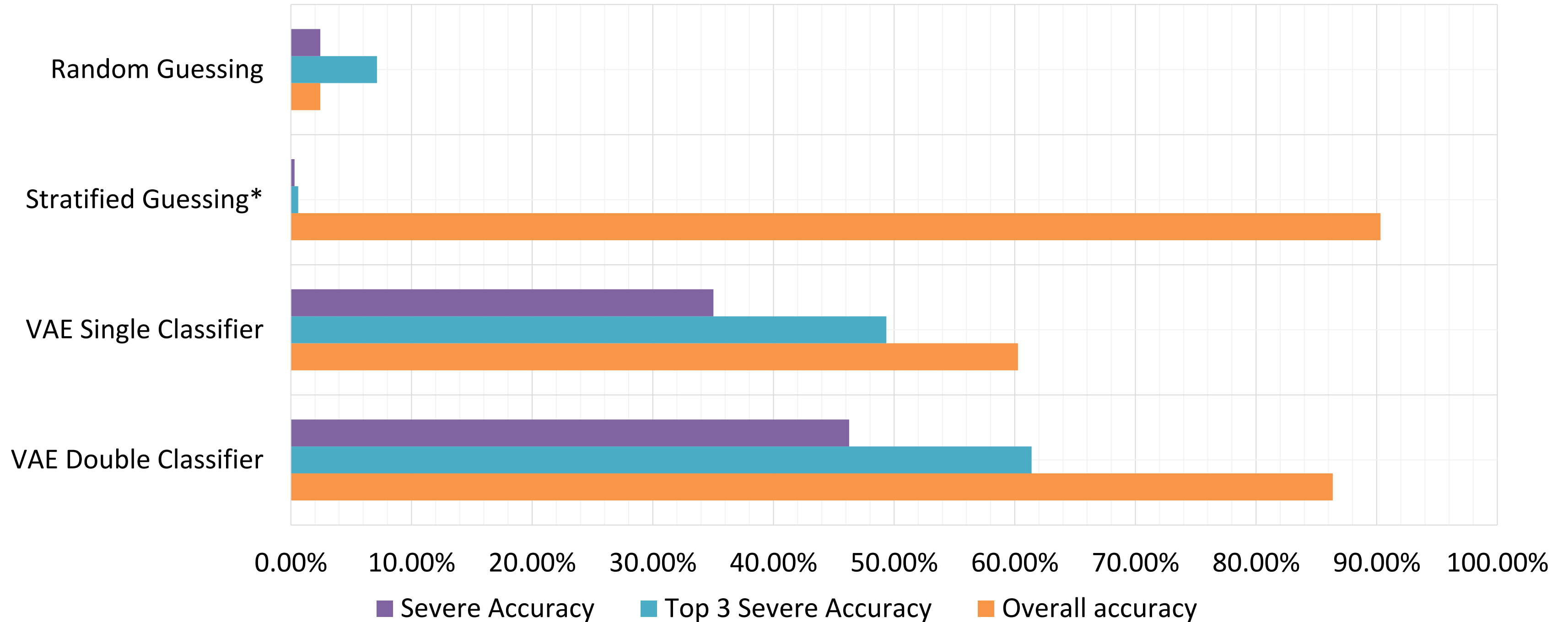
Latent space visualisation via t-SNE



Prediction accuracy by severe interlock



Comparison to other prediction methods

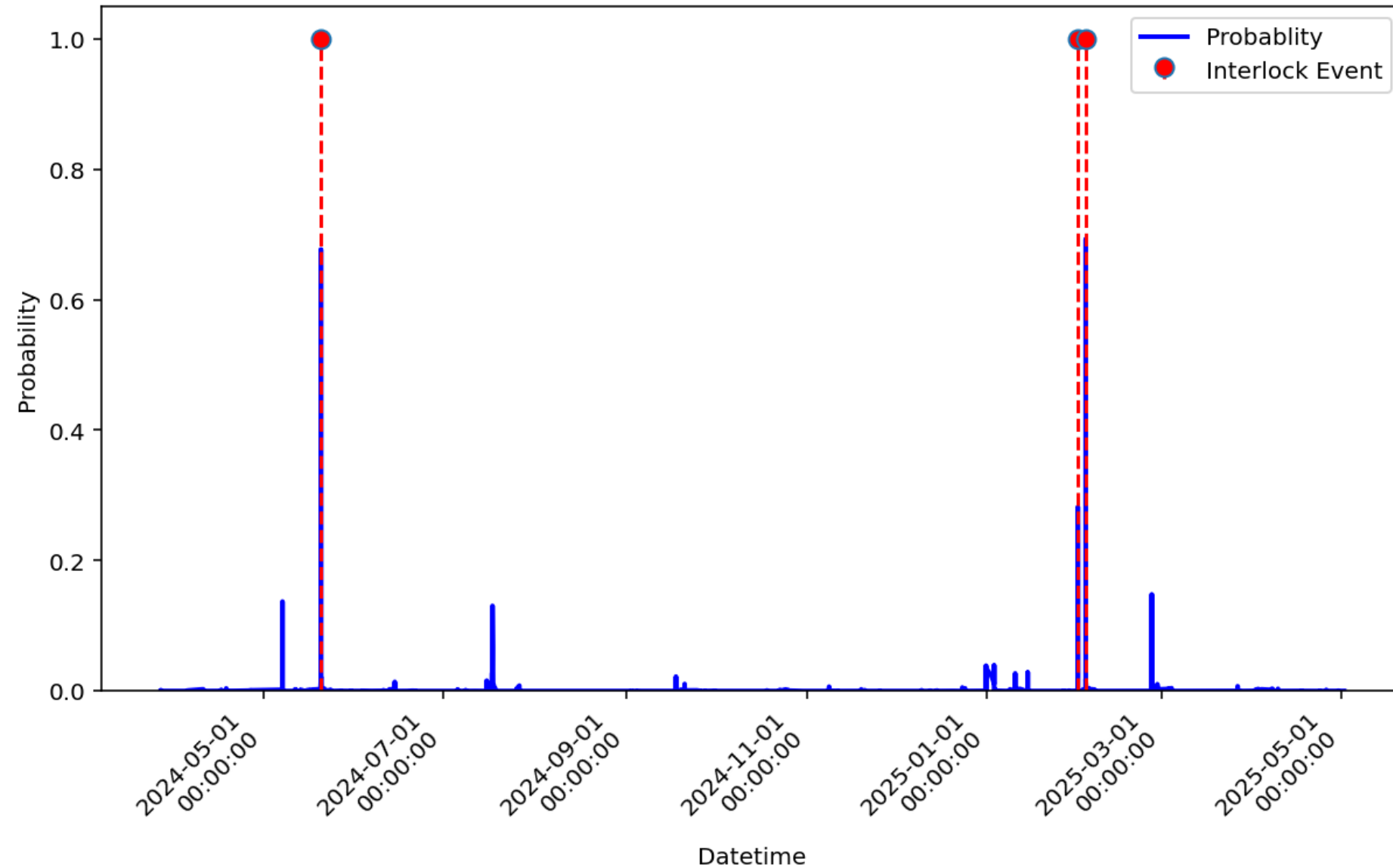


*Overall accuracy of stratified guessing is boosted due to almost exclusively predicting “no severe fault”

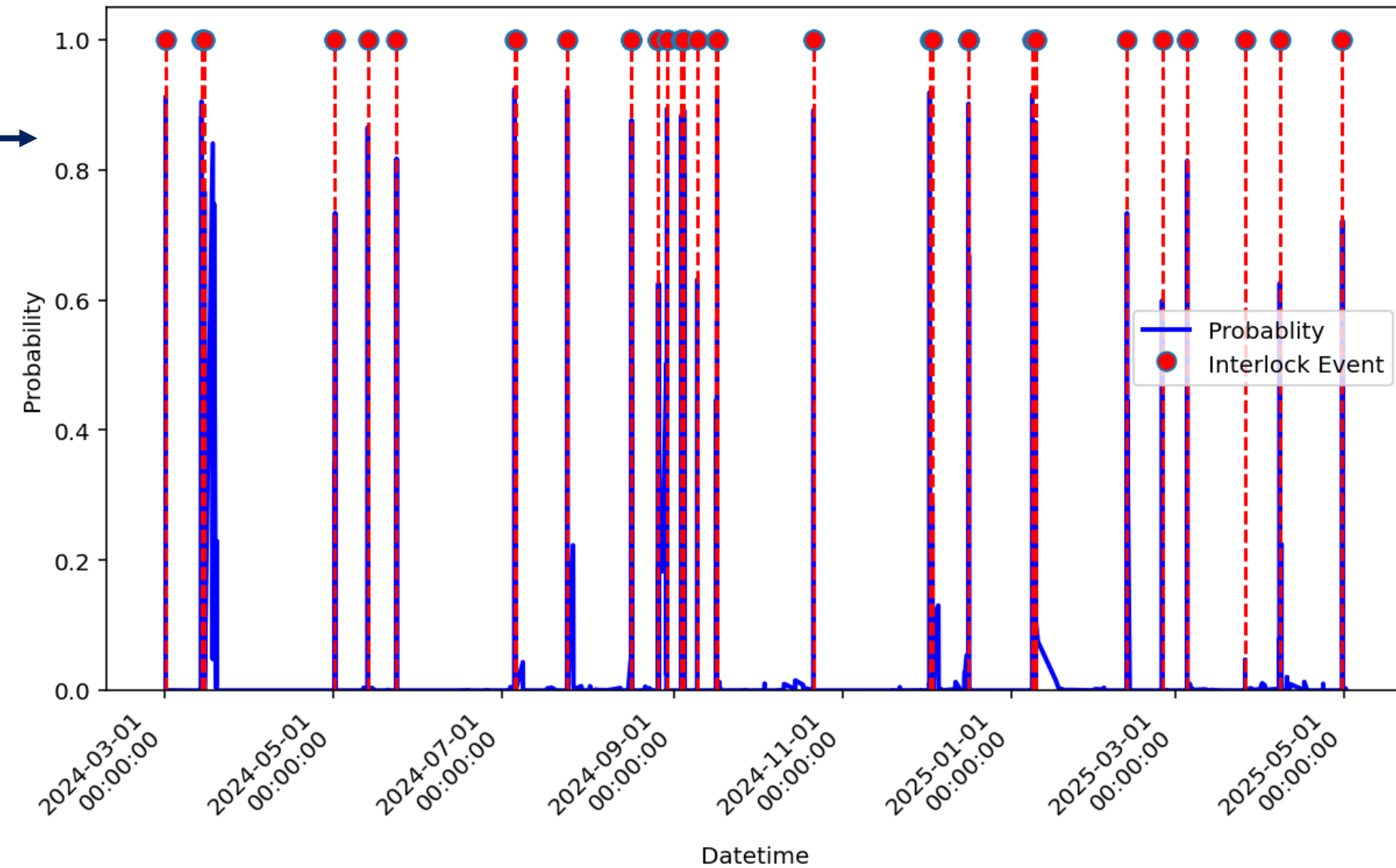
Time-series Probabilities

Interlock 363002 – Laser guard fault, potential failure if often. Medium severity.

Likelihood of interlock 212111 over time with marked events



Likelihood of interlock 363002 over time with marked events



Interlock 212111 – Target under dose rate, potential HV Thyatron problem. Medium severity.

Next Steps

- This fault prediction process can be generalised away from the Varian TrueBeam.
 - Algorithm is applicable to any other Varian machine, and any RT machine with a similar logging style.
 - Approach is *data-agnostic* so can be applied to any machine with a similar fault reporting system, regardless of function.
- Transfer learning will allow customisation of models to a treatment centre's needs.
 - Models can be generally trained on a central database, then tweaked by a user with their own data.
 - This doesn't require any release of data by a treatment centre, allaying concerns about privacy.
- Proof of concept for fault prediction opens the door to more powerful ML algorithms.
 - Transformers can capture more information about contextual and long-term relationships with inherent temporal encoding and attention mask.



Leadley, S. (2025). Predictive Modelling of Radiotherapy LINAC Downtime using Variational Autoencoders [Poster]. VHEE'25 conference, Daresbury.

Thank you!

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Variational AutoEncoder – Neural Network

