Machine Learning Models to Predict Kidney Stone Composition and 24-Hour Urine Abnormalities From Electronic Health Record-Derived Features
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Introduction:

- Machine learning models allow for analyzing complex data
- Could predict stone type or 24hr urine parameters based on demographic information
- <u>We sought to demonstrate the feasibility of predicting this outcomes using machine learning methods</u>

Methods

Retrospective review of 1245 stone patients w/ 24hr urines

- Demographics
- Past medical history
- Medications
- 24-hour urine values

Target variable: Kidney stone composition

- 0 = Calcium oxide monohydrate
- 1 = Calcium oxide dihydrate
- 2 = Hydroxyapatite
- 3 = Uric acid
- 4 = Other

Input Features

- Demographics:
  - Age
  - BMI
  - Race
  - Sex
- Past medical history:
  - Hypertension
  - Gout
  - Diarrhea/IBD
  - Diabetes
  - CAD/MI
  - Osteoporosis, immobility, hyperparathyroidism
  - Epilepsy, migraine
  - CVA
  - GERD
- Medications:
  - Allopurinol
  - Hydrochlorothiazide
  - Potassium citrate

80% training and 20% for testing

- 24 hours urine data
  - Volume at 24 hours (Vol24_closest)
  - SSCaOx_closest
  - Ca24_closest
  - Ox24_closest
  - Clt24_closest
  - SSCaP_closest
  - pH_closest
  - SSUA_closest
  - UA24_closest
  - Na24_closest
  - Mg24_closest
  - P24_closest
  - NH424_closest
  - Sul24_closest
  - UUN24_closest
  - Cr24_corrected
  - Cr24kg_corrected
  - Ca24Cr24_corrected
  - Ca24Cr24_closest

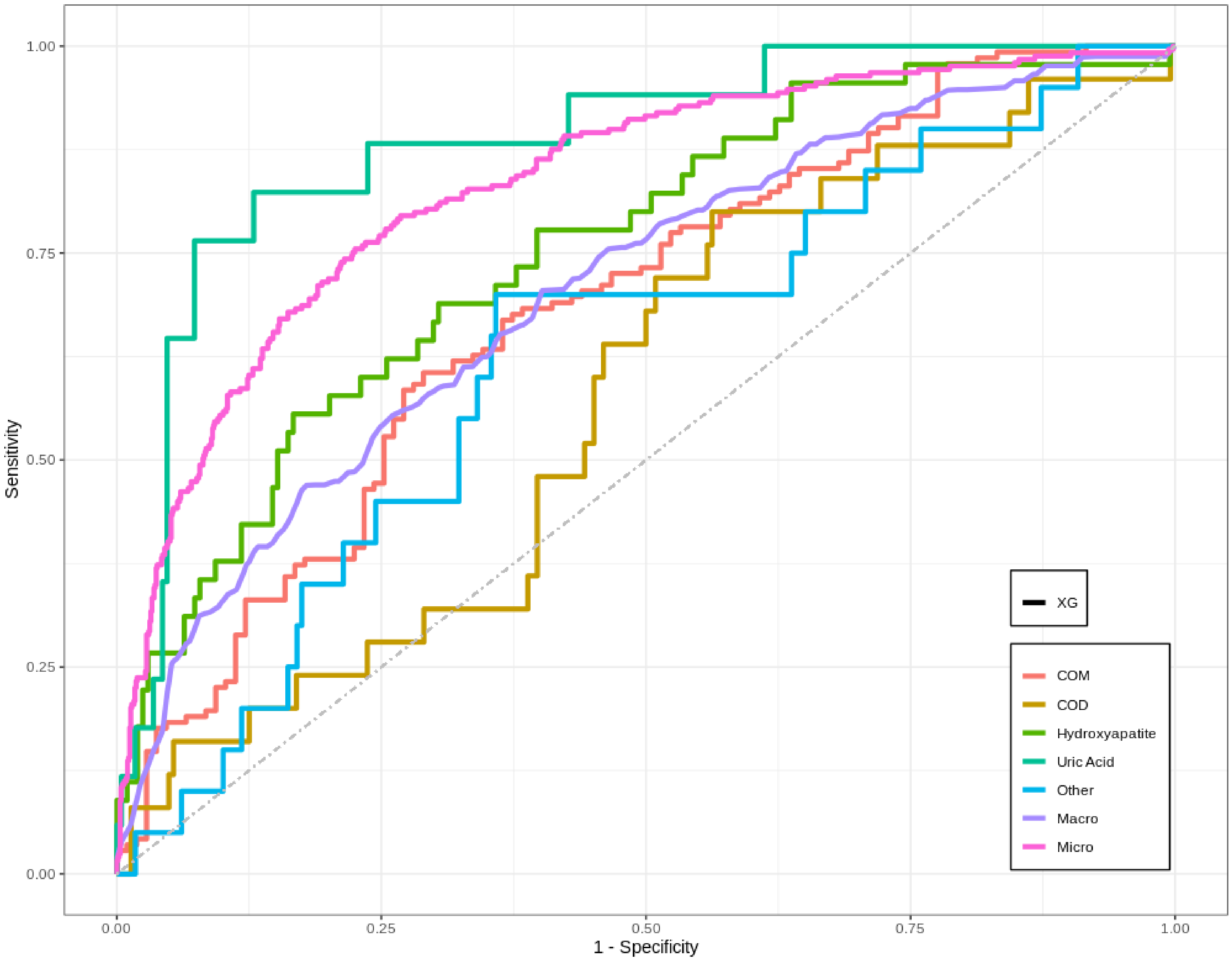
Model Overview

Pre-processing:
- Scaling continuous variables: mean of 0, SD of 1
- One-hot encoding of categorical variables

Baseline performance of XGBoost model with
- Booster: gbtree
- Objective: multi:softprob
- Evaluation metrics: mlogloss
- Accuracy: 58.23%

Hyperparameter tuning using random sampling (100 iterations)
- Accuracy: 62.25%

Examining SHAP values of each target class

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            Accuracy : 0.6225
              95% CI : (0.5591, 0.6829)
 No Information Rate : 0.5703
 P-Value [Acc > NIR] : 0.05416

               Kappa : 0.2408

Mcnemar's Test P-Value : NA
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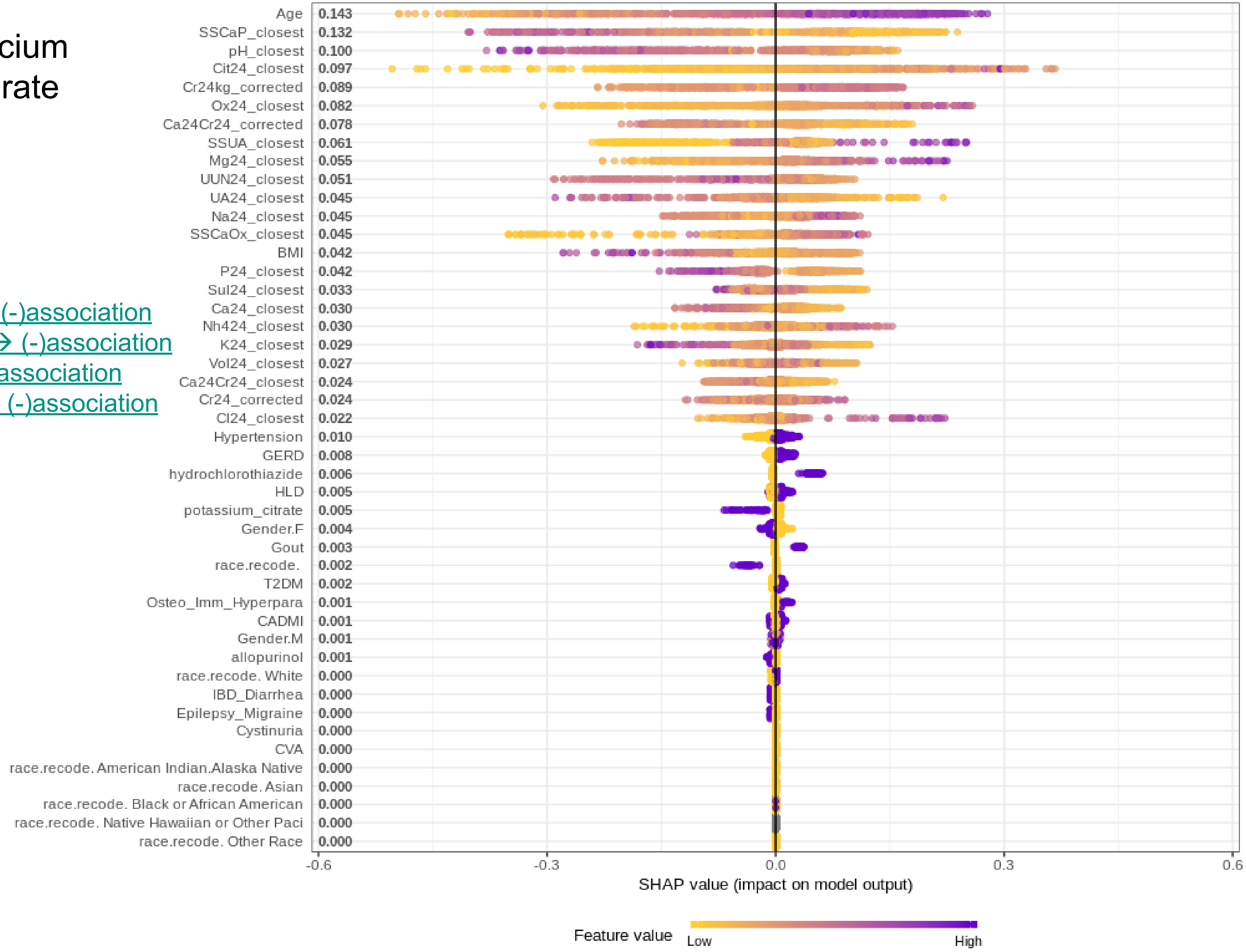
Statistics by Class:

	COM	COD	HA	UA
Sensitivity	0.9366	0.000000	0.40000	0.23529
Specificity	0.2991	0.991071	0.92647	0.99138
Pos Pred Value	0.6394	0.000000	0.54545	0.66667
Neg Pred Value	0.7805	0.898785	0.87500	0.94650
Prevalence	0.5703	0.100402	0.18072	0.06827
Detection Rate	0.5341	0.000000	0.07229	0.01606
Detection Prevalence	0.8353	0.008032	0.13253	0.02410
Balanced Accuracy	0.6178	0.495536	0.66324	0.61334

Target Class: Calcium Oxalate Monohydrate



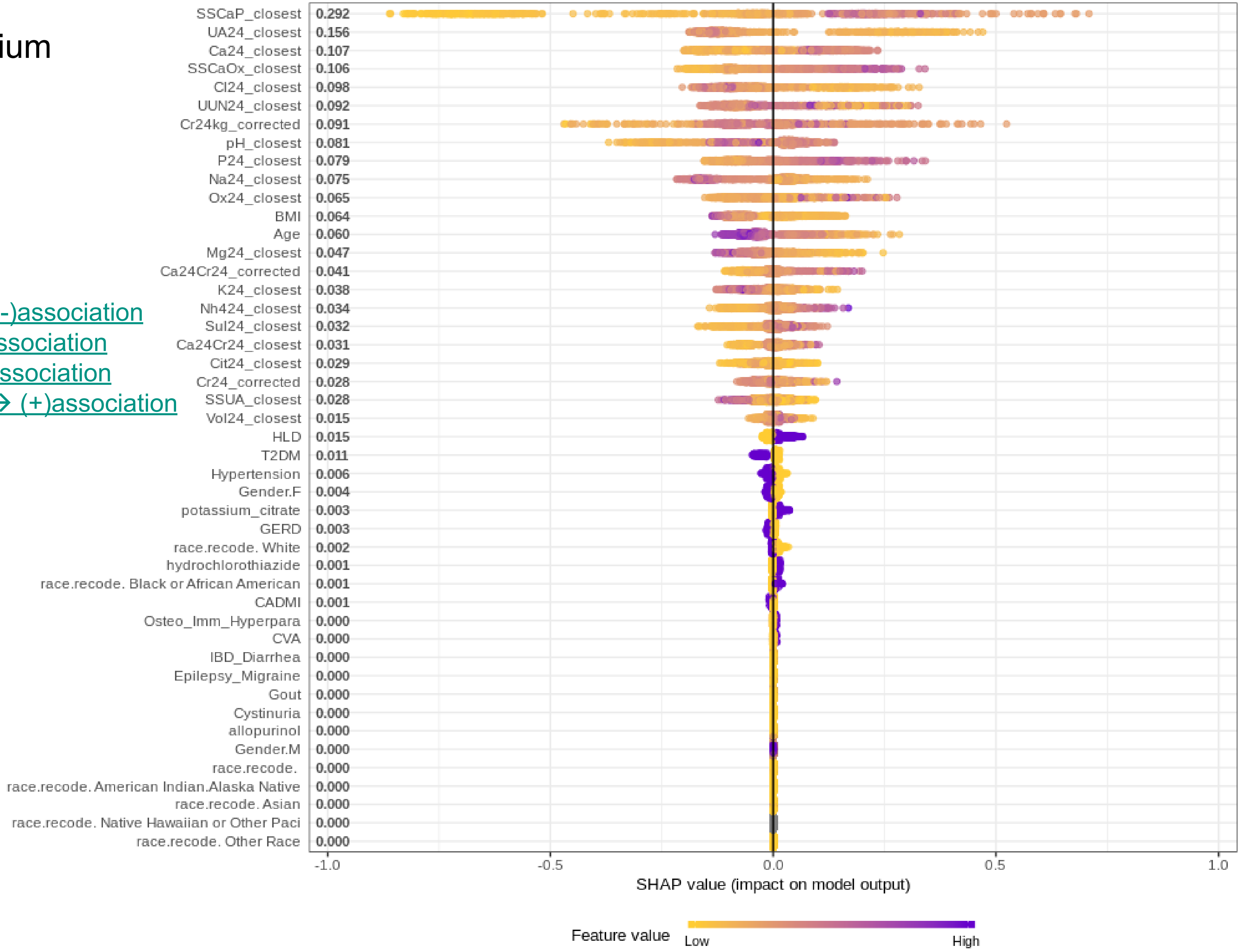
Associations:

- Younger Age → (-)association
- Higher SSCaP → (-)association
- Higher pH → (-)association
- Lower Citrate → (-)association

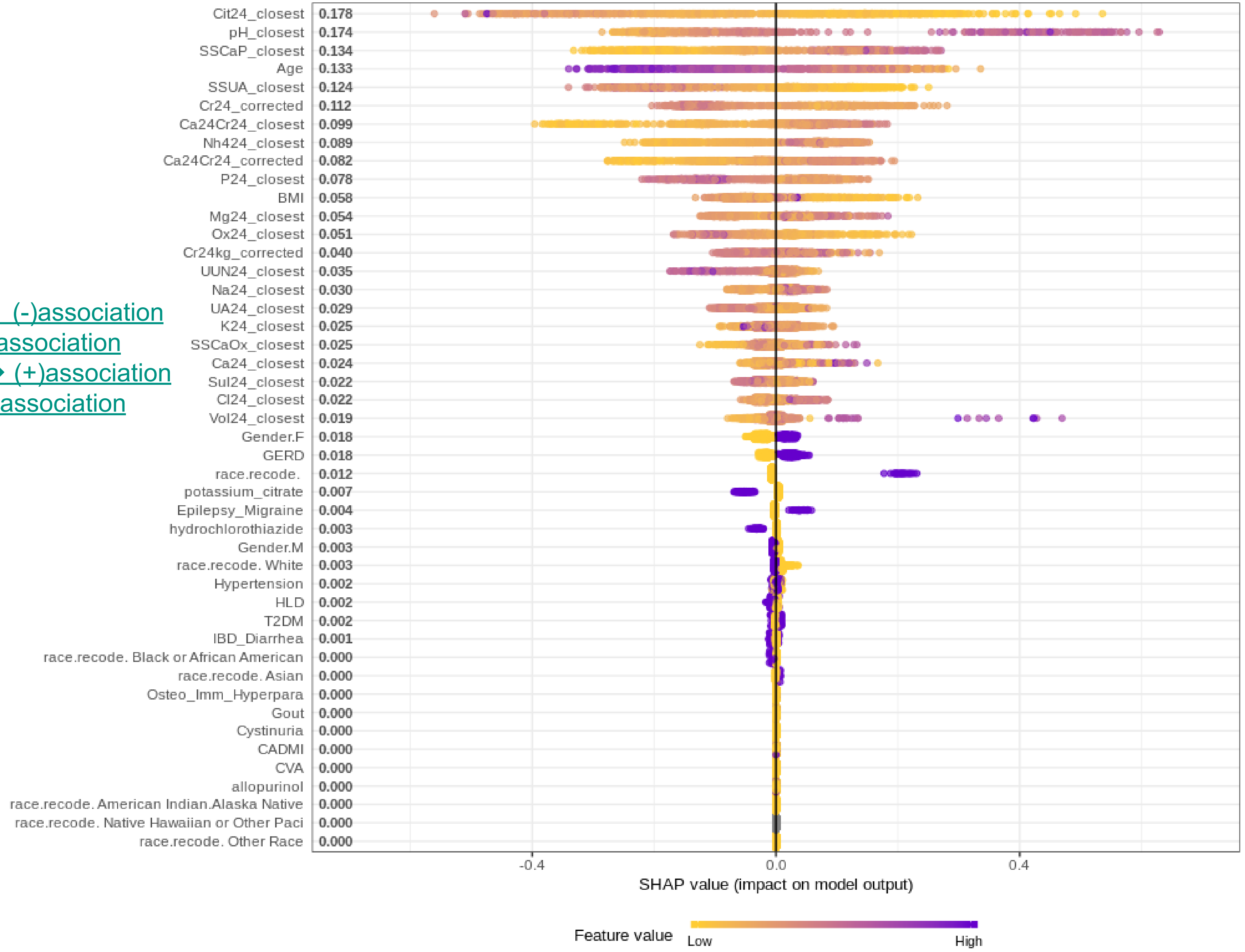
Target Class: Calcium Oxalate Dihydrate

Associations:

- Lower SSCaP→ (-)association
- Lower UA → (+)association
- Higher Ca → (+)association
- Higher SSCaOx → (+)association



Target Class: Hydroxyapatite



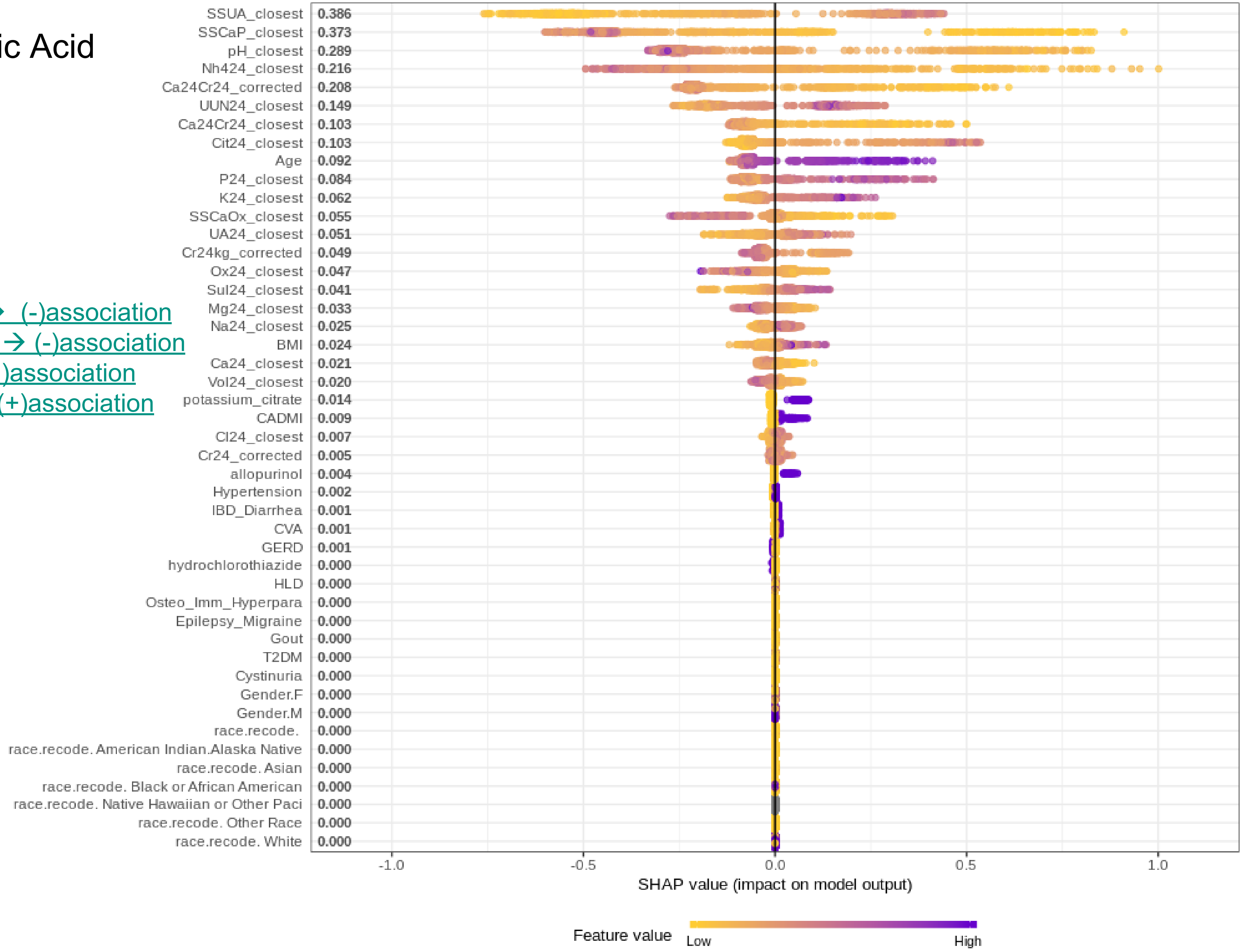
Associations:

- Higher Citrate → (-)association
- Higher pH → (+)association
- Higher SSCaP → (+)association
- Higher Age → (-)association

Target Class: Uric Acid Stones

Associations:

- Lower SSUA → (-)association
- Higher SSCaP → (-)association
- Lower pH → (+)association
- Lower NH4 → (+)association



Conclusions

- Stone composition prediction appears feasible with machine learning methods
- Features of EHR-derived data were identified and associated with stone composition
- Additional work is necessary to further optimize model performance