

HEARTwise ML

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HEARTwise
REFINED TRIAGE FOR SMART EVALUATION

Hospital and Home Early Warning
AI-Refined Triage with Wearables and Instruments for Smart Evaluation



Introduction - HEARTwise

- Belgian Project approved within FOD innovation initiatives
- Duration: July 2024 - December 2025
- Collaboration between 4 Belgian hospitals:
 - Jan Yperman Hospital: coordinating hospital
 - University Hospital Antwerp
 - AZ West Veurne
 - Sint-Andries Tielt



Project scope:

Improving the Early Warning Score (EWS) process

- EWS: A standardized method used in healthcare to assess a patient's clinical condition



Projectscope: Improving the Early Warning Score (EWS) process

- How?

Automatic

EWS in the hospital:
Increase frequency
Automatic/semi-continuous
Measurement via WEARABLES



Visual

Better visualization of EWS data
via dashboard

Telemonitoring

EWS care pathway in the home setting:
Patient goes home with wearables and
is monitored at home for 10 days
Follow-up via patient platform/application
and dashboard

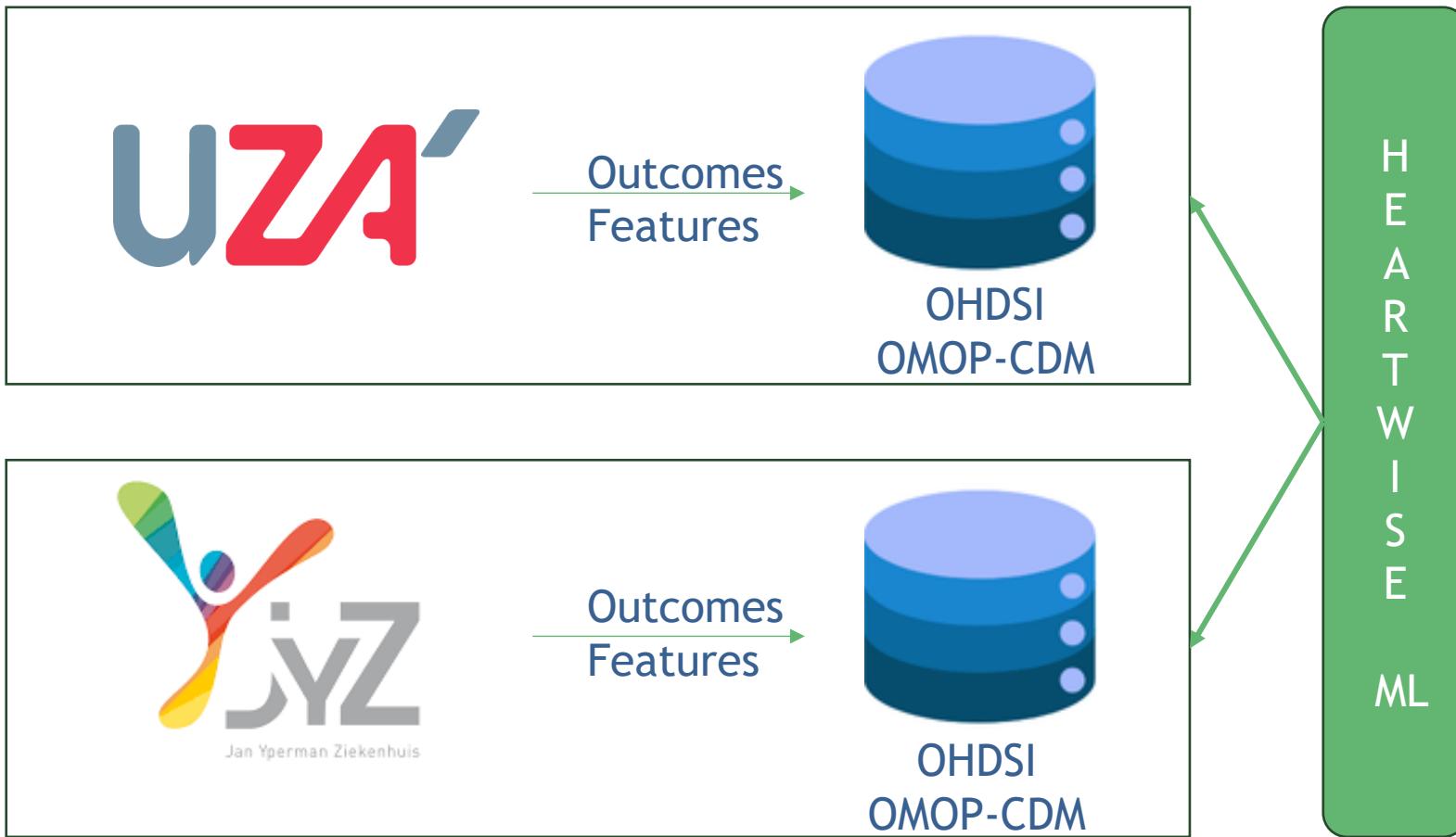
Smarter

Developing an ML model to
predict patient condition
deterioration



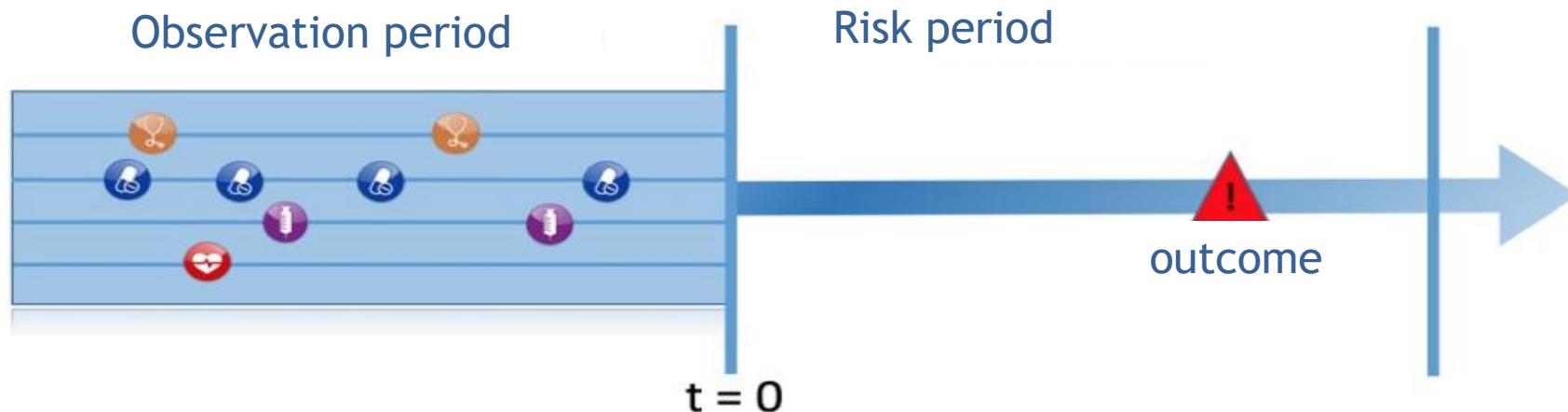
HEARTwise ML

- Leverage OMOP to develop ML framework that can be used to train models at both hospitals



Develop one
framework that
can be deployed
against any
OMOP-CDM
instance

The challenge of predictive models



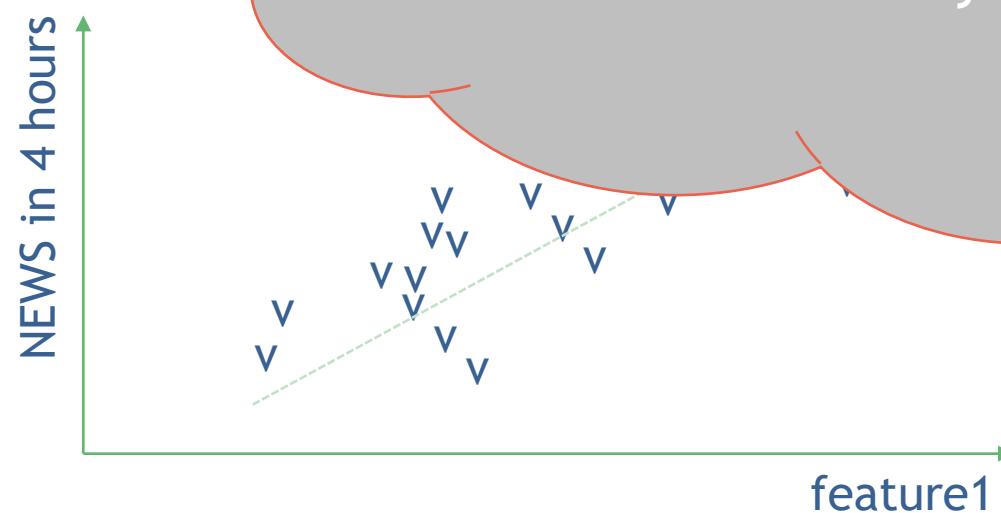
- Can we, using available clinical observations, predict an outcome at $t=0$ (index date) within a defined risk period?
- Target cohort: Patients with at least one visit and more than one NEWS score, aged over 18 years. Pediatric and pregnant patients are excluded. NEWS data collected after April 1, 2021.
- Outcome cohort: Patients experiencing deterioration (various definitions possible).
- Risk period: For example, the next 4, 8, or 12 hours.
- Models: Regression and classification based on age, gender, NEWS, comorbidities, etc.



Regression

- Goal: Predicting a continuous value over time.

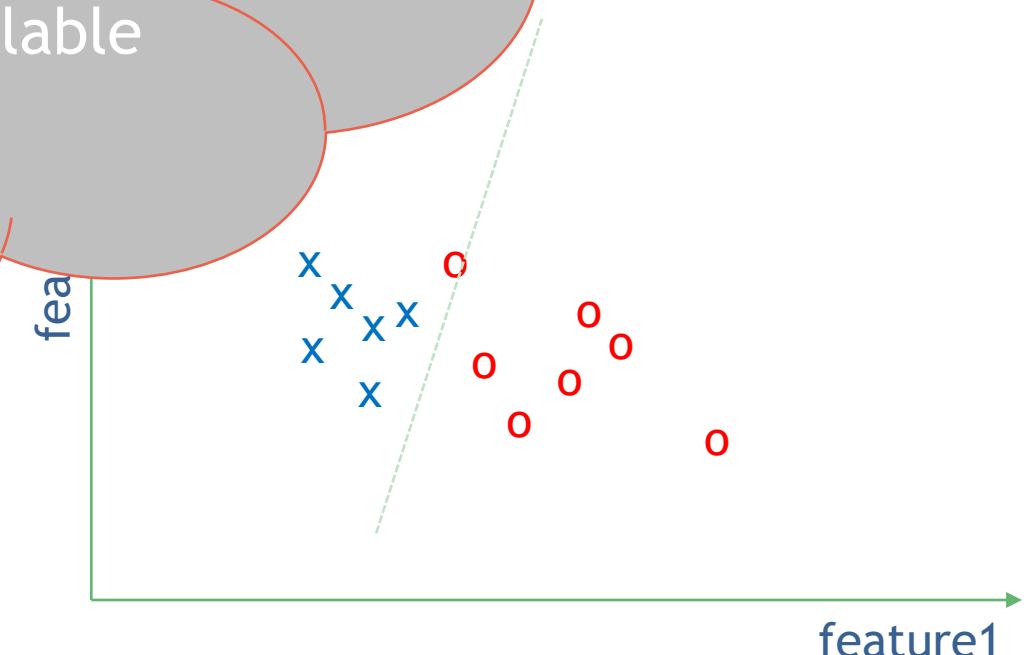
- Example: Accurate prediction of NEWS score at 4, 8, or 12 hours based on previous vital signs and oxygen saturation.



Classification

- Goal: Predict whether a patient will fall into a risk category within 4, 8, or 12 hours.

- Example: Predict whether a patient will fall into a risk category within 4, 8, or 12 hours based on certain NEWS score.



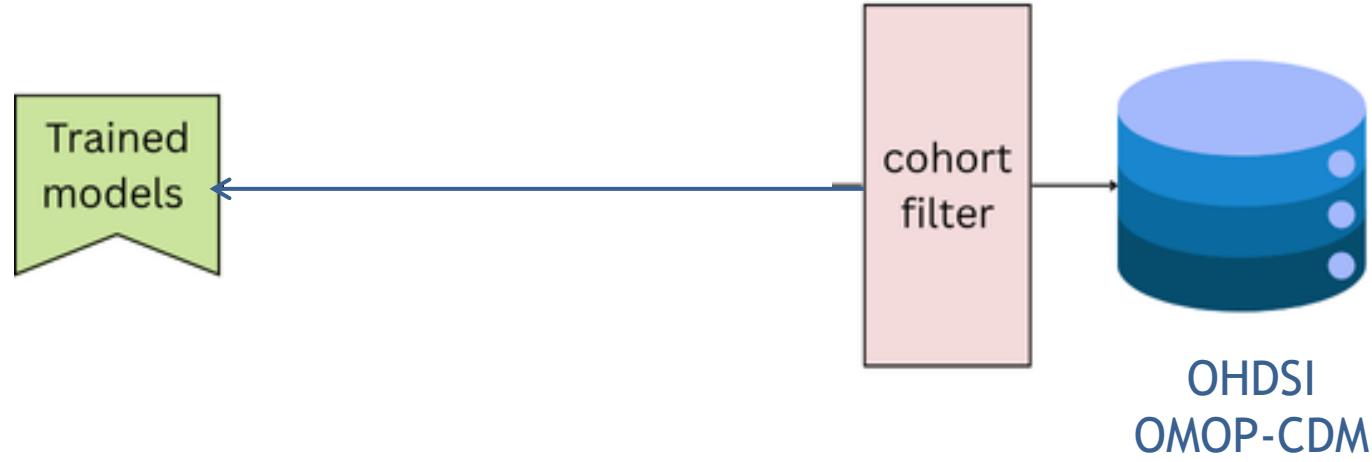
HEARTwise ML framework

- Leverage OMOP to develop ML framework that can be used to train models at both hospitals

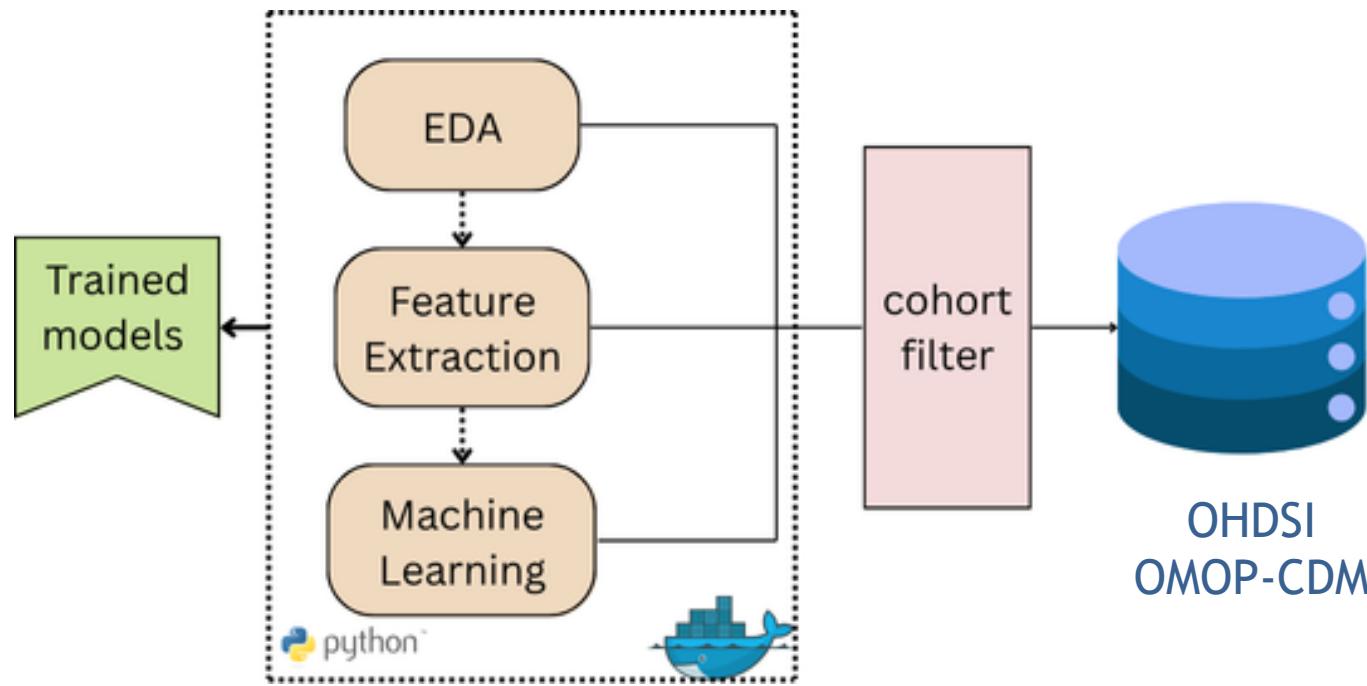




HEARTwise ML framework



HEARTwise ML framework



Modular framework with three main components: Exploratory data analysis, Feature extraction, Machine learning (training)

- Each component can be executed independently
- Containerized and version control applied
- Data analysts can add new features and models

Development of HEARTwise Machine Learning framework to predict patient deterioration using existing OMOP CDM NEWS variables

Three-phase approach to design and develop the HW ML models

Background: The data track of the Belgian FOD innovation project **HEARTwise** is a collaboration between Jan Yperman Ziekenhuis (JYZ), Universitair Ziekenhuis Antwerpen (UZA), and edeniceHealth. It focuses on the development of a scalable and flexible ML pipeline to predict the deterioration of a patient's health status. The models will be trained using historical data in existing OMOP-CDM databases, primarily NEWS variables. NEWS is an early warning system used to assess a patient's risk of deterioration, facilitating early detection and response to clinical deterioration in adult patients.

Methods: The three-phase approach to the ML framework (Figure 1) is designed with a focus on modularity, allowing for fast technical iterations and extensibility for future enhancements (e.g., additional machine learning models).

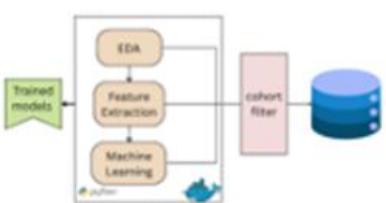


Figure 1: The workflow of the framework (left) and the three-phased approach of the project (right).

Results: The same patient selection criteria are applied to the JYZ and UZA datasets to compare overall distribution during Exploratory Data Analysis (EDA). Due to differences in patient populations and the hospitals' nature (regional vs. university), the patient characteristics are expected to differ. An example comparison is shown in Figure 2.

Insights from EDA have helped to assess data quality of NEWS variables and to inform the initial cohort selection:

1. Patients with at least one visit with more than one NEWS above 18 years of age
2. Exclusion of pediatric and pregnant patients
3. NEWS data collected after April 1, 2021

Conclusion: As a summary, initial ML model is prepared for testing, and the development framework is in progress. The framework has a modular design, which decouples feature extraction and engineering from ML model training, enhancing adaptability and enabling support for diverse data models beyond OMOP CDM.

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edenice Health

HEARTwise poster at the OHDSI Europe 2025 symposium

Exploring the data and technical proof-of-concept (Phase : 1)

- EDA
- Prototype ML pipeline with Linear regression model (age, gender, NEWS)

Enrichment of models and features (Phase : 2)

- Robust pipeline for new feature inclusion
- Advanced machine learning models
- Assessments based on common metrics

Applicability in a real-world context (Phase : 3)

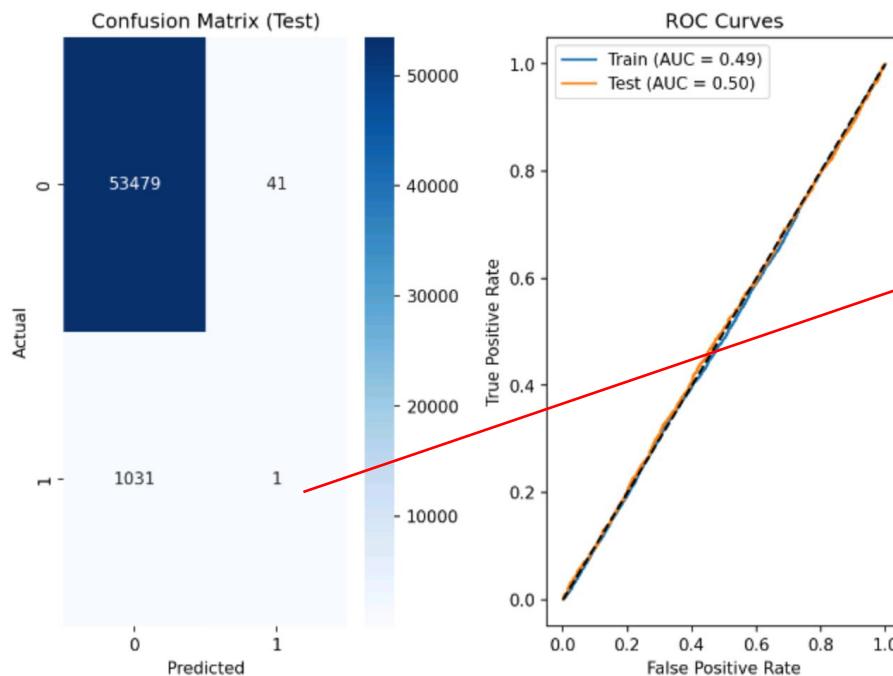
- Refinement of models
- Incorporating explainability techniques
- Investigating next step to develop scalable and production ready models

Example: predicting patient deterioration

Developing a flexible framework:

- Run multiple models on multiple outcomes and feature sets.
- Compare model performance.
- Execute a QA suite after each training round.

Examples of automated QA output for a random classifier:



In the test set: the random model correctly predicted the >7 NEWS within 4 hours outcome only once.

Model: random

Outcome: ne

Model Type:

Device: cpu

Features: [

Training sa

Test sample:

Performance

Test Accu

Test Prec

Test Reca

Test F1:

Test ROC

Overfitti

Model: random

Outcome: ne

Model Type:

Device: cpu

Features: [

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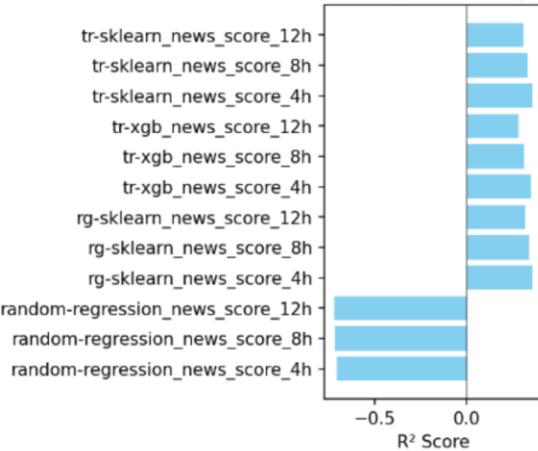
Test Precision: 0.0102

Test Recall: 0.0007

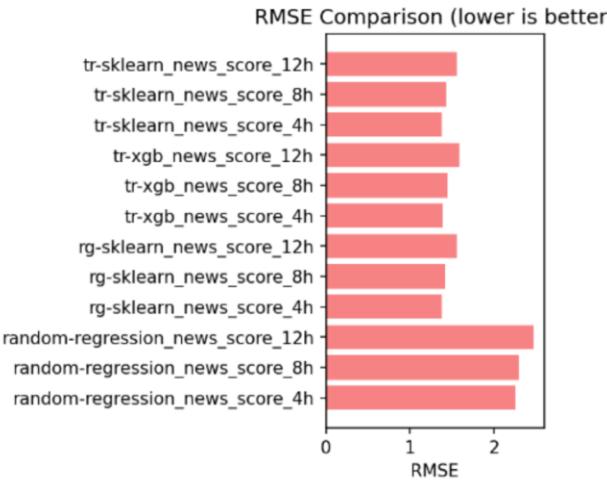
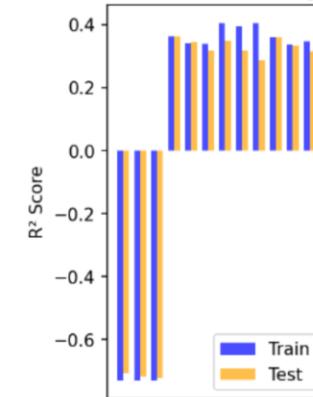
Test F1: 0.0014

Test ROC AUC: 0.4945

Overfitting: No

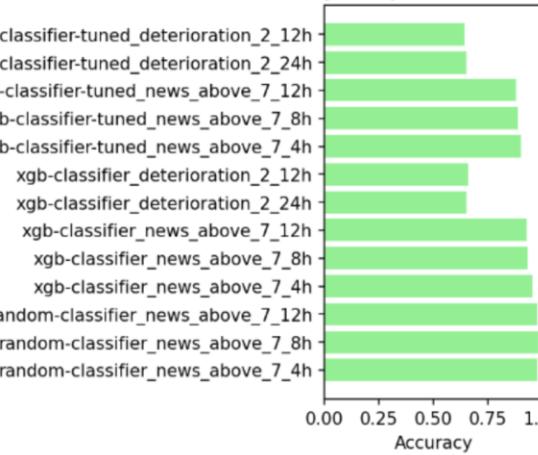
R² Score Comparison (Regression)

Model Performance Comparison

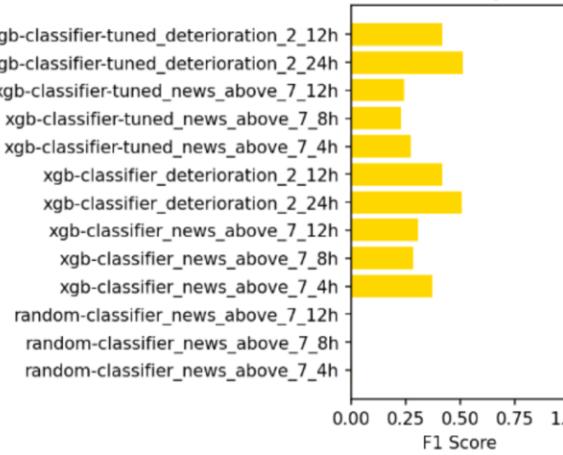
Train vs Test R² (Overfitting Check)

Comparisons of model performances

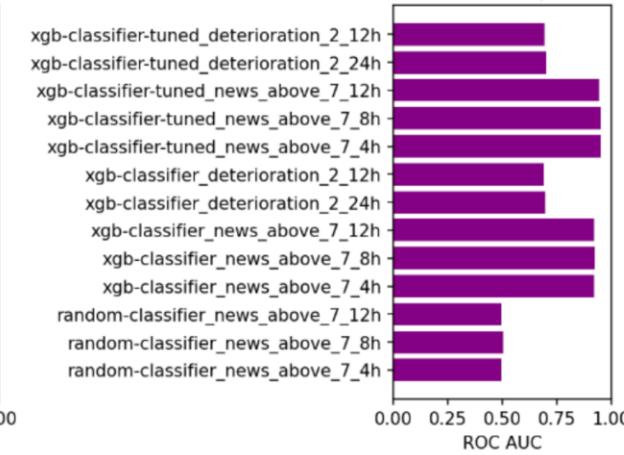
Accuracy Comparison (Classification)



F1 Score Comparison



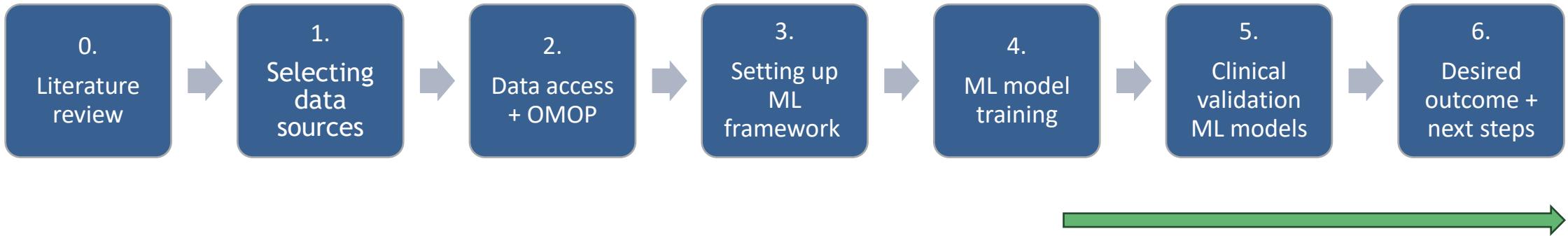
ROC AUC Comparison



Automated models

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Current status ...



We are here: iterating and
model explainability/validation

... and next steps

- Validation and explainability: workshop with clinicians
- Investigation and reporting on path to production/useage
- Dissemination and onboarding



Thank you!

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