Frailty Detection and Management
Enhancing Interventions with Interpretable Machine Learning

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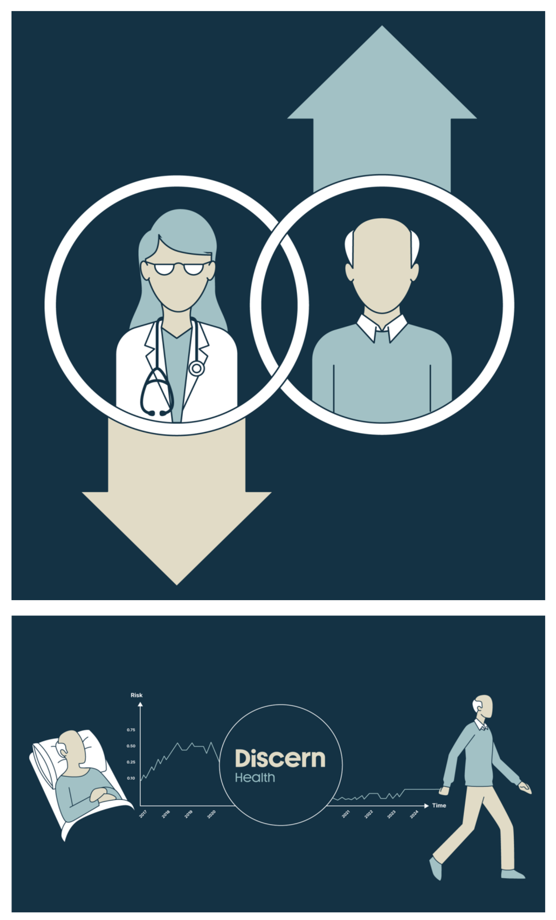
Definition & Motivation

- **Frailty** — Reduced ability to perform activities of daily living ADLs and a significant source of vulnerability for older population (disability, falls, hospitalization and even death)
- Growing older adult population
- Increasing social, psychological, and financial burdens on healthcare systems



Objectives

Develop	Develop a novel claims-based frailty model for time-to-event frailty and adverse event detection
Analyze	Analyze clinical and socioeconomic data to uncover frailty phenotypes and understand their progression
Validate	Validate models to demonstrate cost savings, clinical outcome improvements, and operational efficiency

Framework/Approach

Feature Engineering
- Kim et al. Features
- Custom Features
  - Relative Payment
  - Readmission
- Feature Selection

Frailty Detection
- Frailty in One Year
- Frailty Score
  - CFI & SFI

Frailty Modeling
- Phenotype Modeling
- Mortality Modeling
  - Classification
  - Time-to-Event

Methodology

Preprocessing

Feature Selection & Analysis
- ANOVA
- Mutual Information
- Chi-Square Test
- Lasso & Tree Models

Top 50 Feature Model Evaluation
- Logistic Regression
- Decision Tree
- Random Forest

Performance Metrics
- F1-Score
- Recall
- Sensitivity
- Calibration Curve
- AUC Curve
- Precision Recall Curve

Cut-off Selection
- Review Visualizations
- Select Final Features

Final Model
- Build Model: Robust to Pre-Frail/Frail
- Build Model: Pre-Frail to Frail
- Evaluate Metrics

Frailty Detection

Predict current month target → Predict 3 months ahead → Predict 6 months ahead → Predict 9 months ahead → Predict 12 months ahead

Data Sources
- MCBS Patient
- Kim et al. Features [CFI & SFI]
- ELIXHAUSER, HCC, and ADL Grouped Features

Pre-Processing
- Top 5, 10, ..., 30 Features -> **Lasso**
- One-hot encoding on Gender & Race Features

Methodology
- Target - **kim_cfi_score**
- Quantile Regression
- Linear Regression

Mortality

Features
- Patient
- Claims
- Survey
- ELIXHAUSER
- HCC

Criteria: Patients with Death Date

Proceed to: Calculate Days to Death

Predict Patient's Death
- 1 Month
- 3 Months
- 6 Months
- 9 Months
- 1 Year

Time-to-Event Model

Cox Proportion Hazards Model Remove Features with Low Cardinality

Time Observed → Event → Hazard

Phenotypes

Data Sources
- MCBS Patient
- Kim et al. Features [CFI & SFI]
- ELIXHAUSER, HCC, and ADL Grouped Features

Feature Sets
- Entire Processed Feature set
- Top 10 Important Features/ Target -> **Lasso**

Methodology
- Target – 53 Survey Features: Phenotypes

Primary Metrics
- BC -> ROC AUC Patient
- MC -> Avg. ROC AUC from One vs Rest

Further Specific Modeling

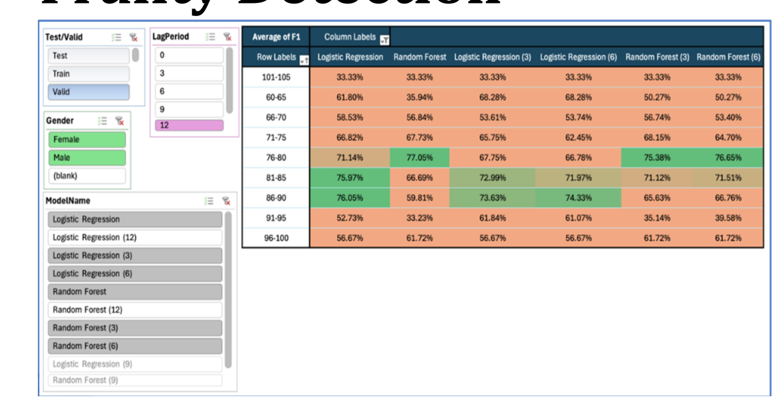
Faster Processing
- Experiment 2
- Top_10_features.json
- -> Top 10 IF/T & it's Lasso Coefficient

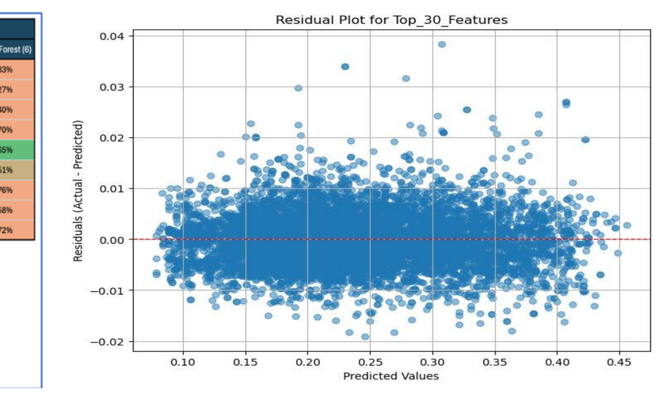

```json
{
  "self_care": 0.13233941165927357,
  "financial": 0.08534966966904885,
  "n_gross_motor": 0.032125997942799626,
  "kim_disorders_of_the_peripheral_nervous_system": 0.017529149099531804,
  "kim_arthropathies_and_related_disorders": 0.012520395191878378,
  "hcc_schizophrenia": -0.011970288585732007,
  "hcc_congestive_heart_failure": 0.009353058941851568,
  "kim_hypertensive_disease": 0.008640921809481162,
  "kim_diseases_of_other_endocrine_glands": 0.0077892106574748024,
  "kim_nephritis_nephrotic_syndrome_and_nephrosis": 0.007333741708015384
}
```


Ø **Top_10_features.json**

Results and Conclusions

Frailty Detection

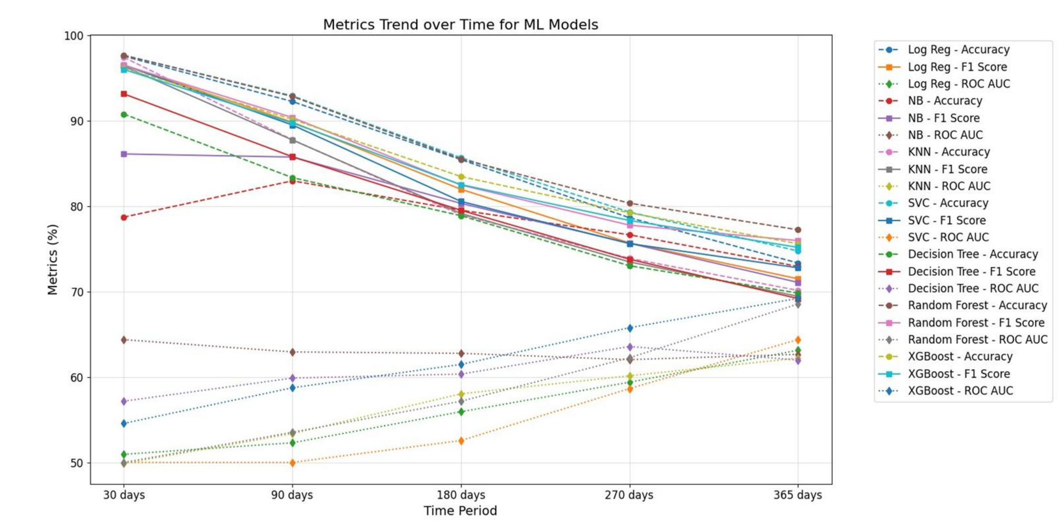




Best Test RMSE: 0.0052

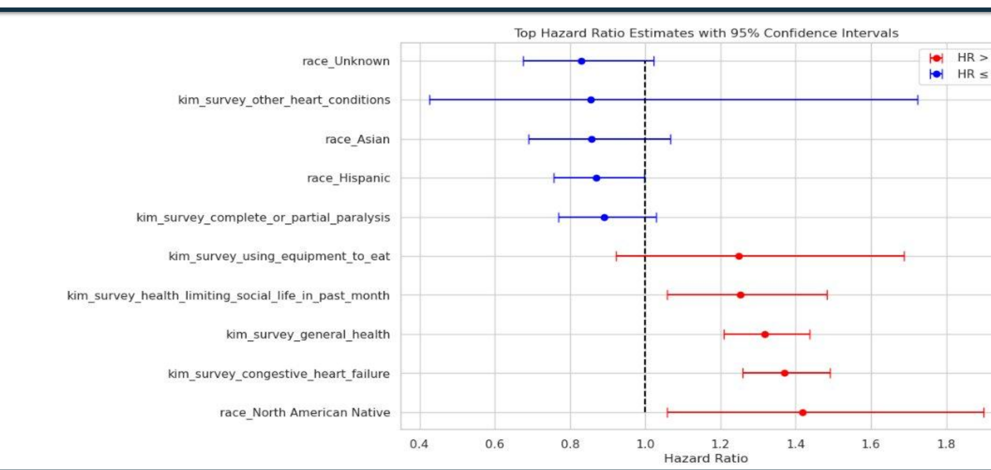
Mortality

- Models become more reliable in predicting mortality within 1 year.
- Random Forest and XGBoost are the most effective models.

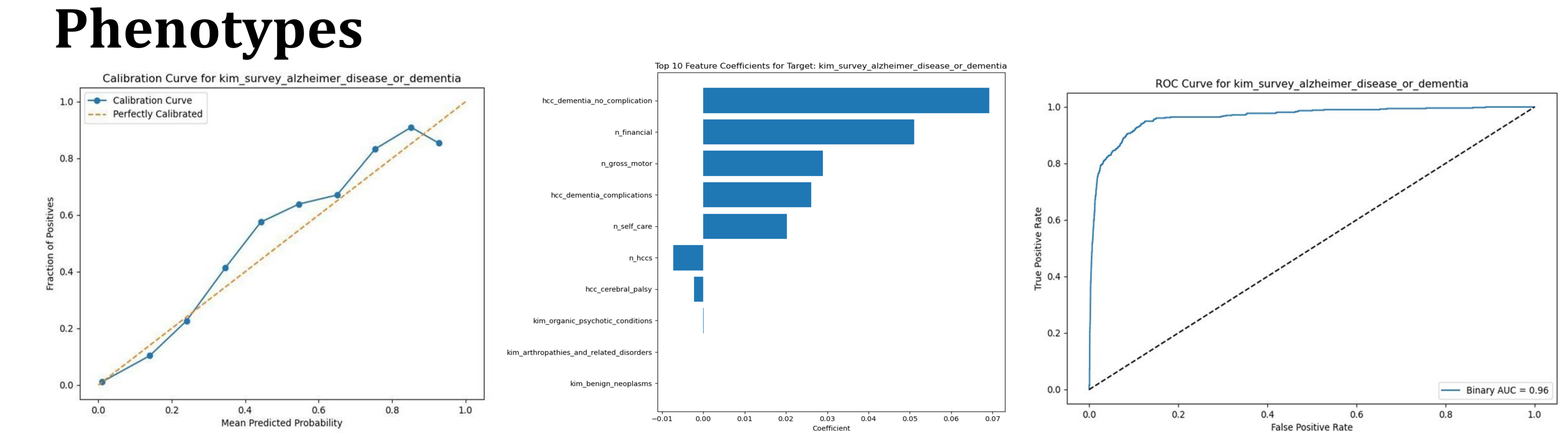


Cox PH Model

(45,023 observations)
C-Index: 0.84



Phenotypes



Best model For Each Target Phenotype - were evaluated on unseen data for all 53 Phenotypes over 6 experiments with Calibration curves, Feature Importance plots, ROC Curves, and the best performing model were logged.

Overall Impact

Our Solution

Frailty Phenotype Modeling – Identify At-Risk Patients → **Frailty Detection** – Predict Frailty Onset → **Mortality Modeling** – Assess Patient Risk

Outcomes

Informed Interventions – For the right patients → **Reduce Burden of Frailty** – Social, psychological, and financial burdens

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