

Artificial intelligence–driven plasma
metabolomics identifies metabolic signatures of

FEED EFFICIENCY IN BEEF CATTLE

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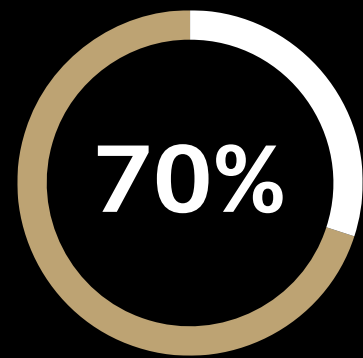
Beef cattle production plays a critical role in global food security and national economies, particularly in Brazil, the world's leading beef producer and exporter.

USDA (2025); ABIEC (2025)

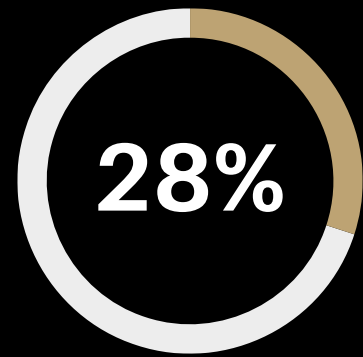


Why feed efficiency matters and why it is hard to predict

RELEVANCE



Major
production cost



Reduction in
CH₄ emissions

RESIDUAL FEED INTAKE



Observed -
expected dry
matter intake

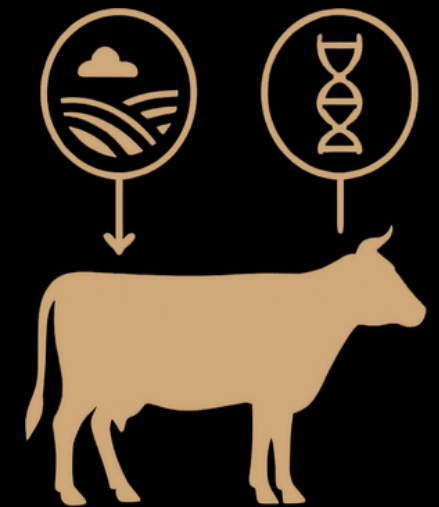
$$\text{DMI} = \text{MBW} + \text{ADG} + \text{RFI}$$

56 to 70 days

BIOLOGICAL COMPLEXITY

Moderate
heritability

Polygenic
phenotype



**Difficult to find
robust biomarkers**

1

Feed intake

2

Digestion

3

Metabolism

4

Activity

5

Thermoregulation

Herd, Oddy and Richardson (2004)

Metabolomics offers a powerful path to unlock the biology of feed efficiency, but its real impact depends on validated biomarkers generated through large-scale studies.

Nunes et al. (2024)

Hypothesis

**Distinct plasma metabolomic signatures enable discrimination
between cattle with high and low feed efficiency.**

Objectives



**Define divergent
feed-efficiency phenotypes**

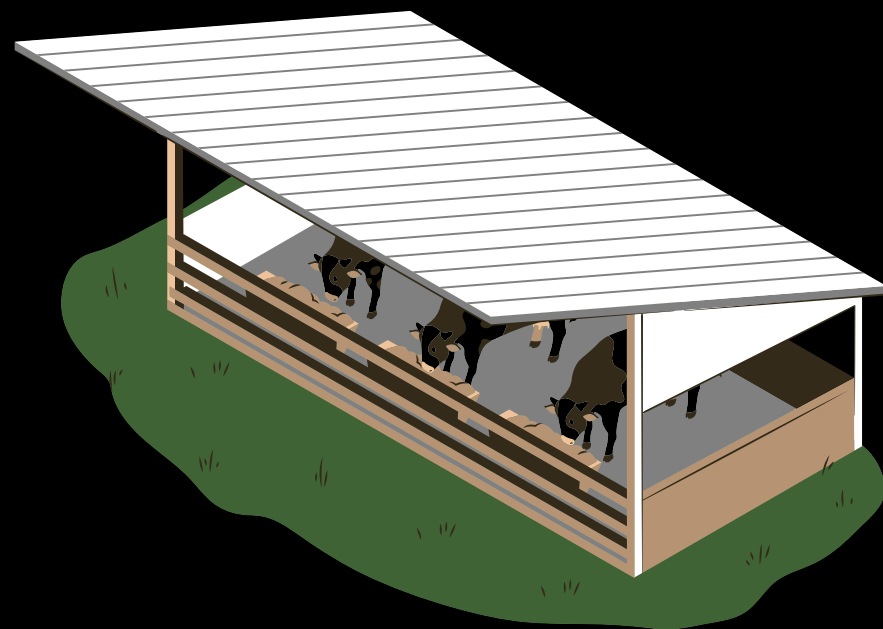
**Identify plasma
metabolic signatures**

**Evaluate their
discriminative potential**

Study design

1

Phenotypic data and sample collection



Upper quartile (HRFI)

Low-feed efficiency (LFE)

Lower quartile (LRFI)

High-feed efficiency (HFE)

**2**

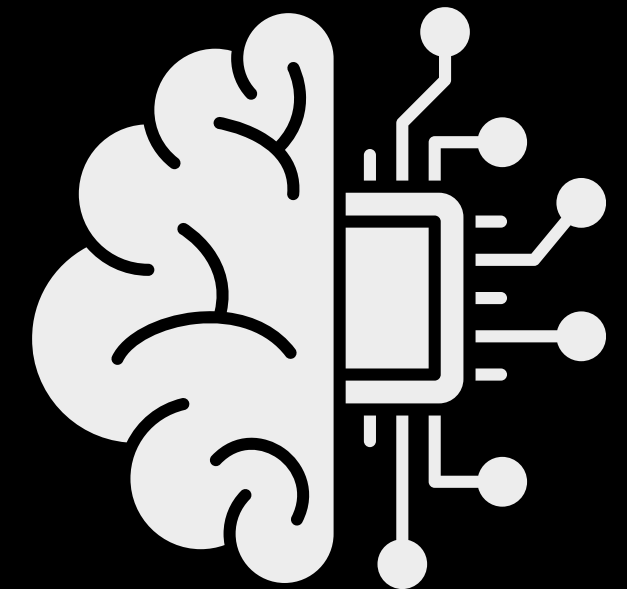
Residual feed intake determination

3

Metabolomics analyses



LC-MS/MS and DFI-MS
TMIC MEGA assay

**4**

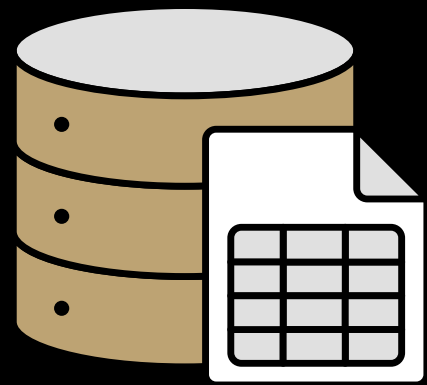
Machine learning analyses

360 animals, 5 cohorts

Nellore, Angus and crossbred cattle

Plasma collection before the feedlot trial

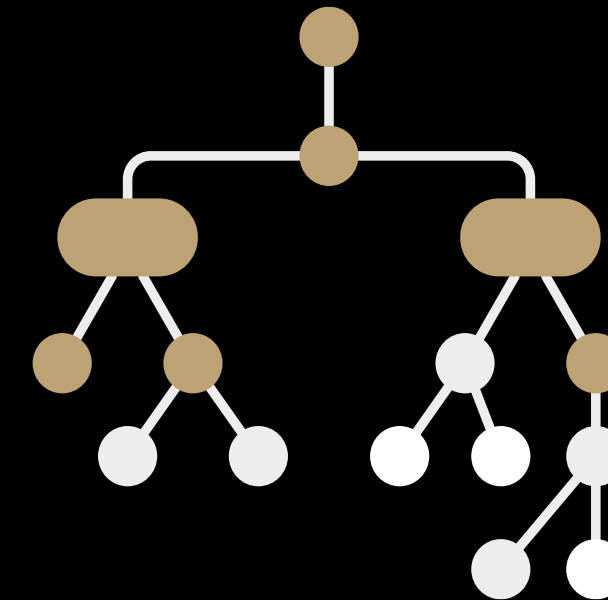
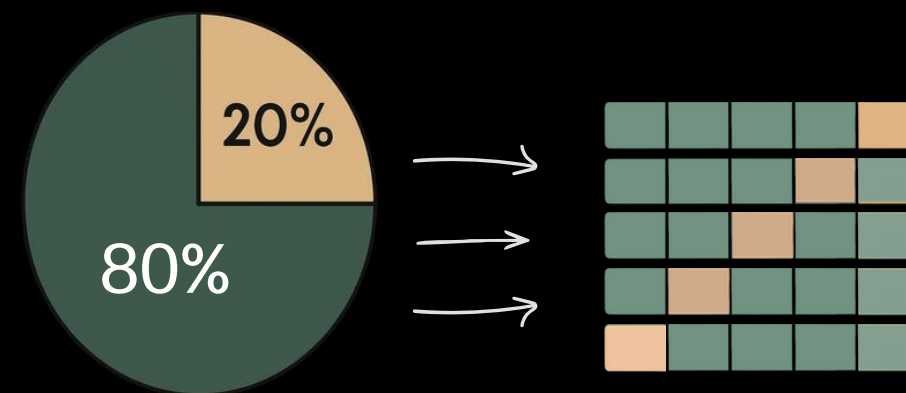
Modeling strategy



Metabolomics dataset preprocessing

<LOD and >ULOQ handling
Missingness filtering and imputation
Log10 transformation and normalization

Train-test split and CV model tuning

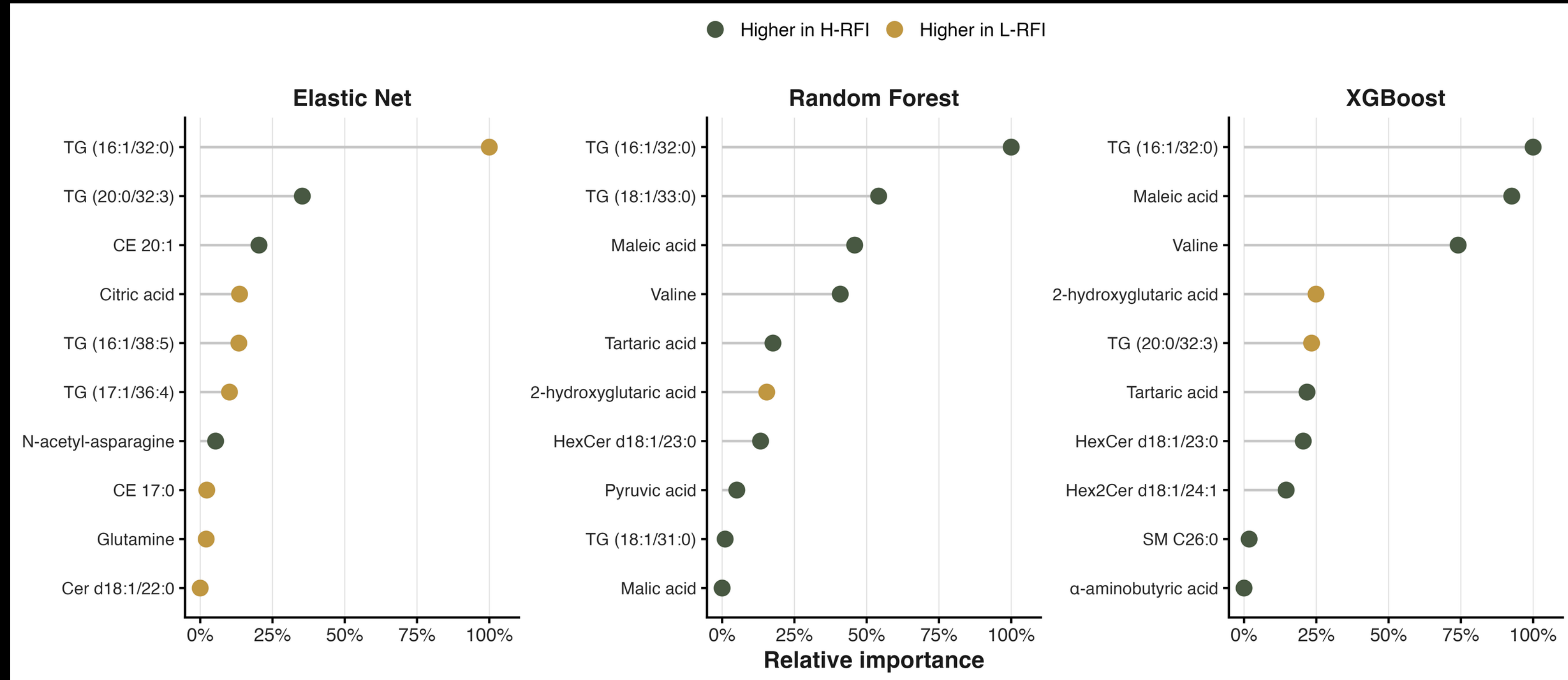


Independent test evaluation

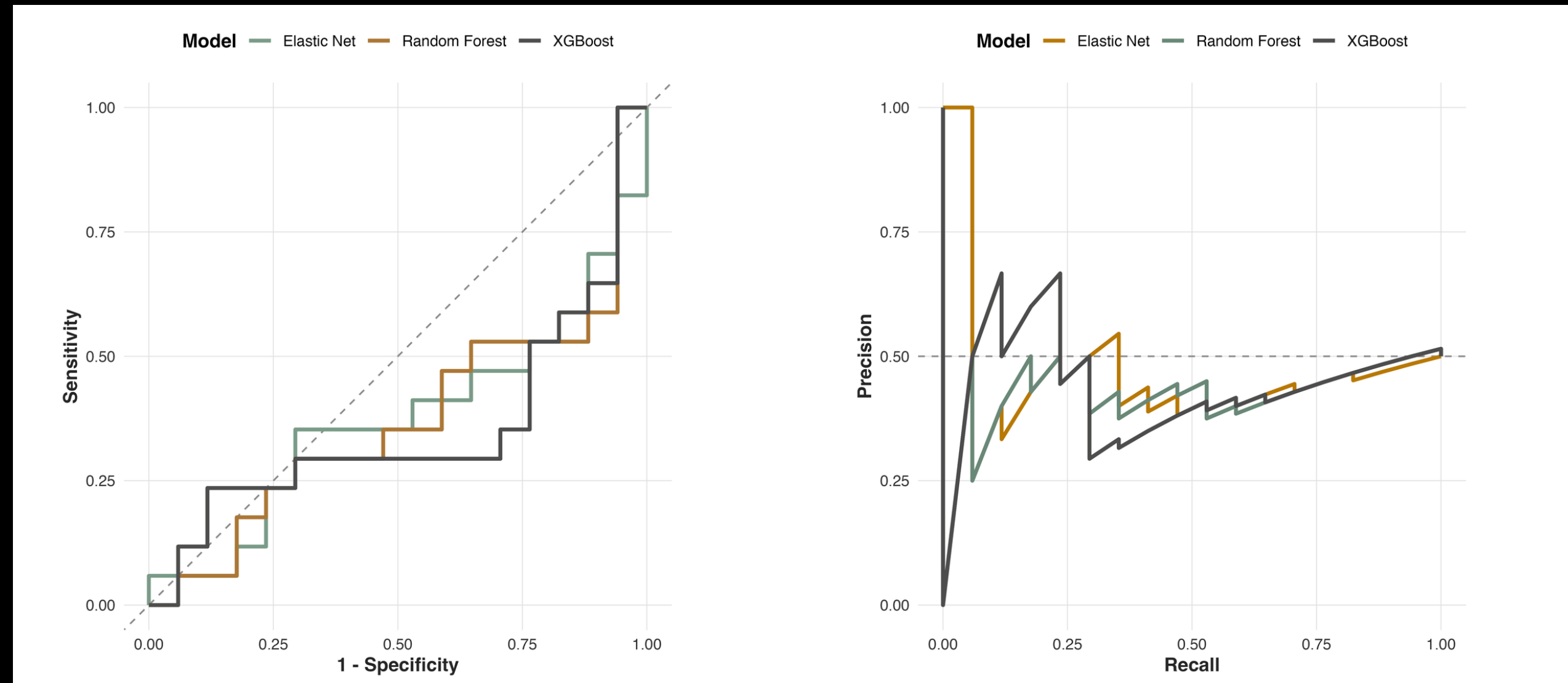
Independent hold-out test set
ROC-AUC and Brier score

Model comparison

Elastic Net, Random Forest, and XGBoost



Metabolites selected by each model



Independent test performance was limited

Low feed efficiency (H-RFI)

Higher lipid-related metabolites

triacylglycerols, cholesteryl esters, sphingolipids

Higher energy-related metabolites

succinate, pyruvate and hexose

Suggests altered lipid handling and post-absorptive energy metabolism

VS

High feed efficiency (L-RFI)

Higher amino acid-related metabolites

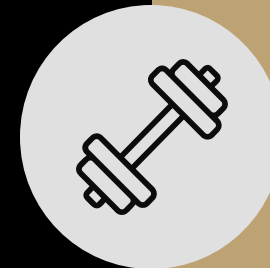
methionine, tyrosine and N-acetyl-tryptophan

Higher microbial/host co-metabolites

hippuric acid, p-hydroxyhippuric acid and indoxyl sulfate

Suggests rumen microbiome–host metabolic contribution

Strengths



- Well-defined phenotype
- Multiple supervised models
- Independent hold-out test set
- Cross-model consensus biomarkers

Limitations



- Separation was modest
- No external validation yet
- Biomarker reproducibility across populations still unknown
- Heterogeneous population: increased biological variability

Take-home message

01

AI-guided targeted plasma metabolomics

identified metabolic signatures associated with
feed efficiency

02

Independent test performance was modest

results should be interpreted as exploratory

03

Cross-model consensus metabolites

suggests biologically meaningful differences in energy
metabolism, amino acid turnover, and lipid handling,
which help uncover the biology of feed efficiency

04

External validation

Is needed before proposing biomarkers
for feed efficiency selection

2

THANK YOU!

Questions?



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