Hemodynamic monitoring parsimony: minimal information for rapid hemorrhage detection

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Disclosures

- Funding: NIH R01NR013912 (Don’t know)
- No commercial conflict of interest

Motivation

We know: Vital sign (VS) collected from invasive and non-invasive sensors can be used to detect onset of hemorrhage in porcine models with performance dependent on the granularity of data used and the presence or absence of an individual baseline. (Wertz et al.)

We asked: How does the availability of sensing modalities affect performance?

Hypothesis:

Models using fewer and even completely non-invasive sensing modalities can still detect hemorrhage, albeit with a degradation in performance.

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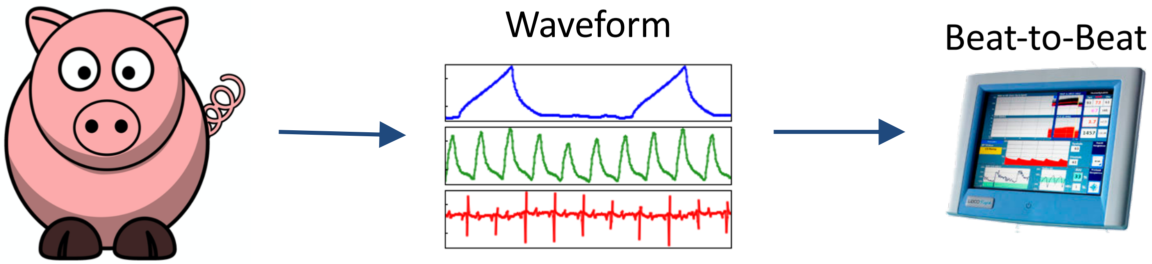
Why evaluate on less rich sensing modalities?

- The previous models utilized central venous (CVC), pulmonary artery (PAC), and arterial (ART) catheters together, but rarely will a patient have all three.
    - *How does performance degrade when sensors are removed?*
- Ideally a patient would have no invasive sensors at all to minimize risk of infection or other complications.
    - *How well can we detect bleed when only non-invasive sensors are used?*

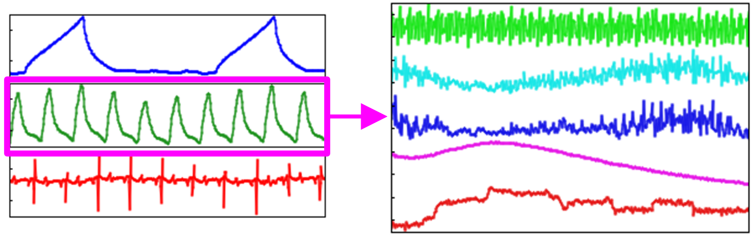
Dataset Collected from Porcine Models

- Pigs were anesthetized and sensors connected for data collection, including:
  - Vital sensor data (arterial, central venous, and pulmonary artery pressures, ECG, plethysmograph, SpO_2, SvO_2) at 250Hz.
  - Beat-to-beat data from LiDCO device.
- They were left to rest for 30 minutes while baseline data was collected.
- The pigs were then bled at a constant rate:
  - 20mL/min until mean arterial pressure dropped below 30mmHg.



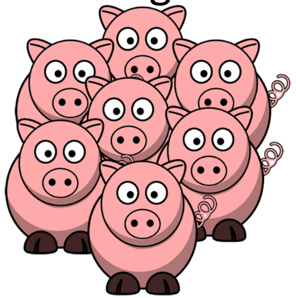
Computational Experimental Design

- The data is featurized and those features are split into different (though not mutually exclusive) groups.



- Those feature sets are used to validate random forest models that classify a pig as bleeding or not in a leave-one-pig-out cross validation framework.

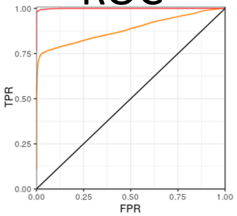
Training Set



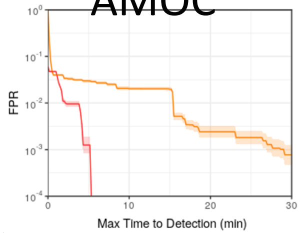
Testing Set

- The detection results are evaluated by means of Receiver Operator Characteristic (ROC) and Activity Monitoring Operator Characteristic (AMOC) curves.

ROC

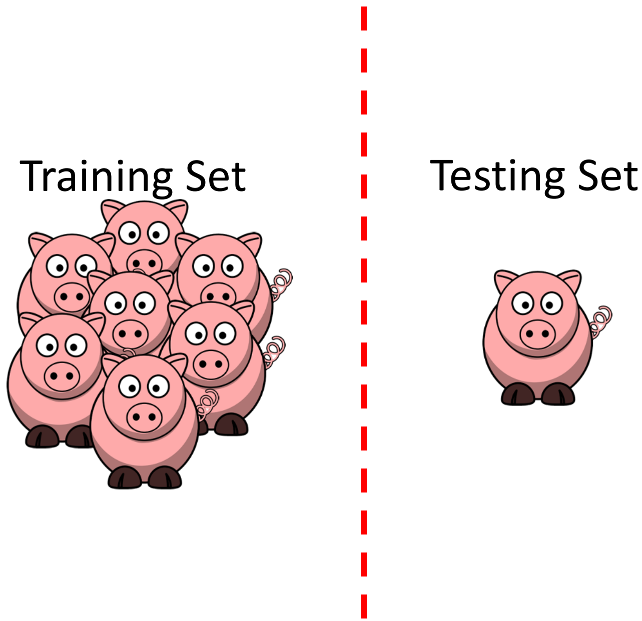


AMOC



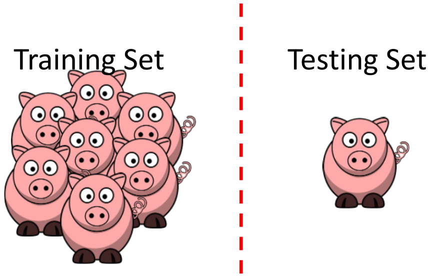
Models Validated using Cross Validation

- Models evaluated in a leave-one-pig-out cross validation framework.



Random Forest Models Validated using Cross Validation

- Models evaluated in a leave-one-pig-out cross validation framework.
- Random forest models trained (Auton Lab variant).
  - Handles missing values.
  - Builds explainable models.
  - Supports non-linear decision boundaries.
  - Successfully used in many other similar projects.



Models Evaluated using *ROC curves*

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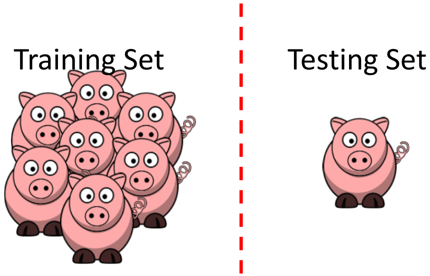
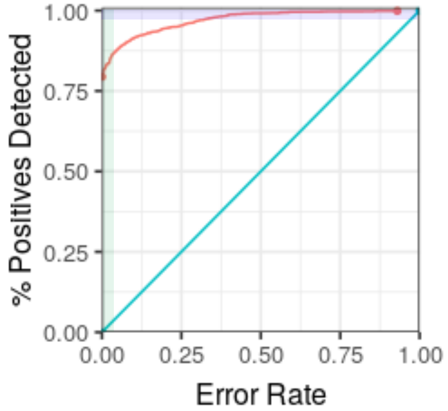
- Performance compared using receiver operator characteristic (ROC) curves.



Positive class: Bleeding
Negative class: Not-bleeding



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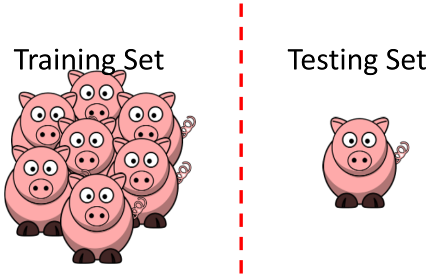

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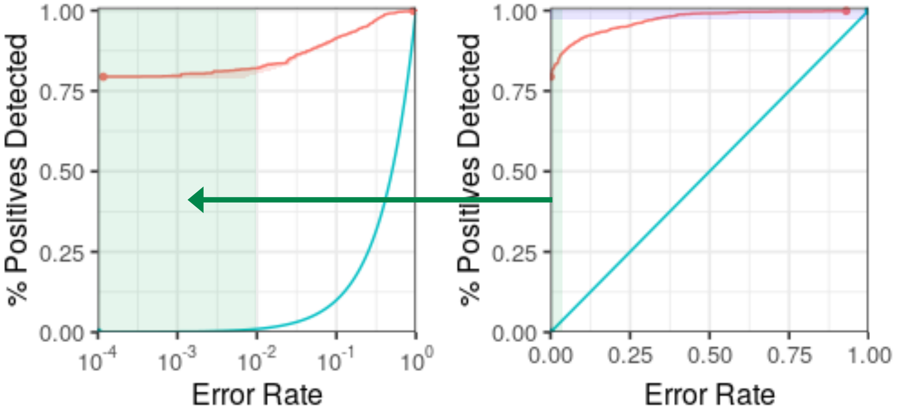

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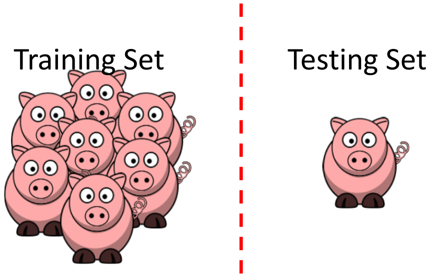

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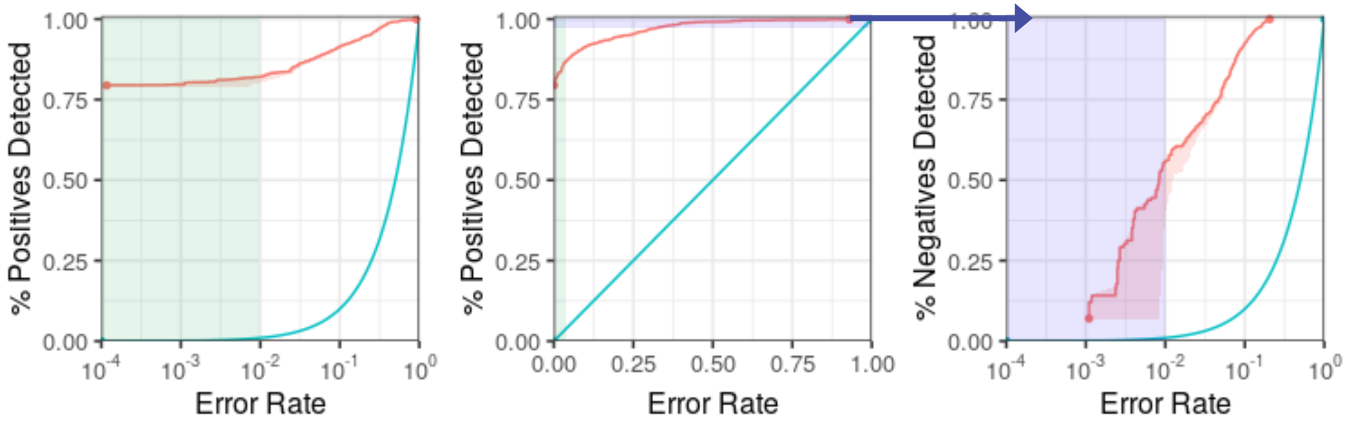

Models Evaluated using *ROCOR* curves

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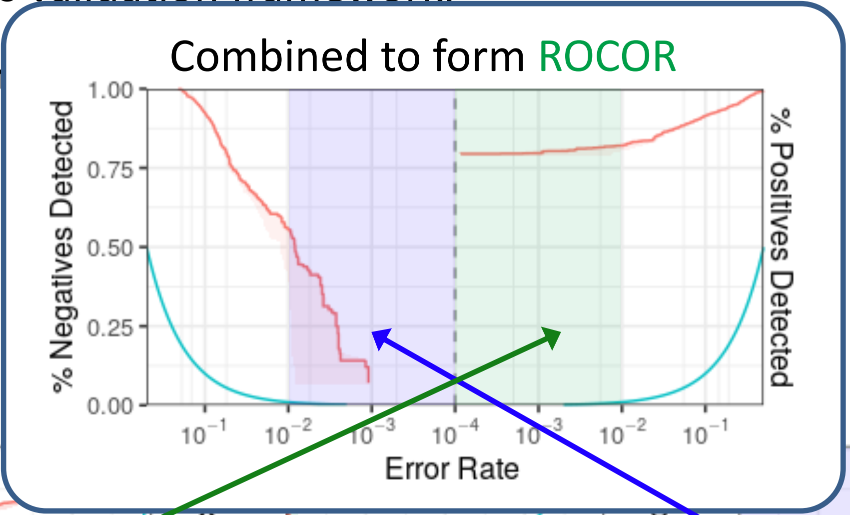
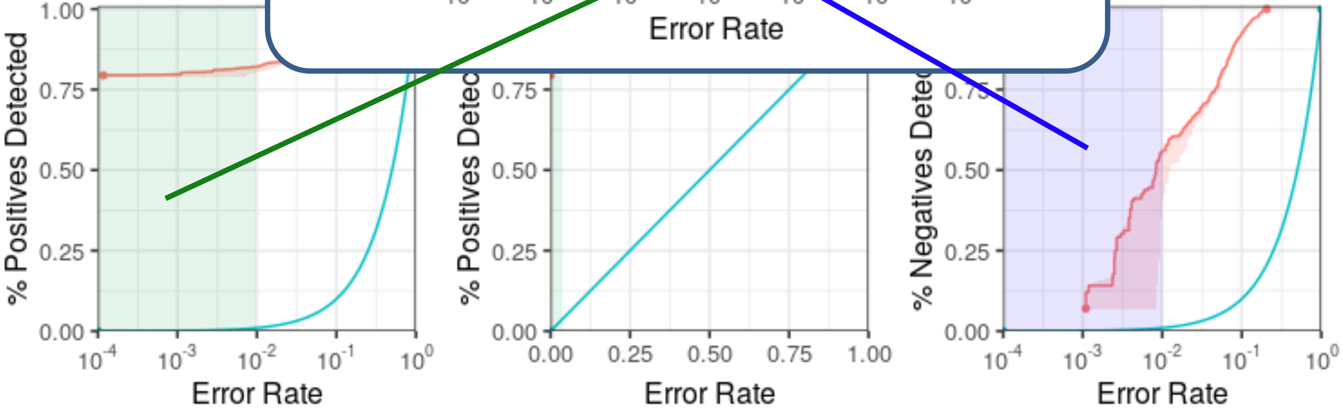
- Performance compared using ~~receiver operator characteristic (ROC) curves~~. *ROCOR variant*

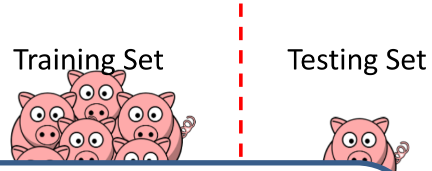
Testing Set

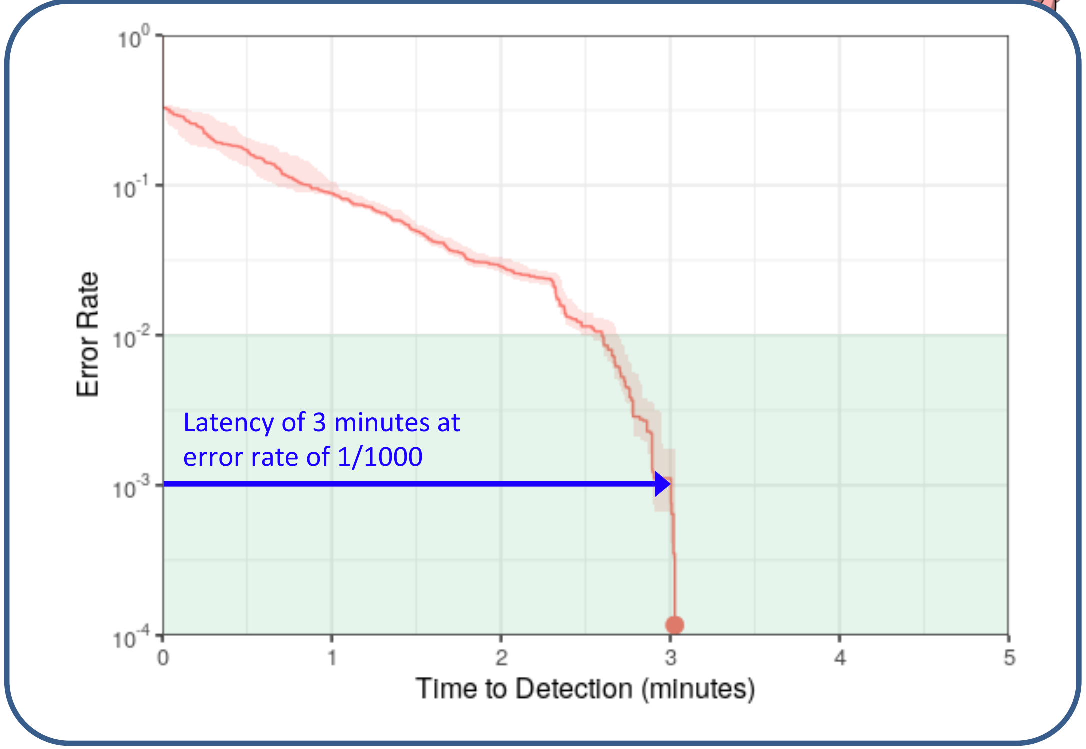




Models *also* Evaluated using *AMOC* curves

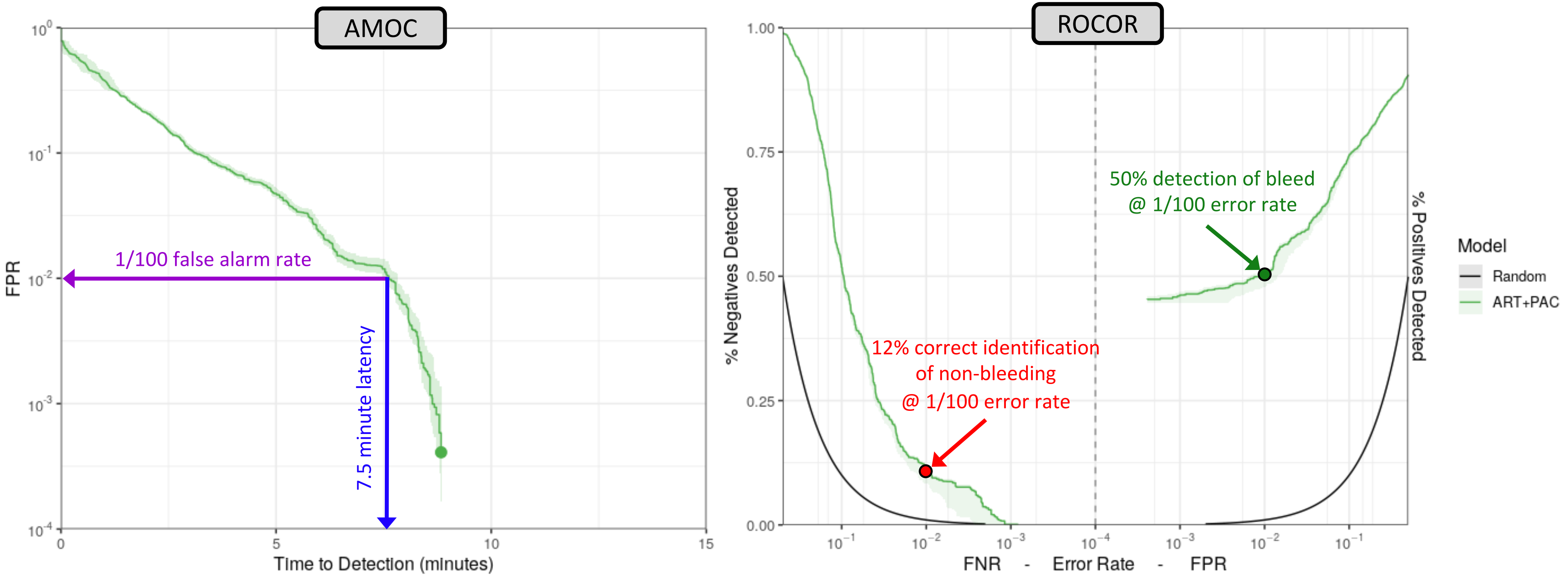
- Models evaluated in a leave-one-pig-out cross validation framework.
- Random forest models trained (Auton Lab variant).
  - Handles missing values.
  - Builds explainable models.
  - Supports non-linear decision boundaries.
  - Successfully used in many other similar projects.
- We'll also use Activity Monitoring Operator Characteristic (AMOC) curves to present detection latency.





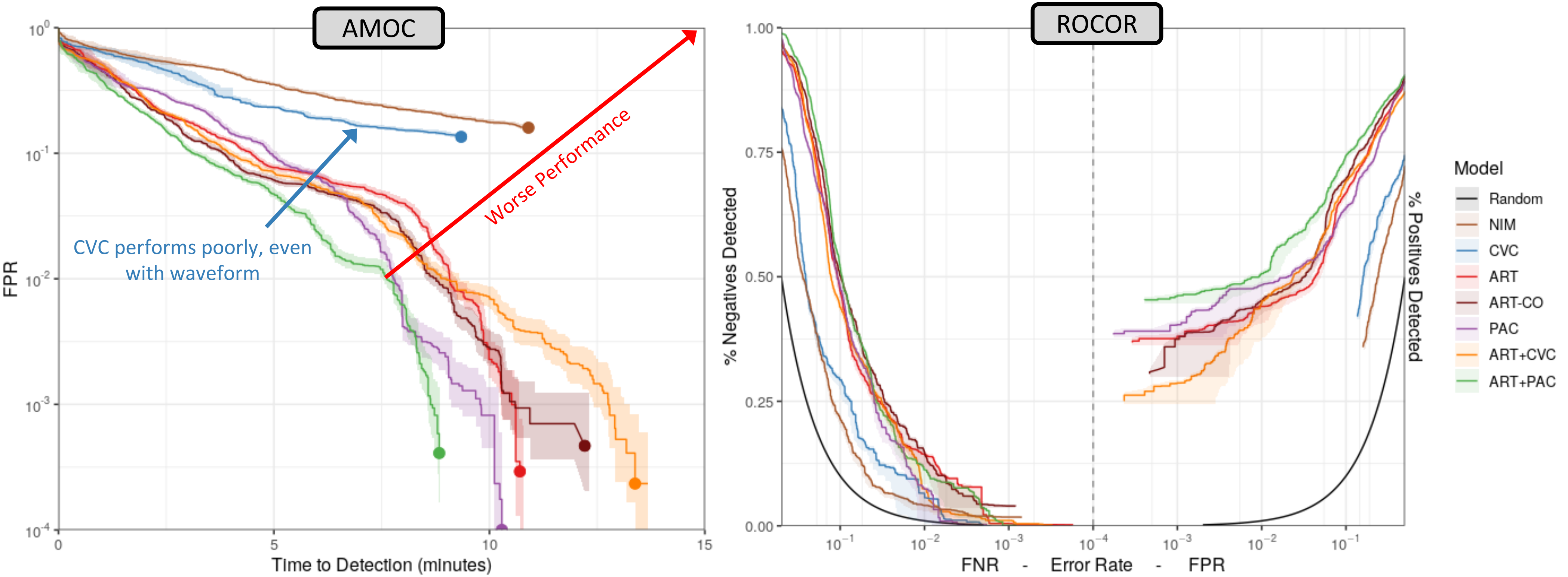
Performance with All Sensors and Universal Baseline

As shown (Wertz et al., 2019) performance without individual baselines but with all sensing modalities at highest granularity (waveform) performs well.



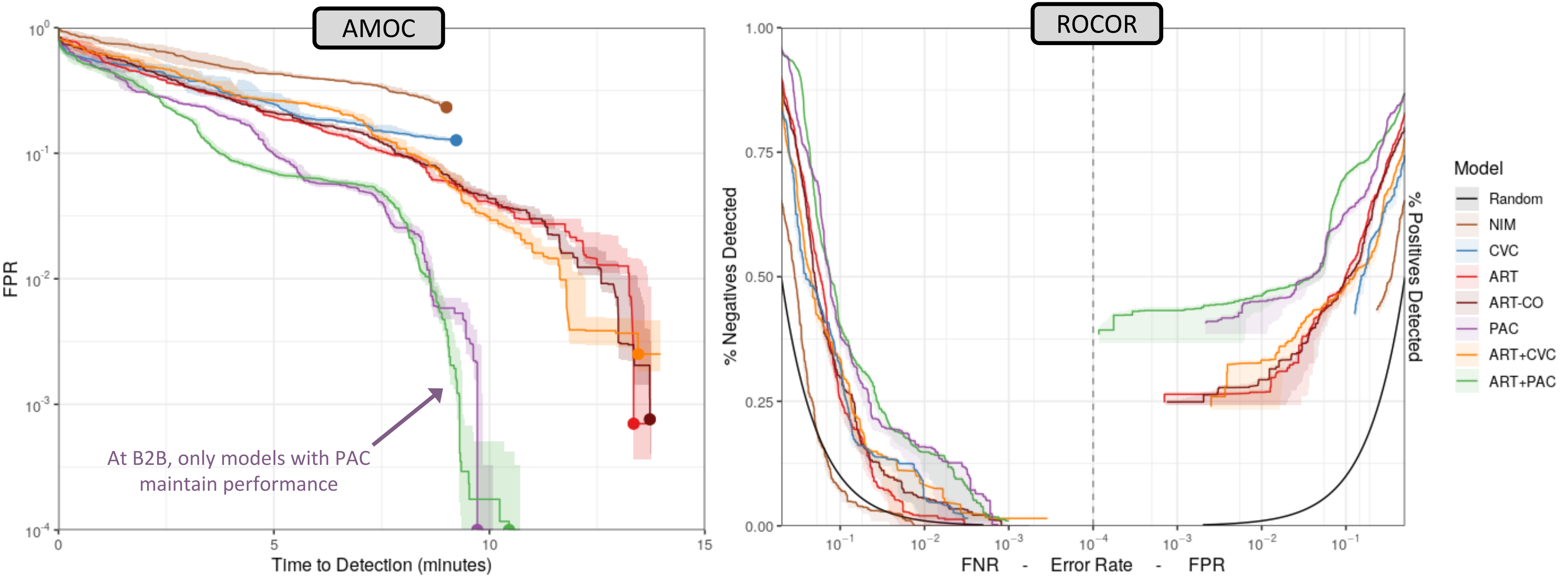
Performance with Universal Baseline and Waveform Data

Performance degrades (longer latencies, higher error rates, lower detection rates) as sensors are removed.



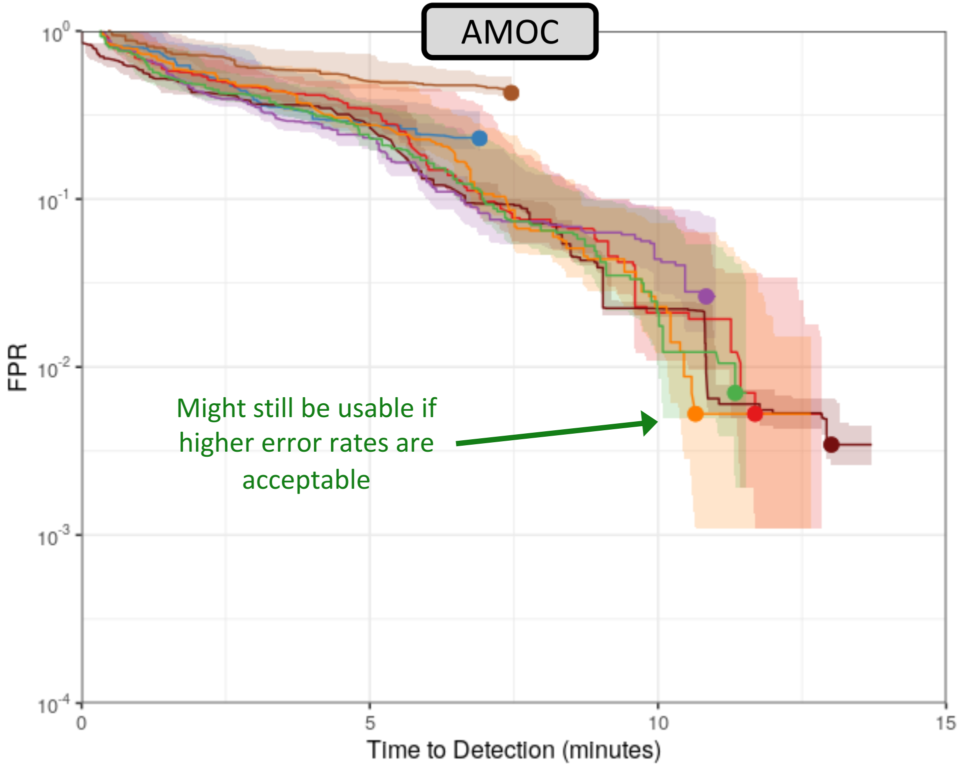
Performance with Universal Baseline and Beat-to-Beat Data

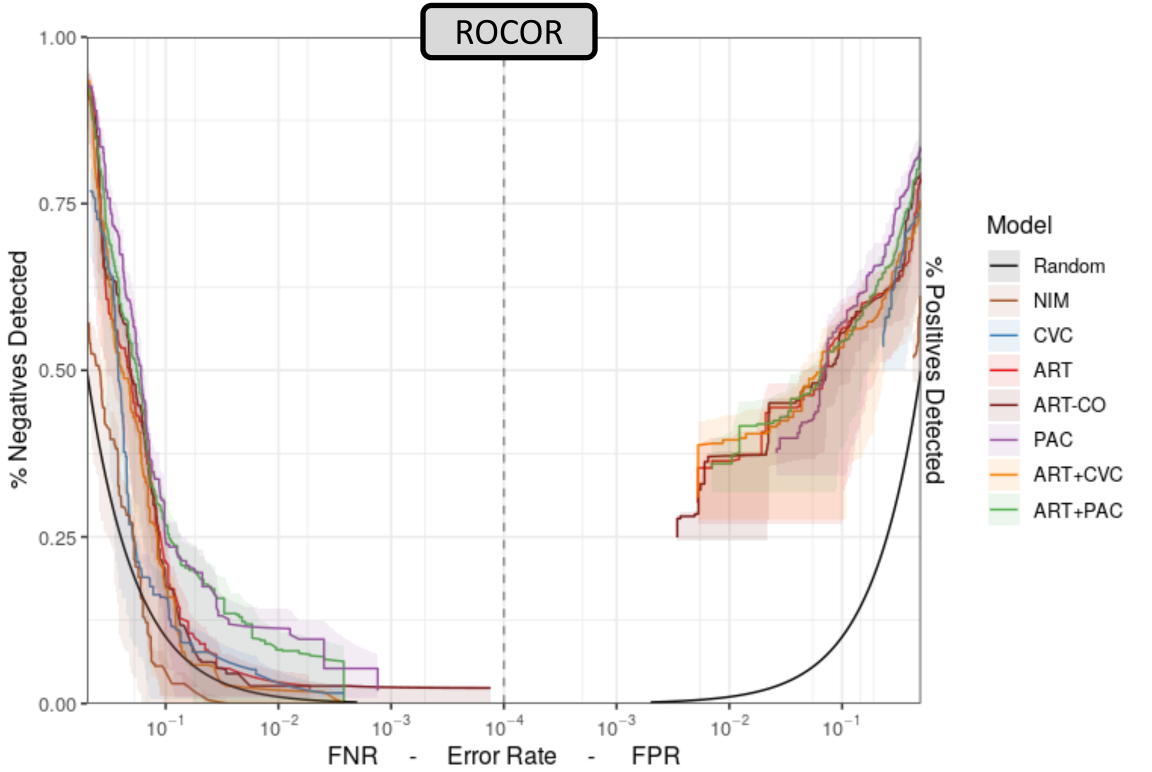
Performance degrades further when granularity is reduced to beat-to-beat.



Performance with Universal Baseline and Simple Metrics

And finally when data is available only intermittently, allowing the use of only simple metrics in the models.

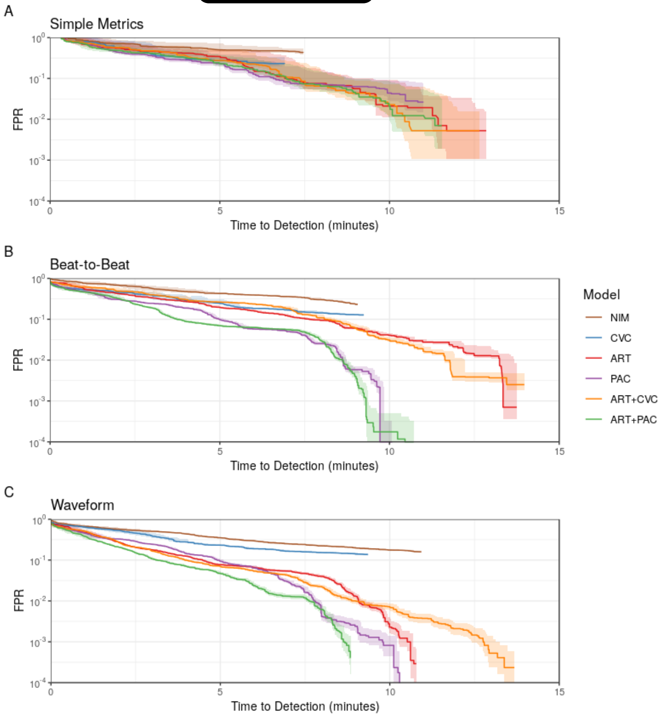




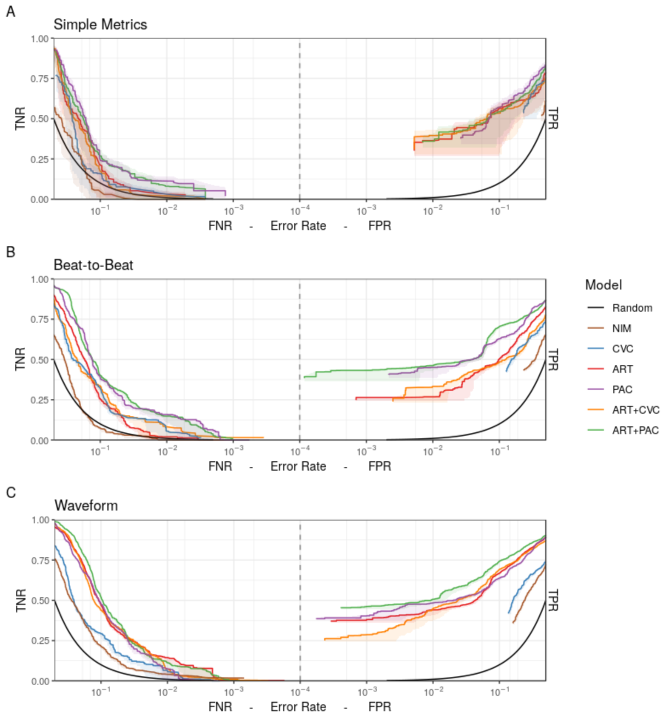
Performance with Universal Baseline

Key Finding: Detection of hemorrhage is possible without individual baselines for all modalities except non-invasive and CVC.

AMOC



ROCOR



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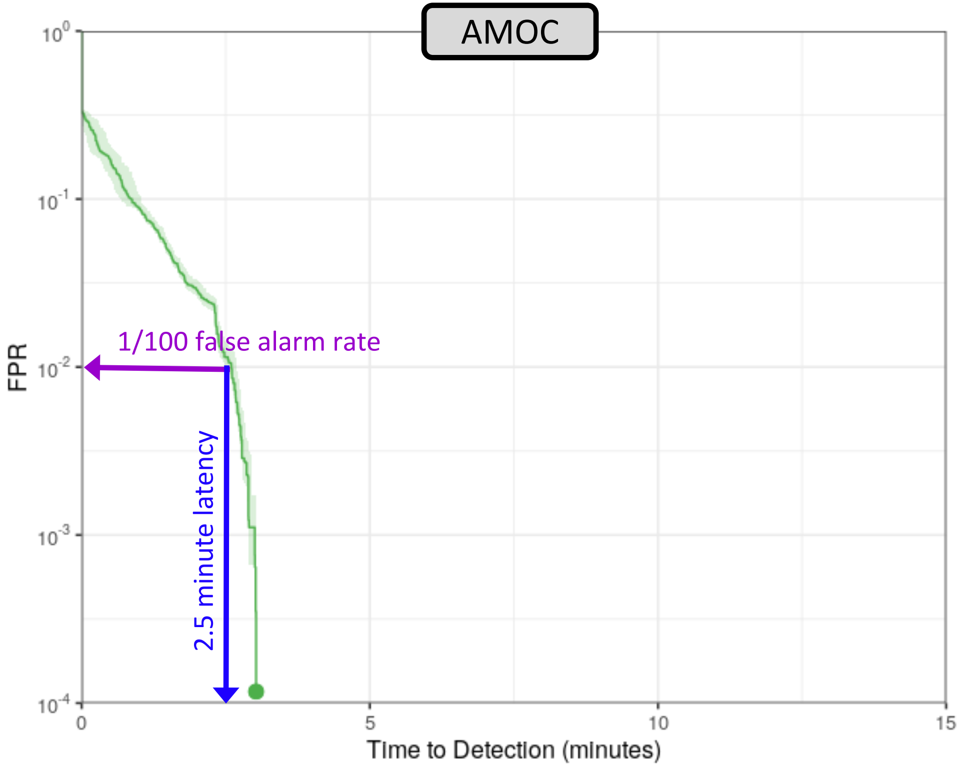
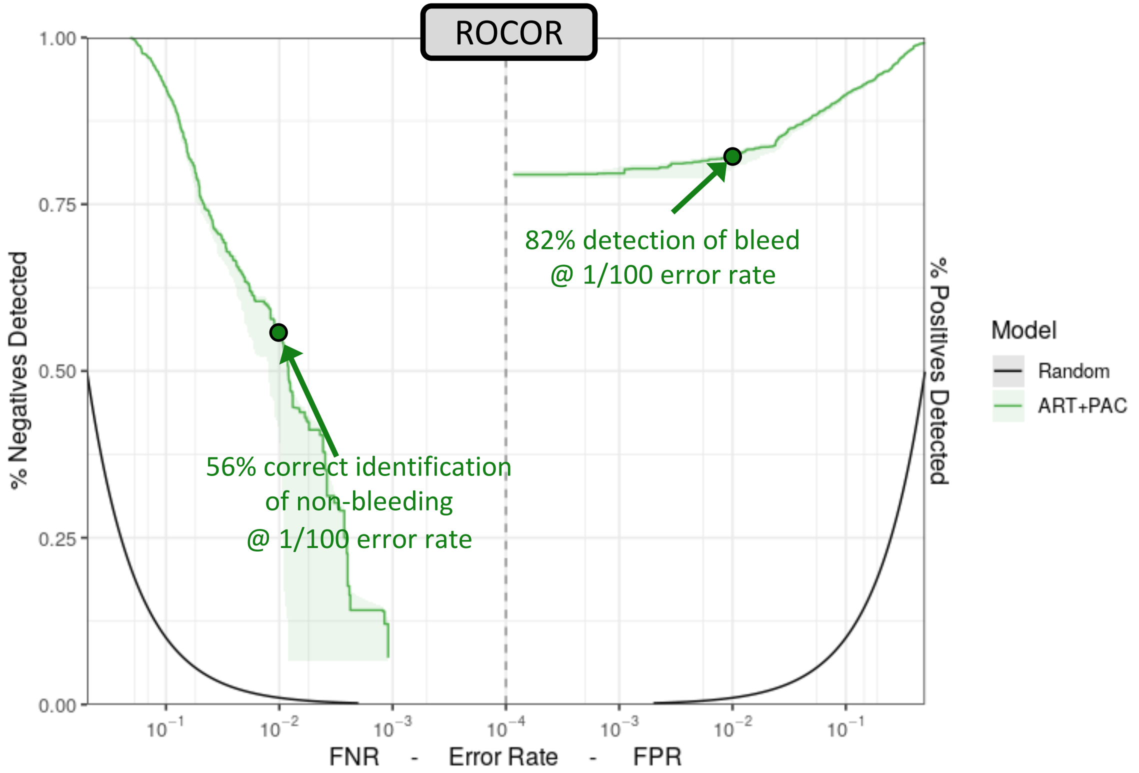
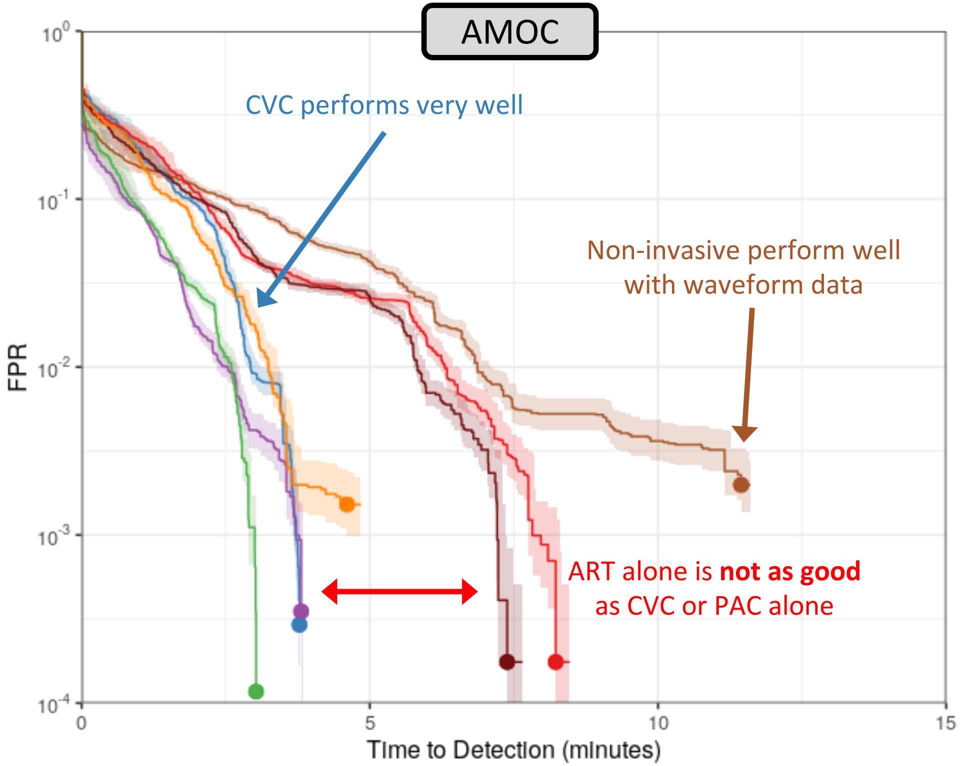
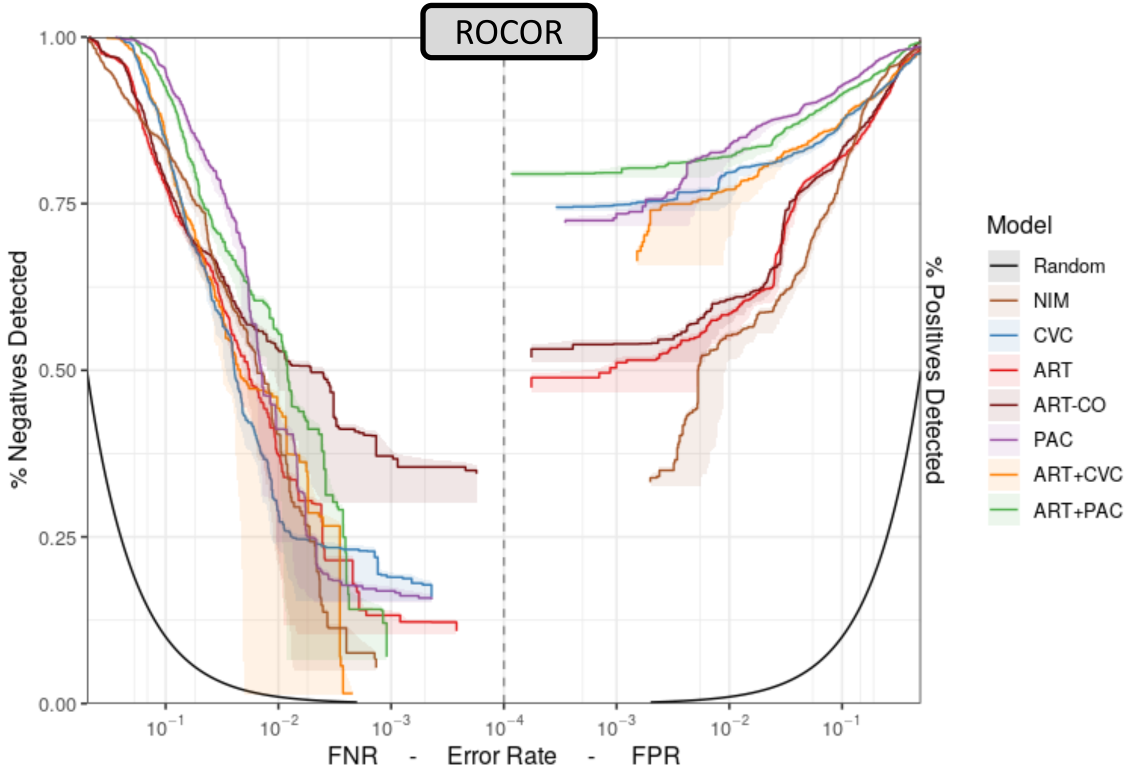




Performance with Individual Baseline and Waveform Data

Performance degrades (longer latencies, higher error rates, lower detection rates) as sensors are removed. Interesting, CVC now performs very well.





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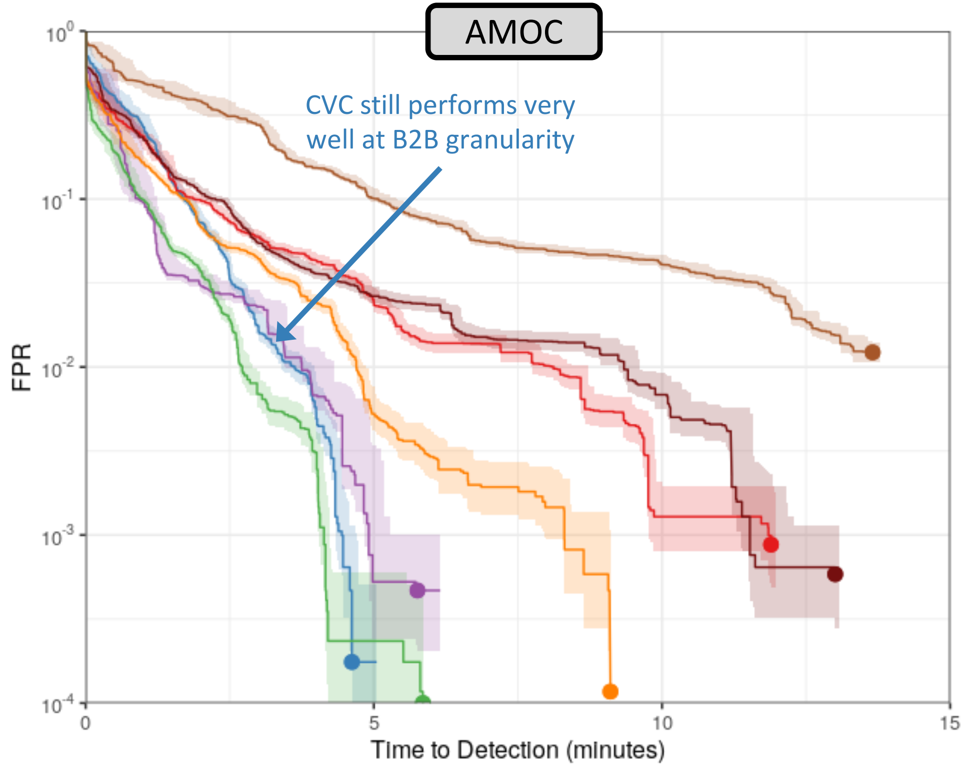

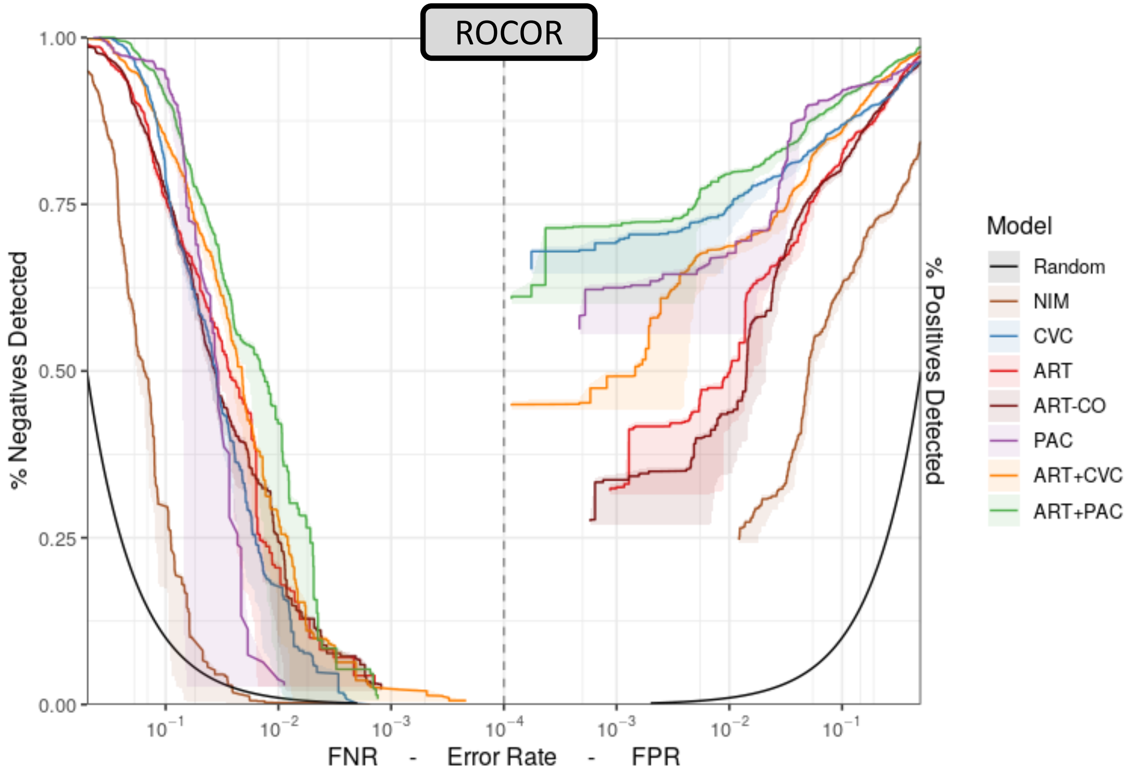

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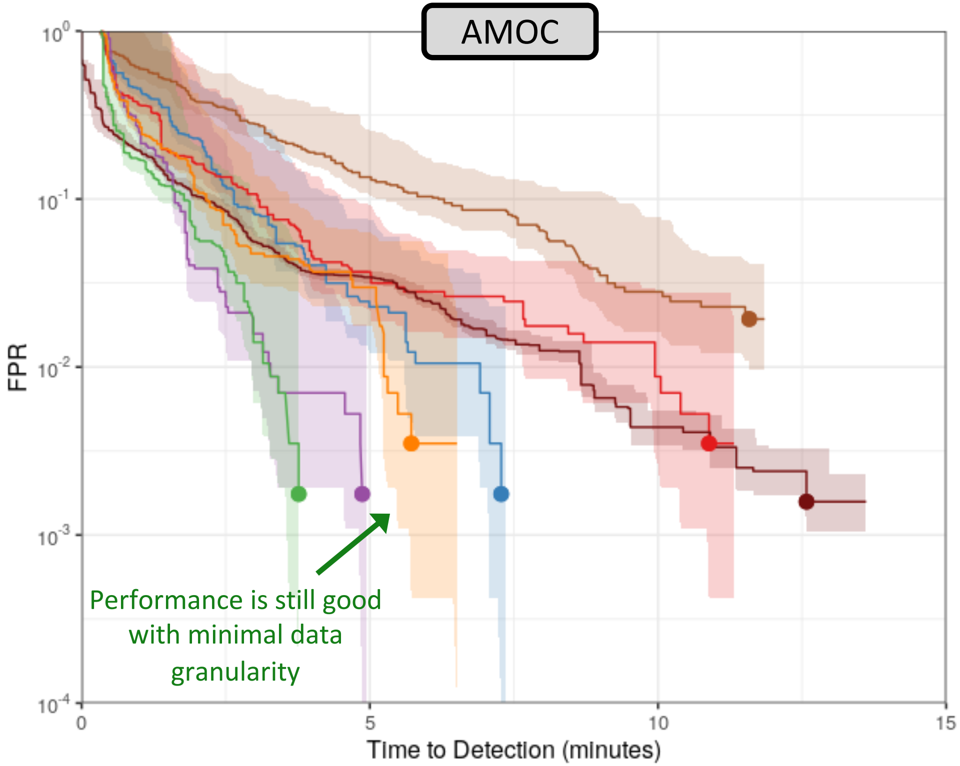
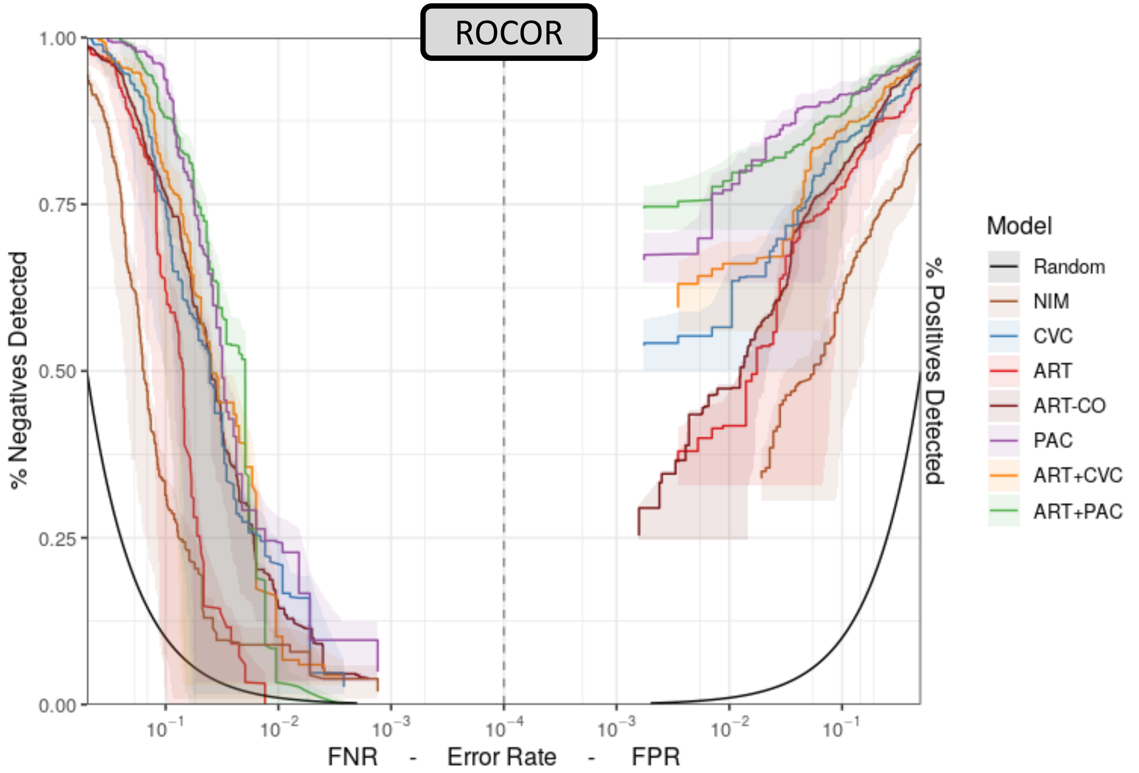
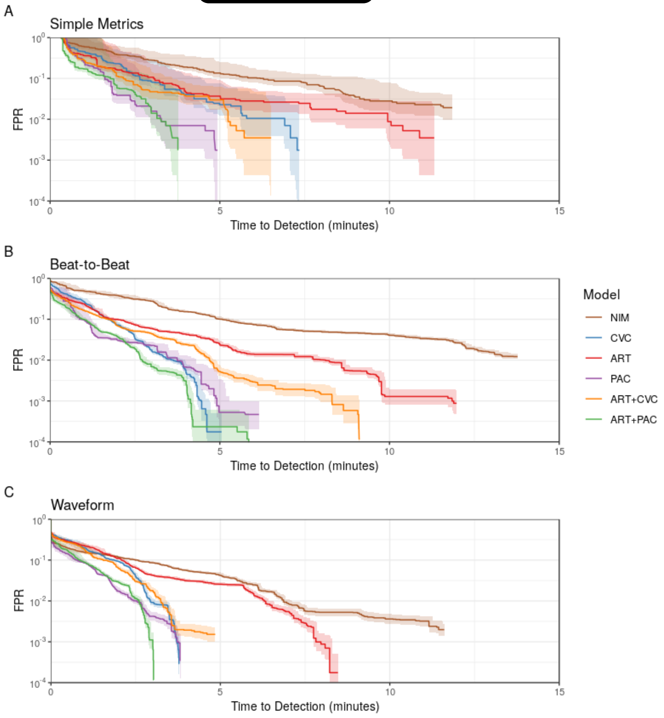




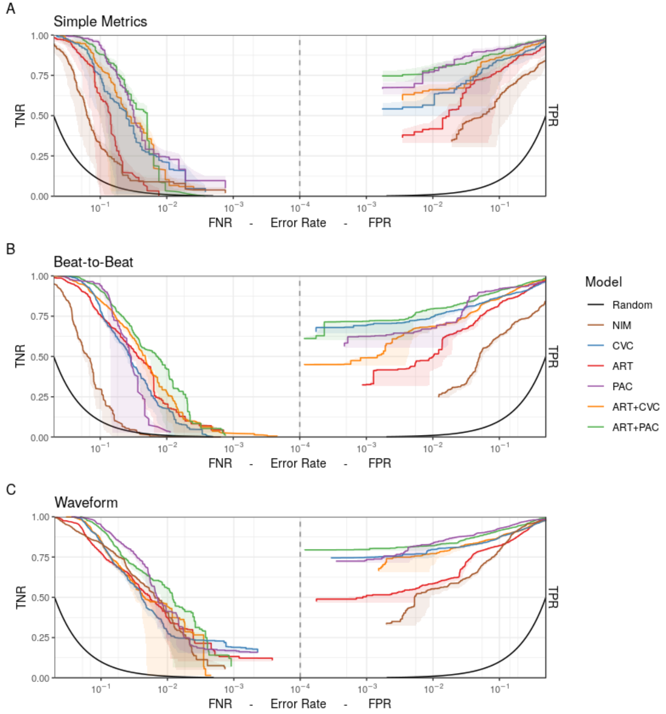
CVC Performs Well with an Individual Baseline

Key Finding: With baseline, CVC is a top performing model and detects well at all data granularities

AMOC



ROCOR



Non-Invasive Can Be Used to Predict Bleed

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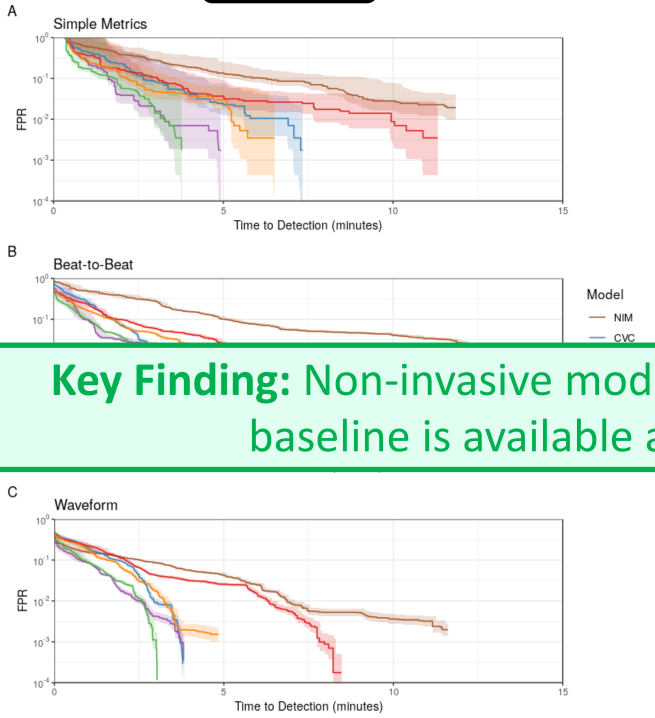
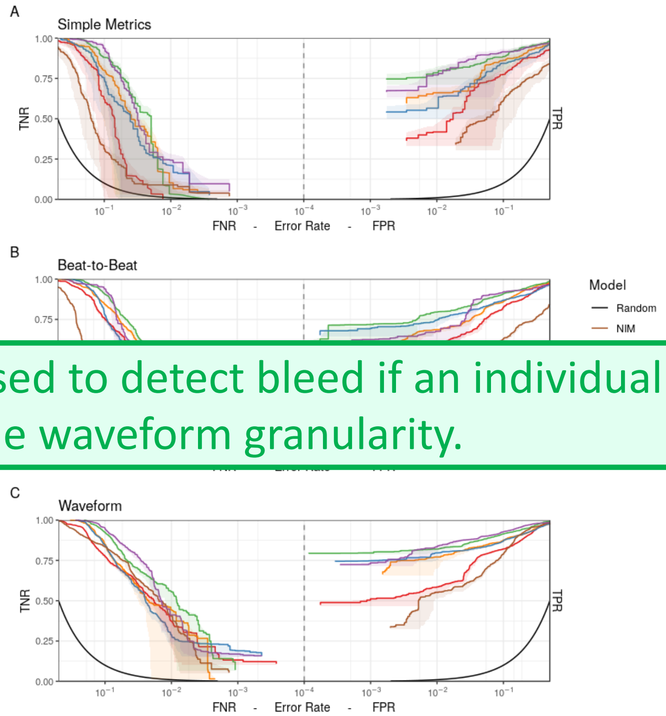


ROCOR



Key Finding: Non-invasive modalities can be used to detect bleed if an individual baseline is available and data is at the waveform granularity.

Rapid Bleed Detection is Possible with Less Rich Modalities

Key Findings

Detection of hemorrhage is possible without individual baselines for all modalities except non-invasive and CVC.

With baseline, CVC is a top performing model and detects well at all data granularities

Non-invasive modalities can be used to detect bleed if an individual baseline is available and data is at the waveform granularity.

Impact (why we care)

The analysis is applicable to a wider range of clinical scenarios which may lack high data granularity, individual baselines, or specific sensing modalities.

The tradeoffs can be more clearly understood and determined based on the specific needs of the clinician.

Next Steps

How well is hemorrhage distinguished from other problems (e.g., hypovolemia due to sepsis)?

How well do these results translate outside of the controlled lab environment and on to human subjects?