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Prediction of Weight Loss and Comorbidity Resolution After Bariatric Surgery Using Machine Learning with the UK National Bariatric Surgery Registry

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Disclosures

- No disclosures

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Background

- Outcomes from bariatric surgery vary widely
- MDT decisions rely on clinical experience
- The NHS is different compared to other nations in patient selection and aims of surgery
- Growing interest in AI models and outcome prediction across surgery[1]
  - SOPHIA prediction tool[2,3]

1. Vitiello et al. Artificial intelligence and machine learning in bariatric surgery: a comprehensive systematic review. Langenbecks Arch Surg 2026. doi: 10.1007/s00423-026-04042-1
2. Bariatric Weight Trajectory Prediction. https://bariatric-weight-trajectory-prediction.univ-lille.fr
3. Saux P, Bauvin P et al. Development and validation of an interpretable machine learning-based calculator for predicting 5-year weight trajectories after bariatric surgery: a multinational retrospective cohort SOPHIA study. Lancet Digit Health 2023; 5(10):e692-e702.

NBSR

- National Bariatric Surgery Registry[1,2]
- Entries expected for all NHS/private primary and revisional bariatric procedures
- Annual report published in collaboration with BOMSS[3]

1. National Bariatric Surgery Registry. https://nbsr.e-dendrite.com
2. Miras AD, Kamocka A, Patel D, et al. Obesity surgery makes patients healthier and more functional: real world results from the United Kingdom national bariatric surgery registry. Surg Obes Relat Dis. 2018;14(7):1033–40
3. British Obesity & Metabolic Specialist Society. https://bomss.org

What is Machine Learning?

- Machine Learning (ML):
  - A way for computers to learn patterns of data and make predictions without being explicitly programmed.
- Potential in healthcare to:
  - Identify trends
  - Predict outcomes
  - Support clinical decision making

XGBoost

- E**X**treme **G**radient **Boost**ing
- Starts with a decision tree and tests it
- Evaluate the error
- Build a new decision tree that refines the error
- Repeats based on starting parameters specified, including:
  - Tree complexity
  - Learning rate
  - Predictors to use and outcome to predict

1. XGBoost. https://xgboost.ai

Study Aim

To assess the performance of a machine learning model to predict %EWL, T2DM resolution and OSA resolution trained on data from the UK NBSR.

Methods: Data Extraction

- Relevant registry entries between 2018-2023
  - More modern era of bariatric surgery
  - Avoid time period where registry in infancy
  - Allow time for follow up data to be available
- Primary bariatric surgery, excluding endoscopic interventions
- Follow up data taken from closest to 12m post op (9-15 months)
- Exclusion:
  - Suspected duplicate registry entries (matching DOB, gender, operation)
  - No operation data available
  - No follow up data available

Methods: Data Validation

- Surveillance for erroneous data values:
  - 15y < Age < 90y
  - 120cm < Height < 215cm
  - 50 < Weight < 325kg
  - 15 < BMI < 200
  - -50% < %WL < 100
  - -100% < %EWL < 300%
- Reproducible recoding of registry variables for analysability
- Direct calculation of height, weight, BMI, %WL, %EWL based on available data
- Machine learning with XGBoost using R 4.3.3

Methods: ML Model

- 80% training, 20% test
- 5-fold cross validation
- Hyperparameter tuning using grid search
- Early stopping to prevent overfitting
- Separate models per outcome

Results: Data Extraction

- 49,812 unique patient identifiers
- 1375 suspected duplicates excluded
- 19760 entries excluded as no follow up data available
- 14657 entries excluded as no follow up data within 9-15months
- 244 entries excluded after erroneous value screening

- 13,976 eligible primary bariatric operations with reported outcome data 9-15months

Results: Demographics

Total number of patients/operations	13976
Mean Age (SD)	44.79 (11.28)
SG	6216
RYGB	5421
OAGB	1418
Band	920
DS/SADI/BPD	1
Mean Pre-op BMI (SD)	44.54 (7.43)
Pre-op T2DM	3381
Pre-op OSA	2746
Median F/U months (IQR)	11.99 (11.4-12.71)
Mean %WL (SD)	27.26 (10.07)
Mean %EWL (SD)	66.18 (26.75)
Mean F/U BMI (SD)	32.23 (6.42)
F/U T2DM	1069
F/U Persistent OSA	1495

Results: %EWL Prediction

Number of patients	11709
Mean Pre-op BMI (SD)	44.56 (7.31)
Pre-op T2DM	2916
Pre-op OSA	2316
Median F/U months (IQR)	12.02 (11.33-12.78)
Mean %WL (SD)	27.28 (10.04)
Mean F/U BMI (SD)	32.24 (6.32)
F/U T2DM	996
F/U Persistent OSA	1156

Top predictors:

Pre-op BMI

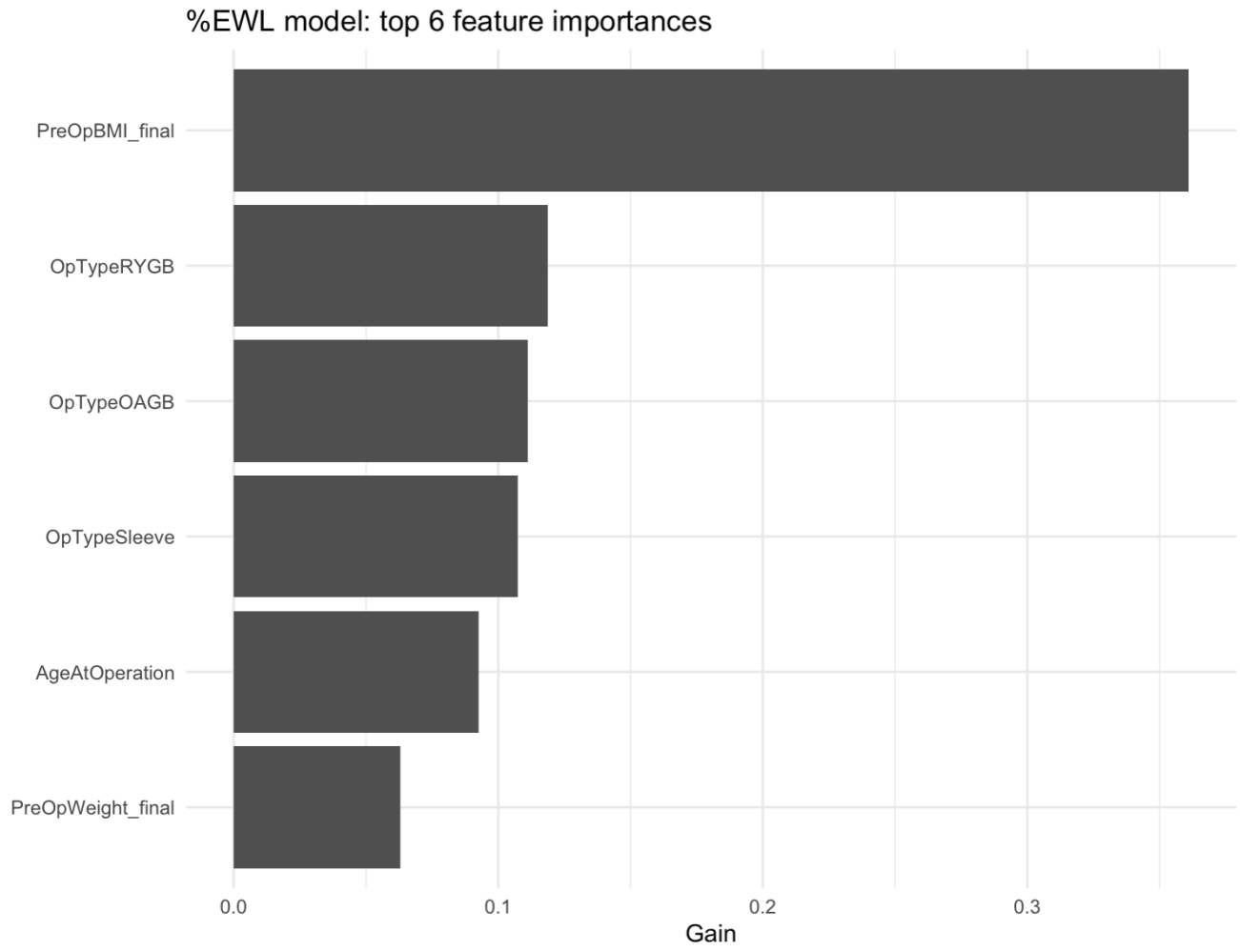
Operation Type

Age

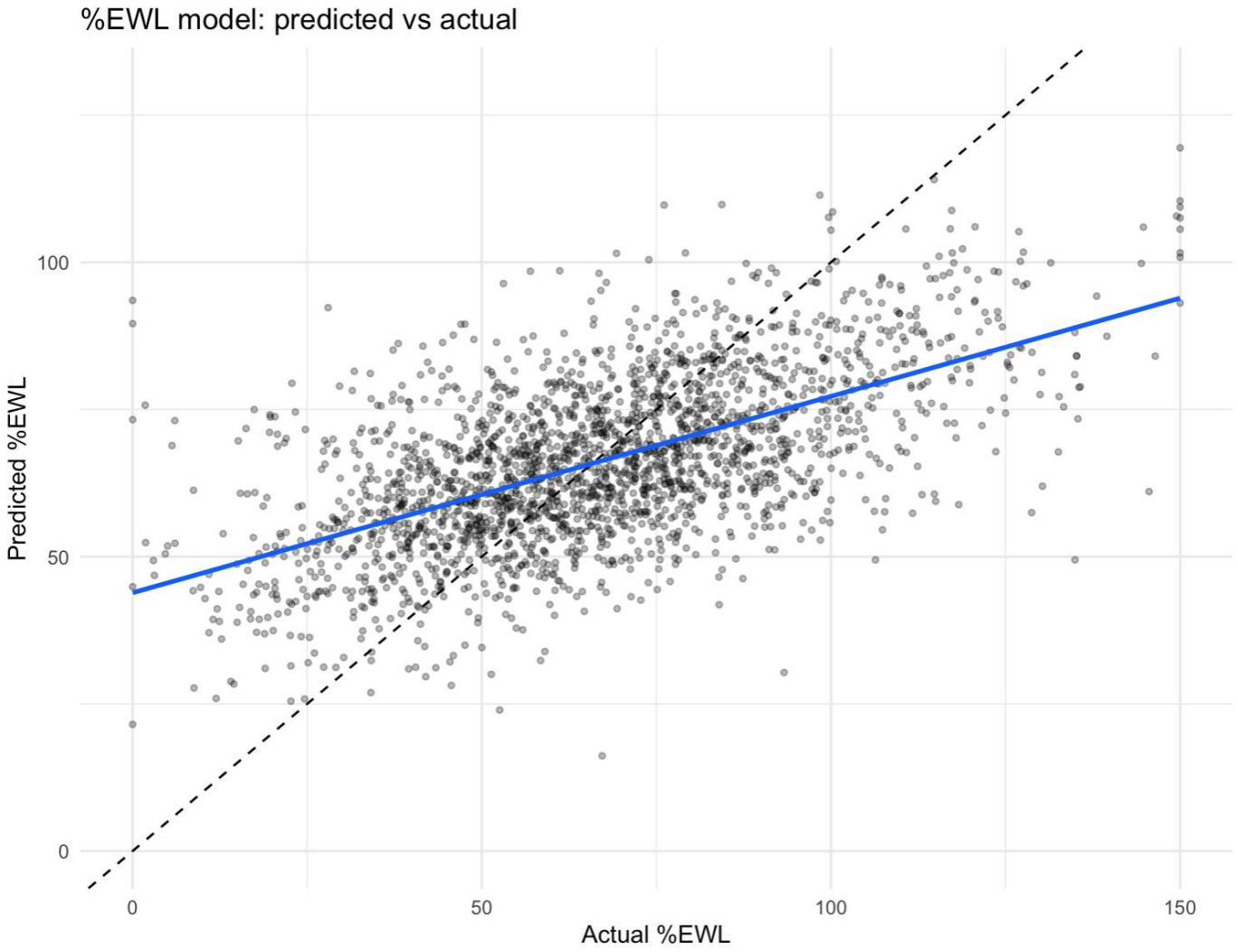
Diabetes severity

Model Performance	
RMSE	21.57
MAE	16.54
R^2	0.348

Results: %EWL Prediction



Results: %EWL Prediction



Results: T2DM prediction

Number of patients	3378
Mean Pre-op BMI (SD)	44.01 (7.36)
Pre-op T2DM	3378
Pre-op OSA	1094
Median F/U months (IQR)	12.02 (11.43-12.78)
Mean %WL (SD)	24.52 (10.25)
Mean %EWL (SD)	60.65 (27.03)
Mean F/U BMI (SD)	32.98 (6.36)
F/U T2DM	986
F/U Persistent OSA	611

Top predictors:

Pre-op T2DM Severity

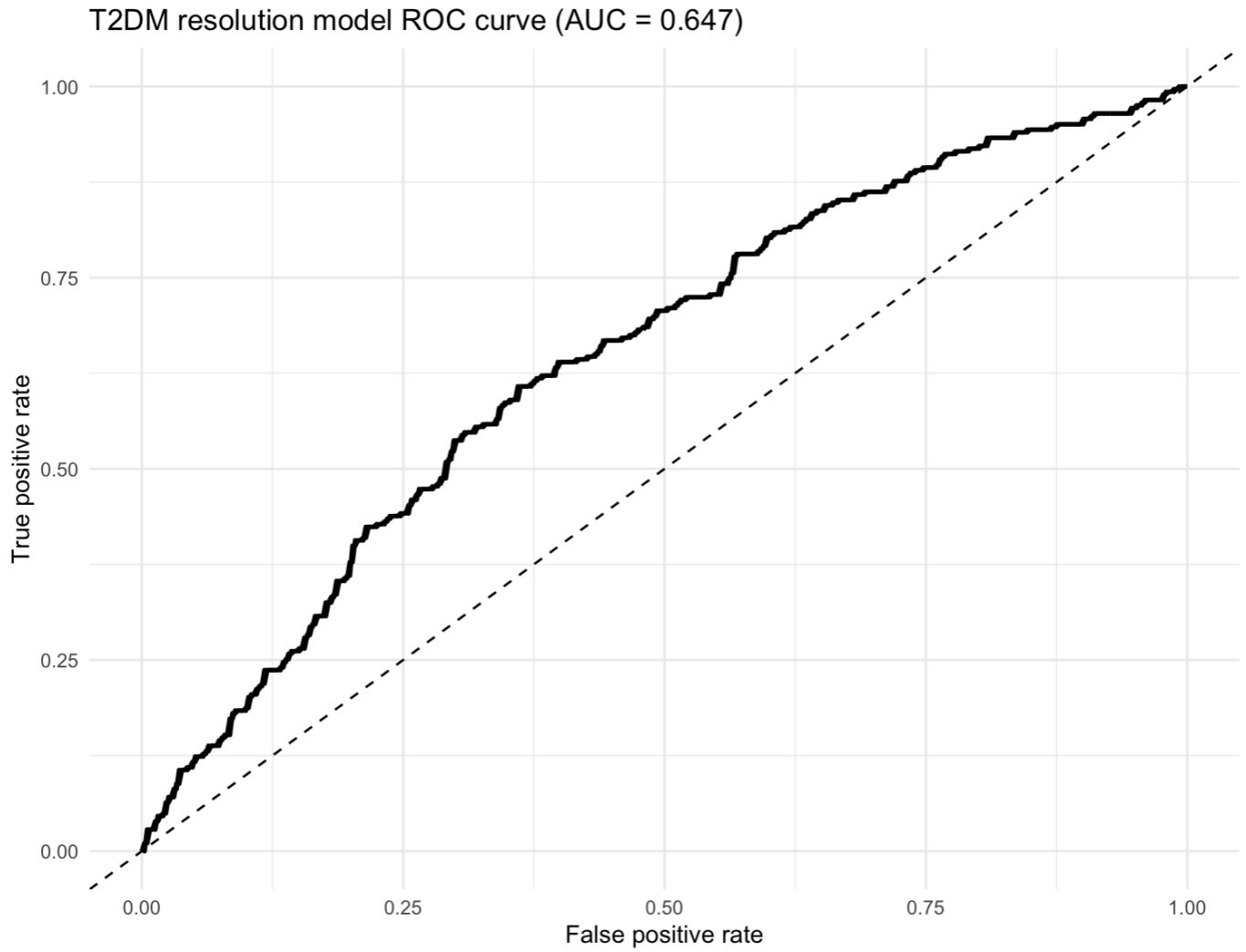
Pre-op HbA1c

Pre-op BMI

Operation Type

Model Performance	
AUC	0.647
Accuracy	0.584
Sensitivity	0.721
Specificity	0.485
Precision	0.502

Results: T2DM Prediction



Results: OSA prediction

Number of patients	2744
Mean Pre-op BMI (SD)	47.07 (8.25)
Pre-op T2DM	1094
Pre-op OSA	2744
Median F/U months (IQR)	12.02 (11.4-12.78)
Mean %WL (SD)	26.07 (10.02)
Mean F/U BMI (SD)	34.48 (7.21)
F/U T2DM	356
F/U OSA	1495

<u>Top predictors:</u>
Pre-op BMI
Functional Status
Age

Model Performance	
AUC	0.589
Accuracy	0.551
Sensitivity	0.617
Specificity	0.498
Precision	0.495

Overall Model Performance

- Machine learning is finding a credible signal in NBSR data
  - Strongest signal is for predicting %EWL
  - T2DM remission is partly predictable
  - OSA resolution is poorly predictable
- Most important predictors are clinically plausible
- No signs in model performance metrics of gross overfitting

Conclusions & Limitations

- Voluntary registry => relative lack of follow up data
- ML models capture predictive signals for %EWL
- Predicting human behaviour / Missing model features
- Registry design to facilitate easier evaluation of ML models
- Strengths:
  - Specific to UK's NHS
  - No gross overfitting detected
- Limitations
  - Lack of follow up data => inherent selection bias for more complete records
- Future work: adapting the registry design, adding model features

THANK YOU

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