ANALYZING LIFESTYLE AND DEMOGRAPHIC RISK FACTORS OF DIABETES WITH BRFSS DATA

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INTRODUCTION

PREDICTING DIABETES USING BRFSS SURVEY DATA

- Diabetes is a major U.S. public health challenge
- BRFSS: largest behavioral risk survey (CDC)
- Goal: classify individuals as
  - Diabetes / No Diabetes / Prediabetes
- **Challenges:**
  - class imbalance
  - self-reported noise
  - hundreds of variables

BRFSS 2024 DATASET OVERVIEW

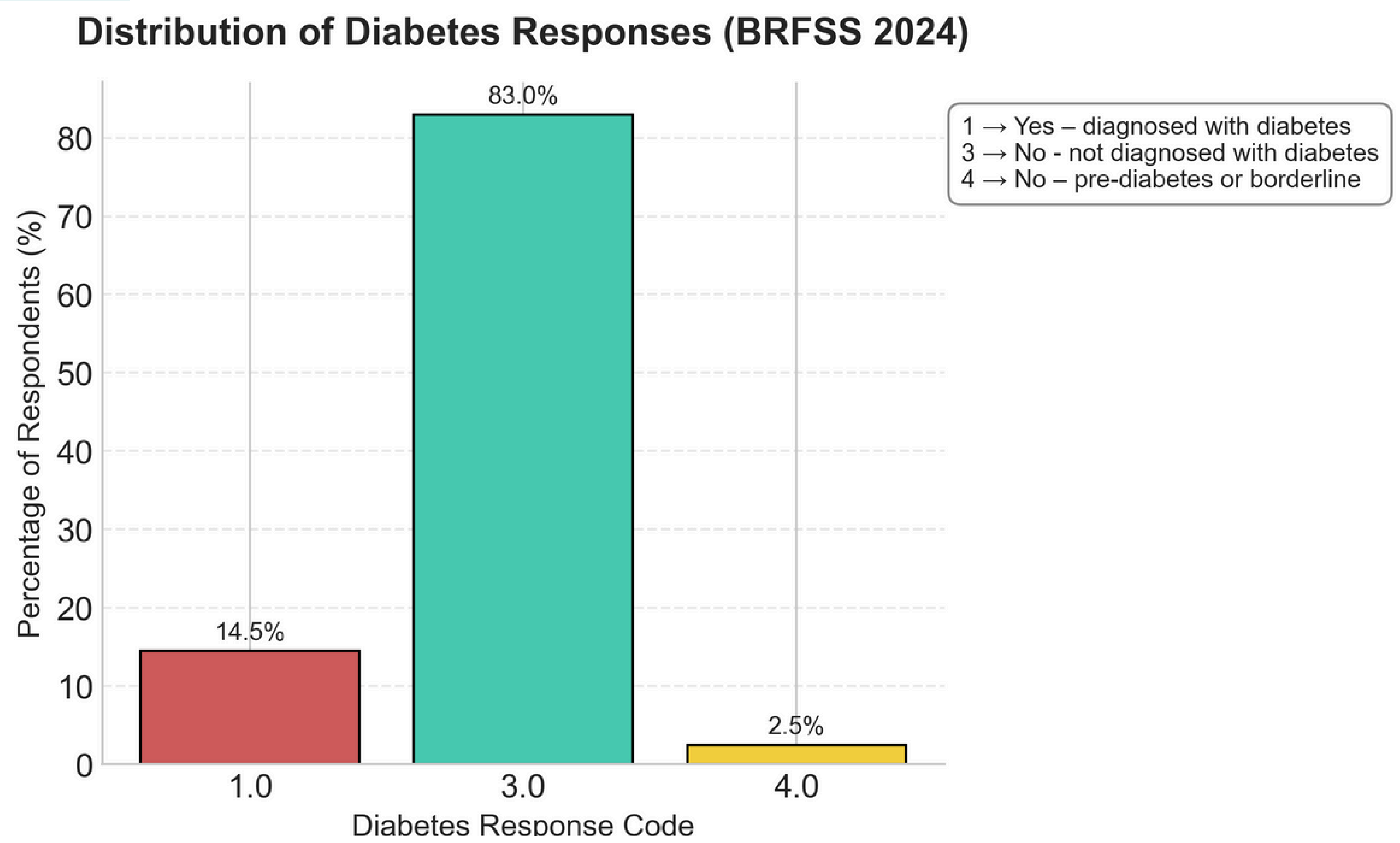
- ~450,000 cleaned samples
- Target variable (DIABETE4) with 3 classes
- 198 engineered + cleaned features
- Categories included:
  - Demographics
  - Lifestyle behaviors (exercise, smoking)
  - Health indicators (BMI, blood pressure, cholesterol)
  - Socioeconomic factors (income, education)

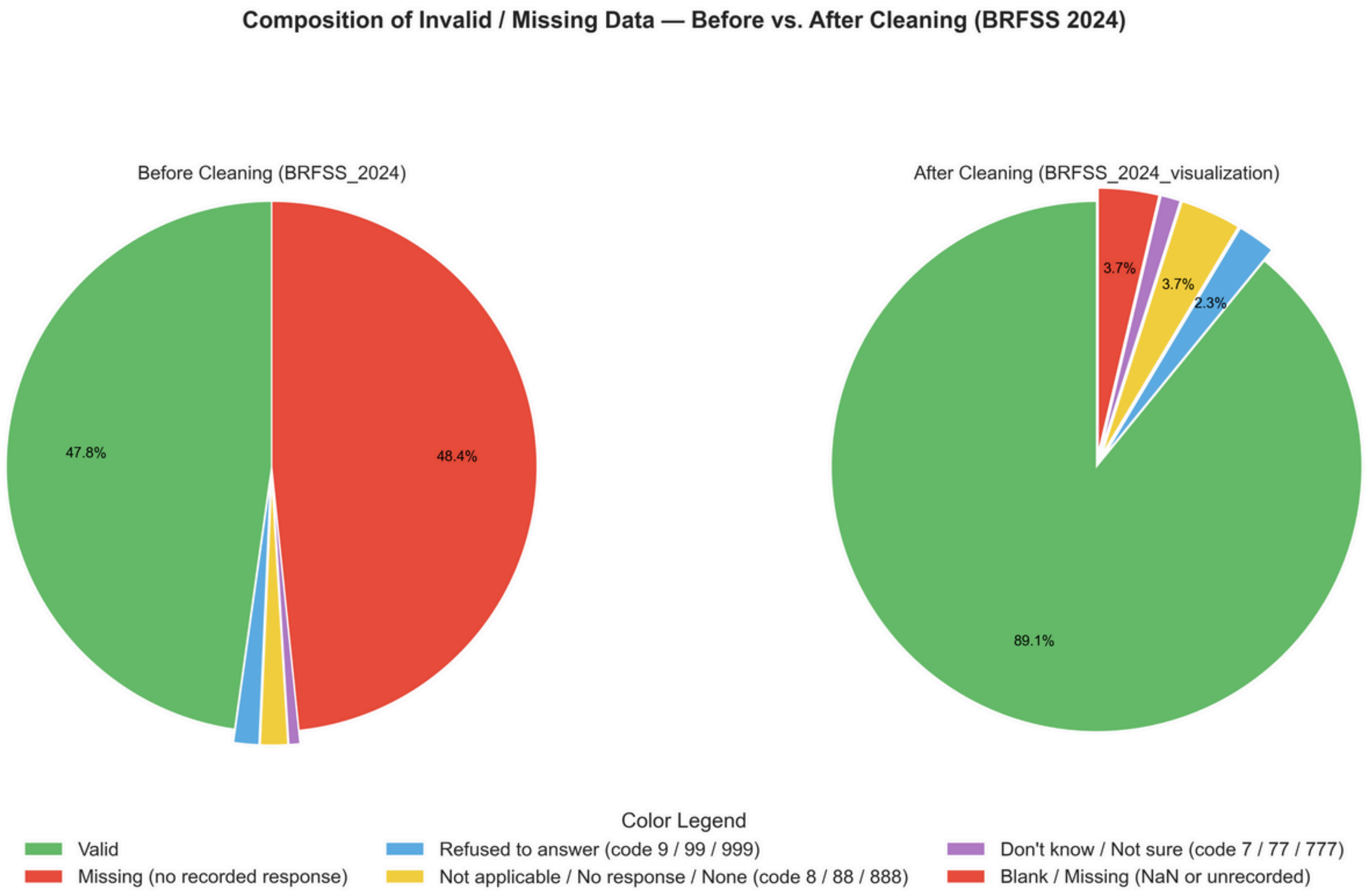
DATA CLEANING & FEATURE ENGINEERING PIPELINE

- Removed invalid BRFSS codes (7, 9, 77, 99 → NaN)
- Dropped features with >30% missing
- Encoded categorical variables
- Handled missing values
- Kept clinically meaningful variables
- Final shape: 198 features × 450K samples

EXPLORATORY DATA ANALYSIS

DATA DISTRIBUTION

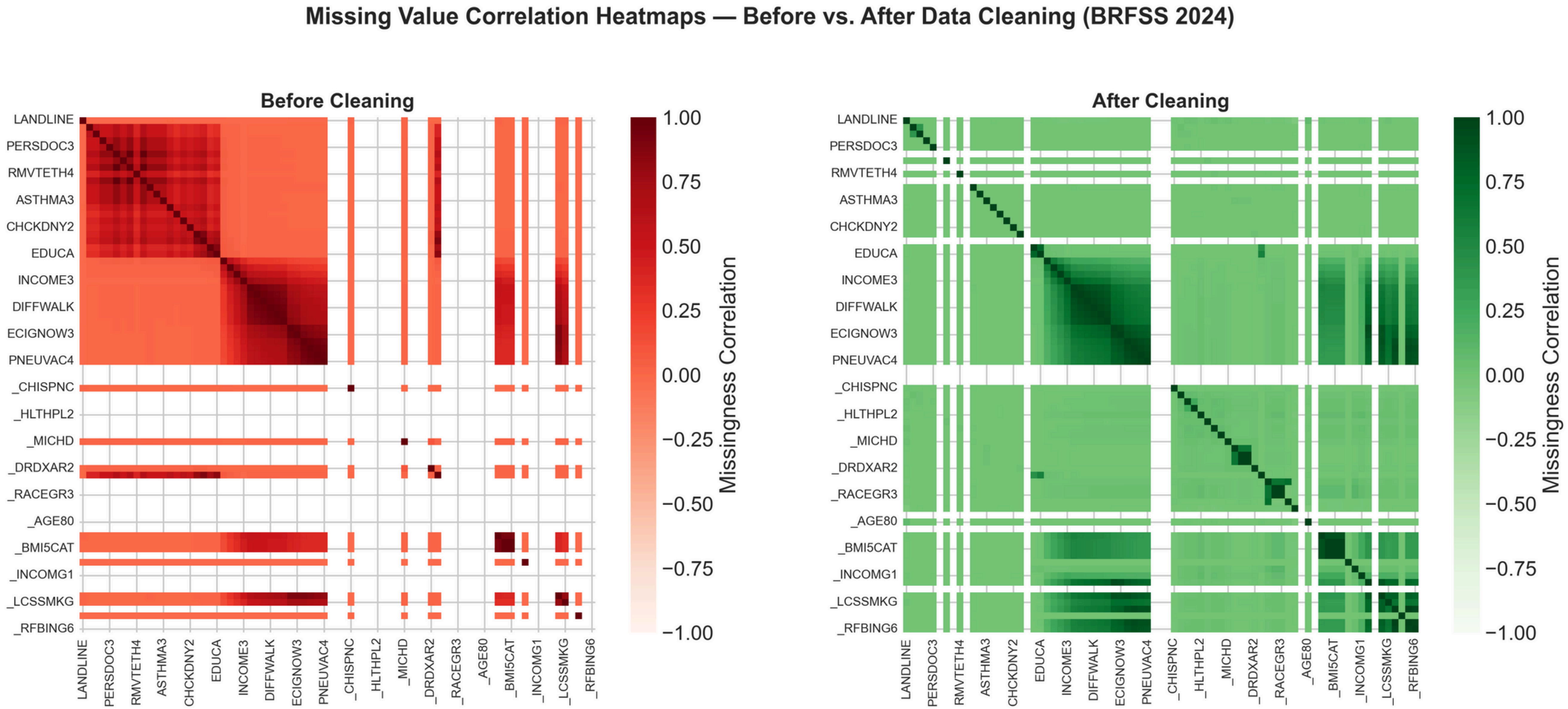




- Majority of respondents report no diabetes diagnosis.
- Only a small fraction fall into diabetic or pre-diabetic categories.
- Strong class imbalance impacts model learning and evaluation.

- High volume of invalid/missing responses before cleaning.
- Cleaning greatly increases the percentage of valid entries.
- Reduces noise and improves dataset reliability.

DATA DISTRIBUTION

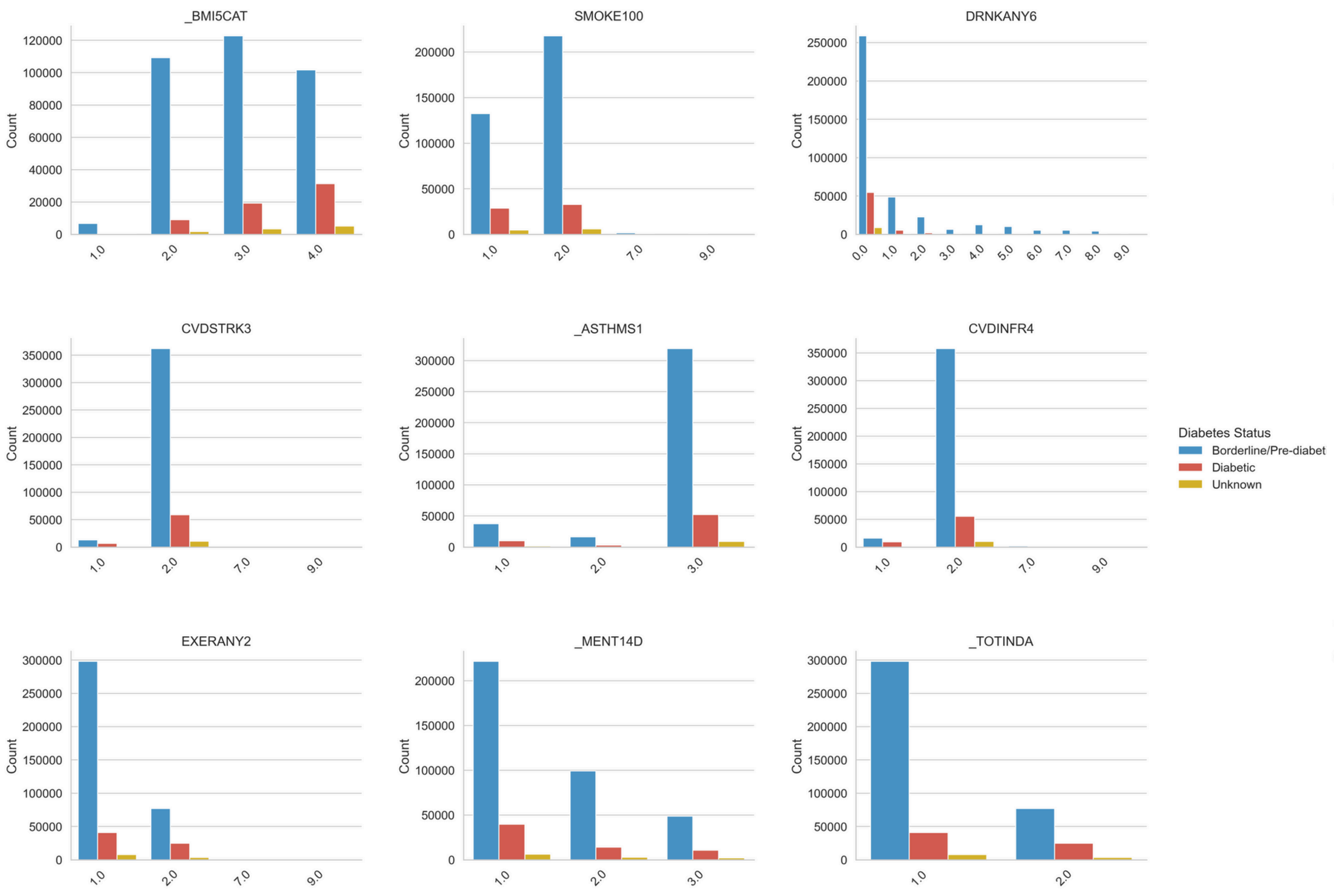


Red / Green Intensity → Strength of correlation in missingness
1.0 → Variables tend to be missing together
0.0 → Independent missingness (no relationship)
-1.0 → Opposite missing patterns

- Before cleaning, several variables show **correlated missingness**.
- After cleaning, missingness patterns shrink or disappear.
- Results in more robust and higher-quality features for modeling.

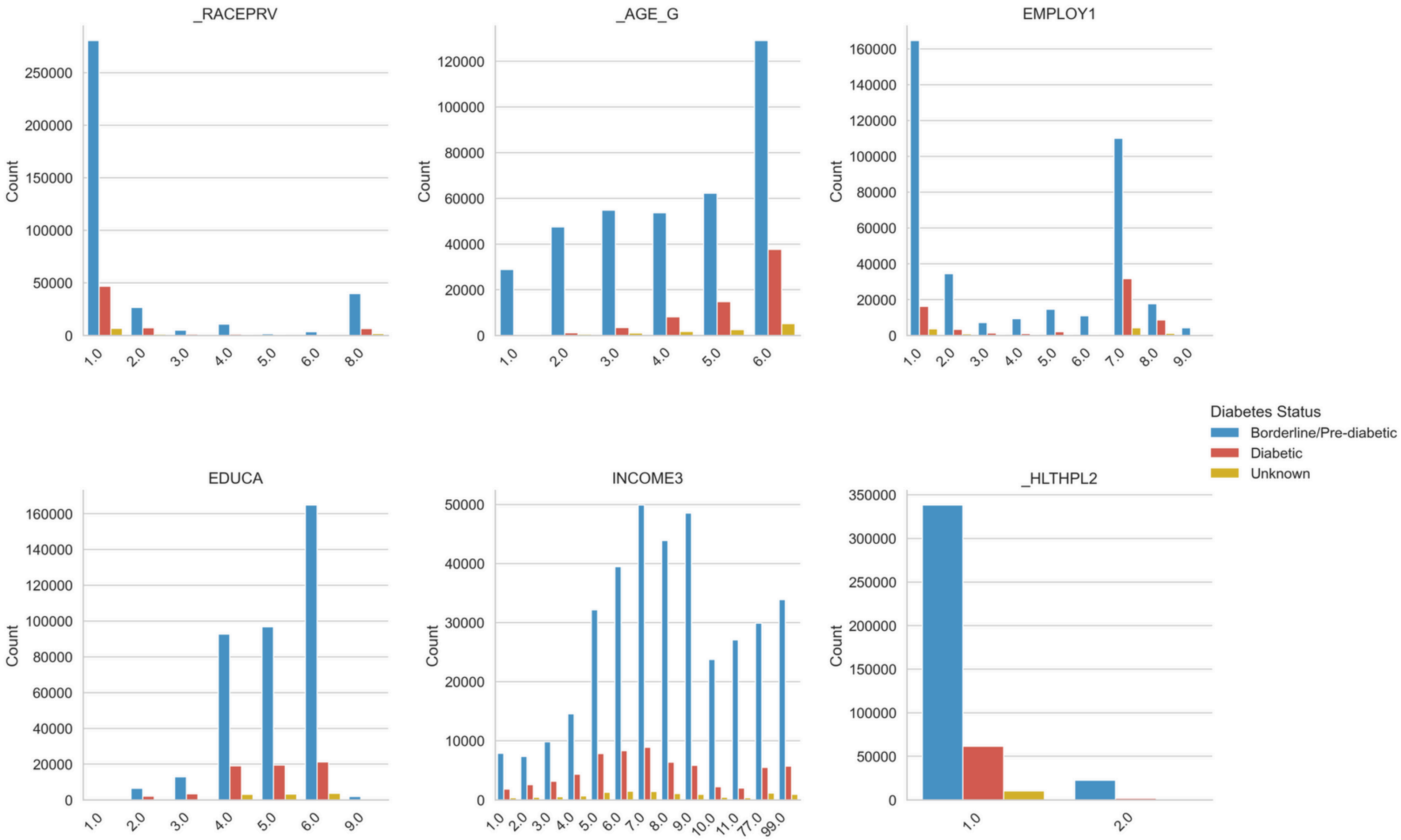
DATA DISTRIBUTION

Distribution of Health & Behavioral Variables by Diabetes Status (BRFSS 2024)



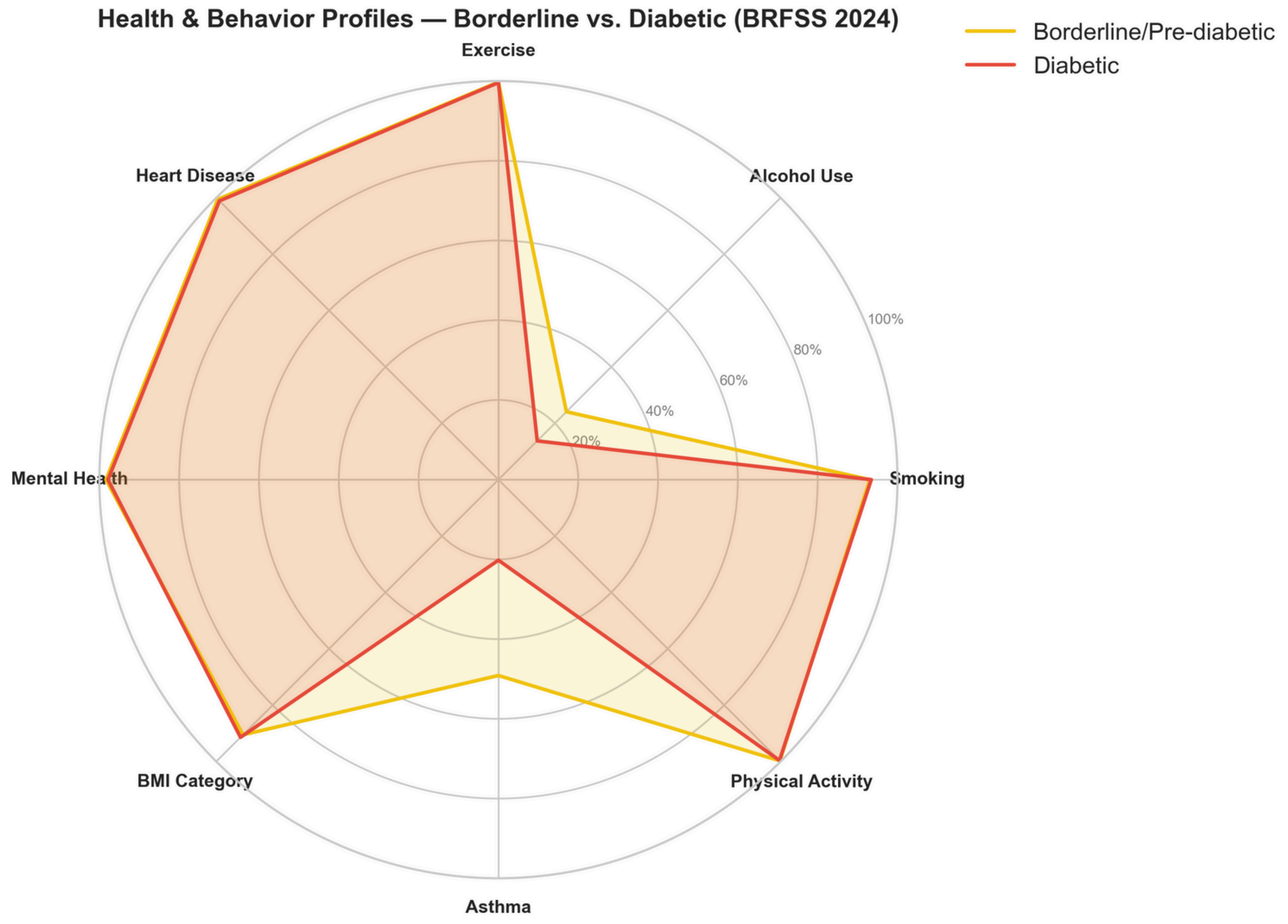
Each facet shows how diabetes prevalence differs across key health and behavior variables.
Variables: BMI Category, Smoking, Alcohol Use, Stroke, Asthma, Heart Disease, Exercise, Mental Health, and Overall Physical Activity.

Distribution of Demographics & Lifestyle Factors by Diabetes Status (BRFSS 2024)



Each facet shows how diabetes prevalence differs across key demographic and lifestyle variables.
Variables: Age, Race, Education, Income, Employment, and Healthcare Access.

DATA DISTRIBUTION



Radar plot comparing proportions of key health and lifestyle behaviors across Borderline/Pre-diabetic and Diabetic groups.
Variables: Smoking, Alcohol, Exercise, Heart Disease, Mental Health, BMI, Asthma, and Physical Activity.

- Compares key health & lifestyle profiles for borderline/pre-diabetic vs diabetic groups.
- Diabetic respondents show a **higher burden of comorbid conditions** (e.g., heart disease, mental health issues, asthma).
- Differences in smoking, BMI, and physical activity highlight behaviors linked to progression from borderline to diabetes.
- Helps identify targets for **intervention beyond blood sugar alone** (lifestyle + overall health).

MODELING

MODELING SETUP & EVALUATION

- 3-class diabetes prediction (No, Pre-, Yes)
- 80/20 train–test split (~360k / 90k)
- ADASYN oversampling + class-weighted loss
- Main loss: weighted cross-entropy (log-loss)
- Metrics: Accuracy, Precision, Recall, F1, ROC-AUC, Log-loss
- Primary metric: macro F1 (imbalanced data)

BASELINE MODELS

- All trained on ADASYN-balanced, class-weighted data
- Naïve Bayes: weakest, strong majority-class bias
- Decision Tree: higher accuracy, overfit, poor on minorities
- kNN: Manhattan > Euclidean, but many minority errors
- Logistic Regression: best macro F1 + log-loss among baselines, interpretable

Model	**Accuracy**	**Precision (Macro)**	**Recall (Macro)**	**F1 Score (Macro)**	**Log Loss**
Naïve Bayes	0.4594	0.4129	0.4754	0.342	8.1898
Decision Tree	0.7772	0.4087	0.4072	0.4057	-
kNN (Euclidean)	0.3921	0.4223	0.4706	0.3142	1.1728
kNN (Manhattan)	0.6171	0.427	0.4999	0.4103	0.8575
Logistic Regression	0.6043	0.4395	0.5303	0.416	0.9061

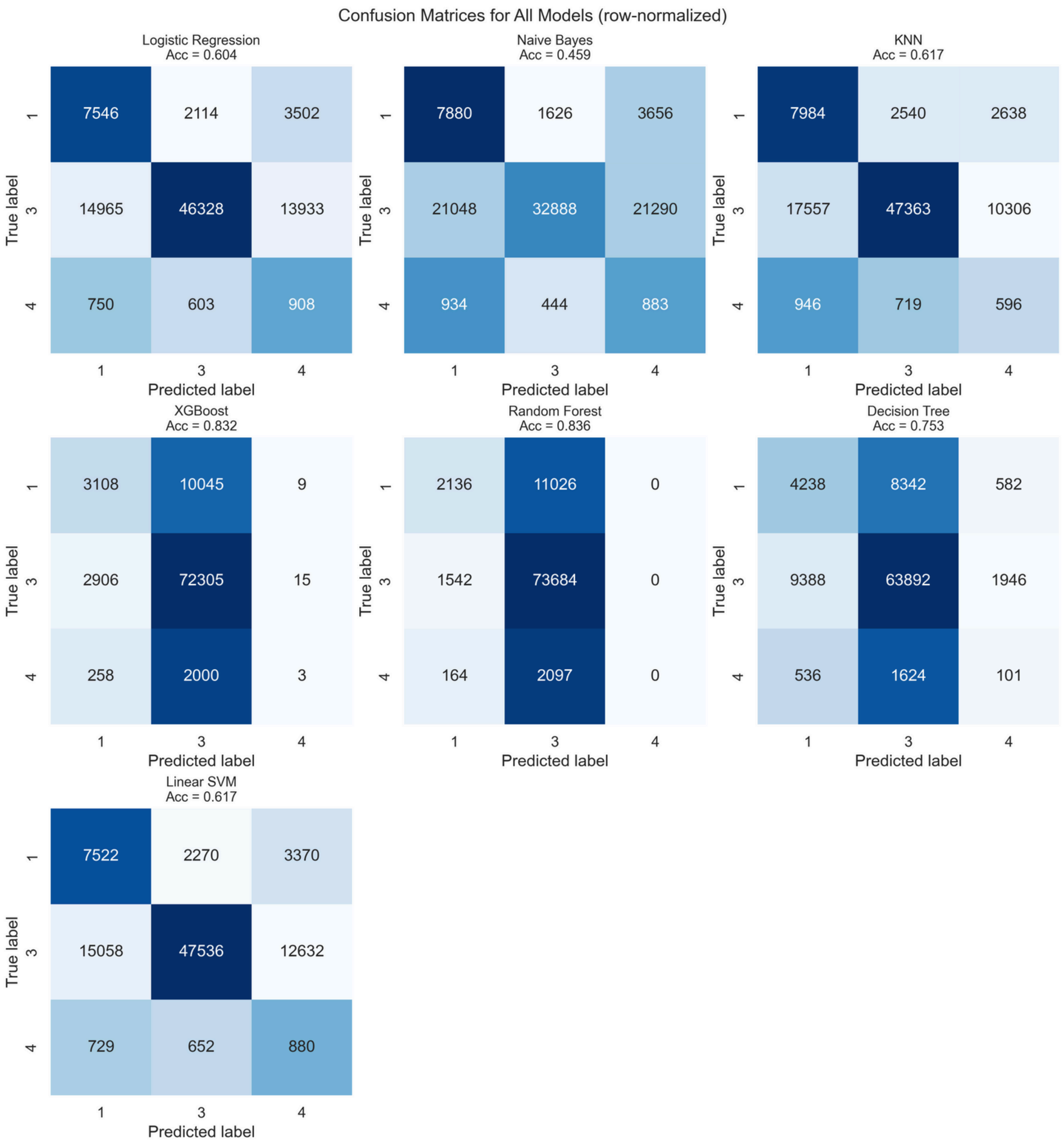
ADVANCED MODELS & TAKEAWAYS

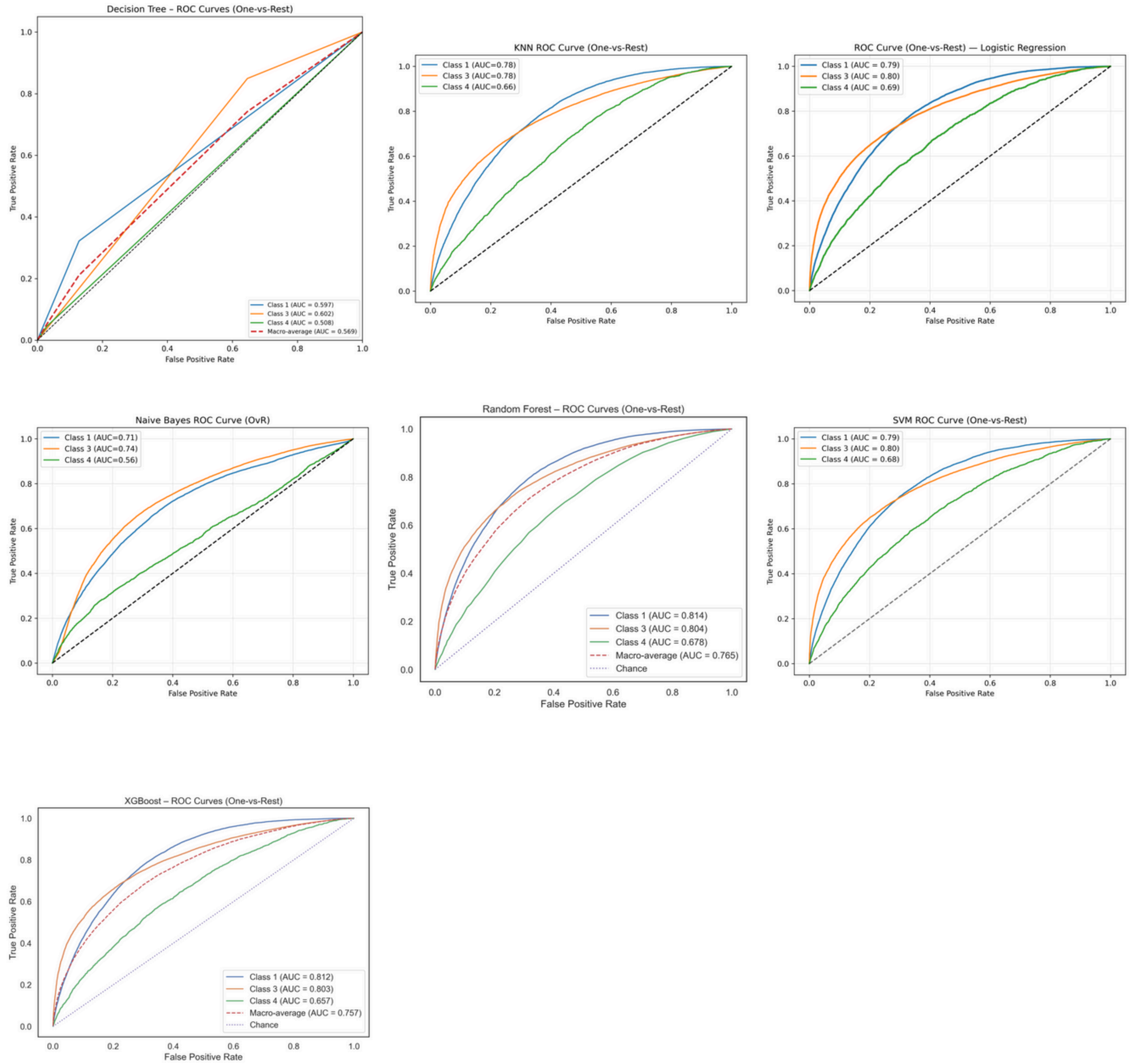
Model	Accuracy	Precision (Macro)	Recall (Macro)	F1 Score (Macro)	Log Loss
Random Forest	0.8364	0.4683	0.3806	0.3869	0.4508
Linear SVM	0.6171	0.439	0.5309	0.4203	-
XGBoost	0.832	0.4879	0.3995	0.4096	0.4458

- Only linear SVM (RBF too expensive on full dataset)
- RF & XGBoost: highest accuracy (~0.83), low log-loss
- XGBoost: best macro precision, strong overall balance
- Linear SVM: highest macro recall & F1; best at minority detection, lower accuracy
- Overall:
    - For minority sensitivity → LogReg / Linear SVM
    - For calibrated risk scores → XGBoost / Random Forest

POST-MODELING VISUALIZATIONS

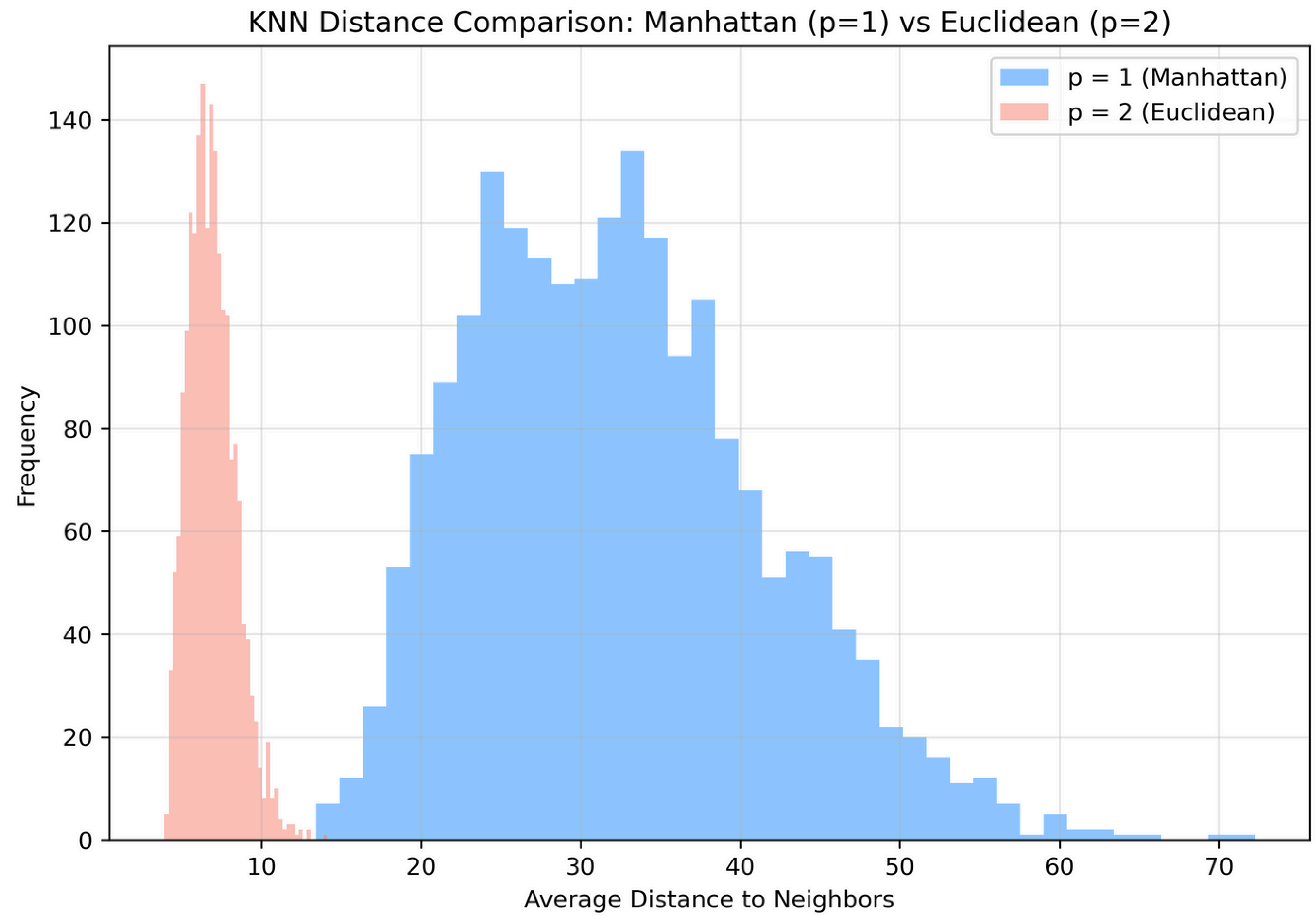
CONFUSION MATRIX & ROC CURVES

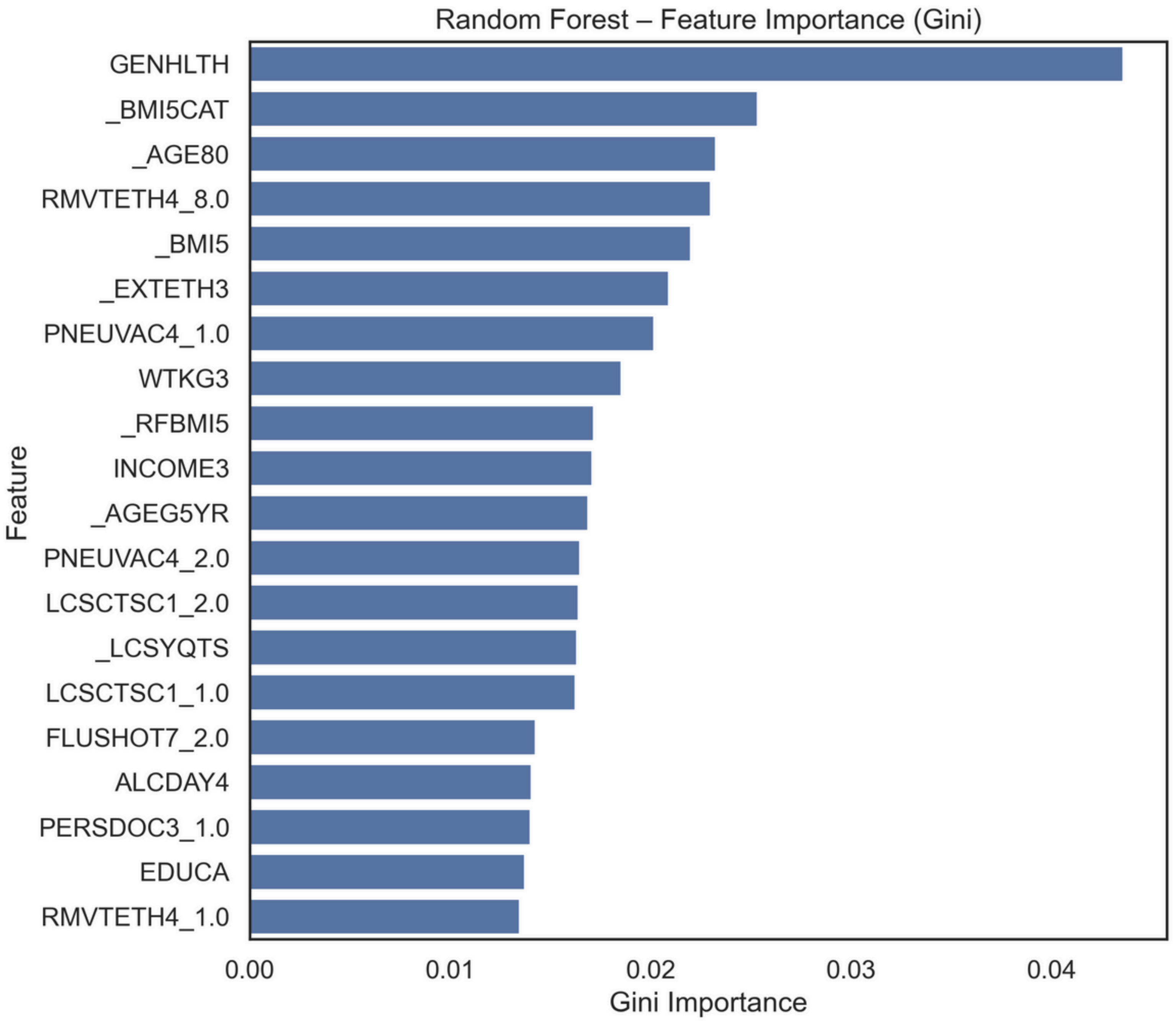




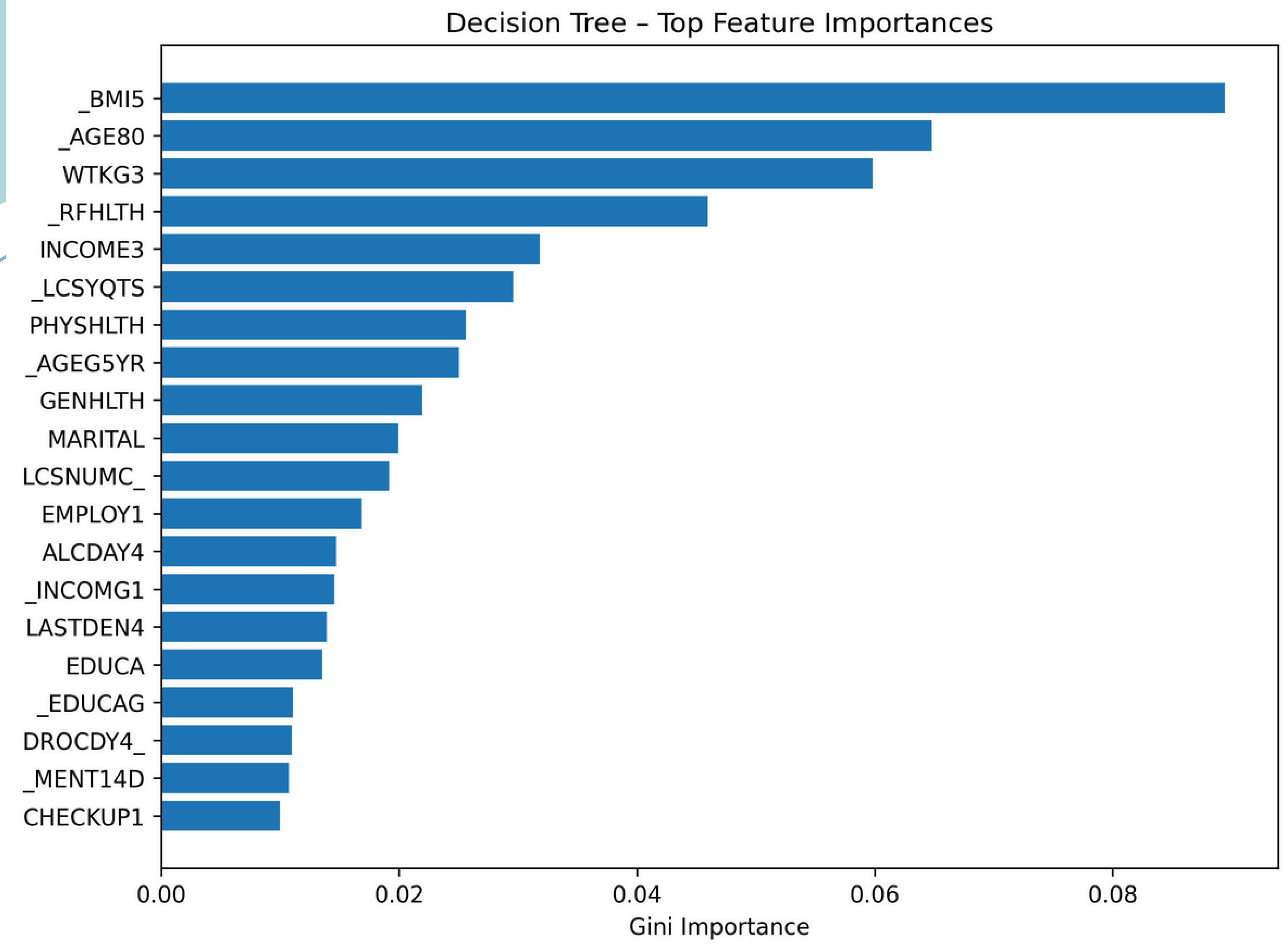
Interactive Confusion Matrix here

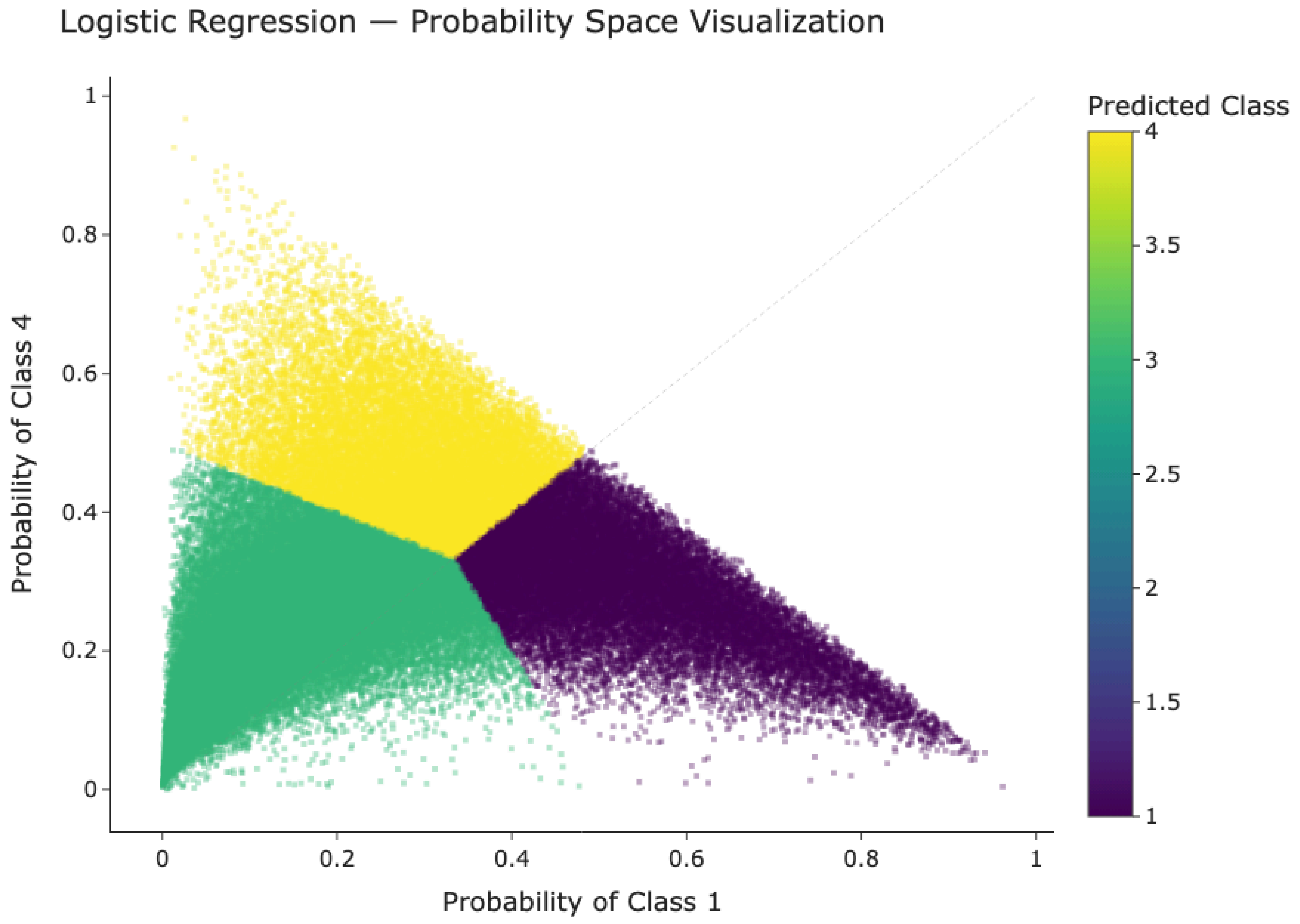
MODEL VISUALIZATIONS





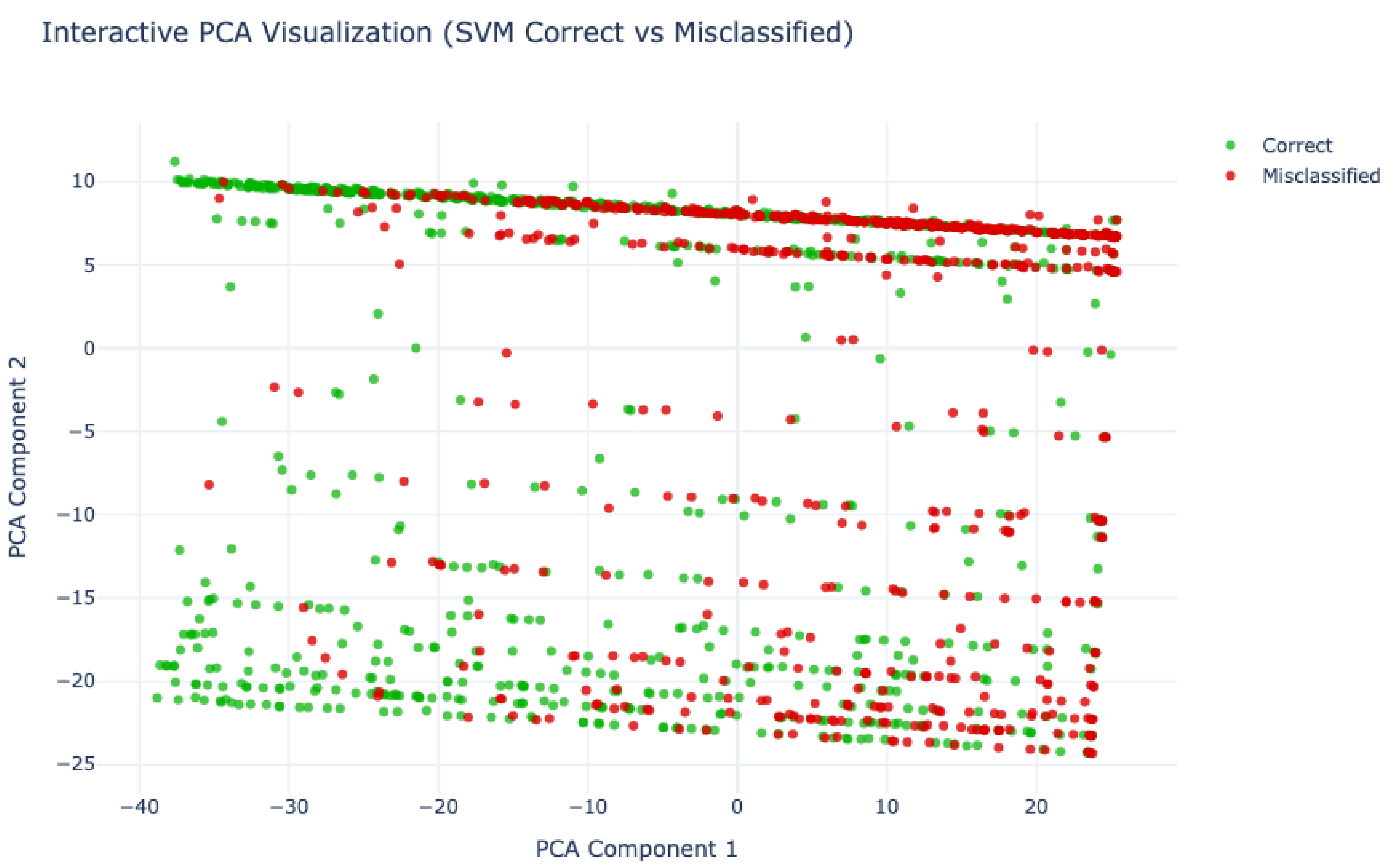
MODEL VISUALIZATIONS

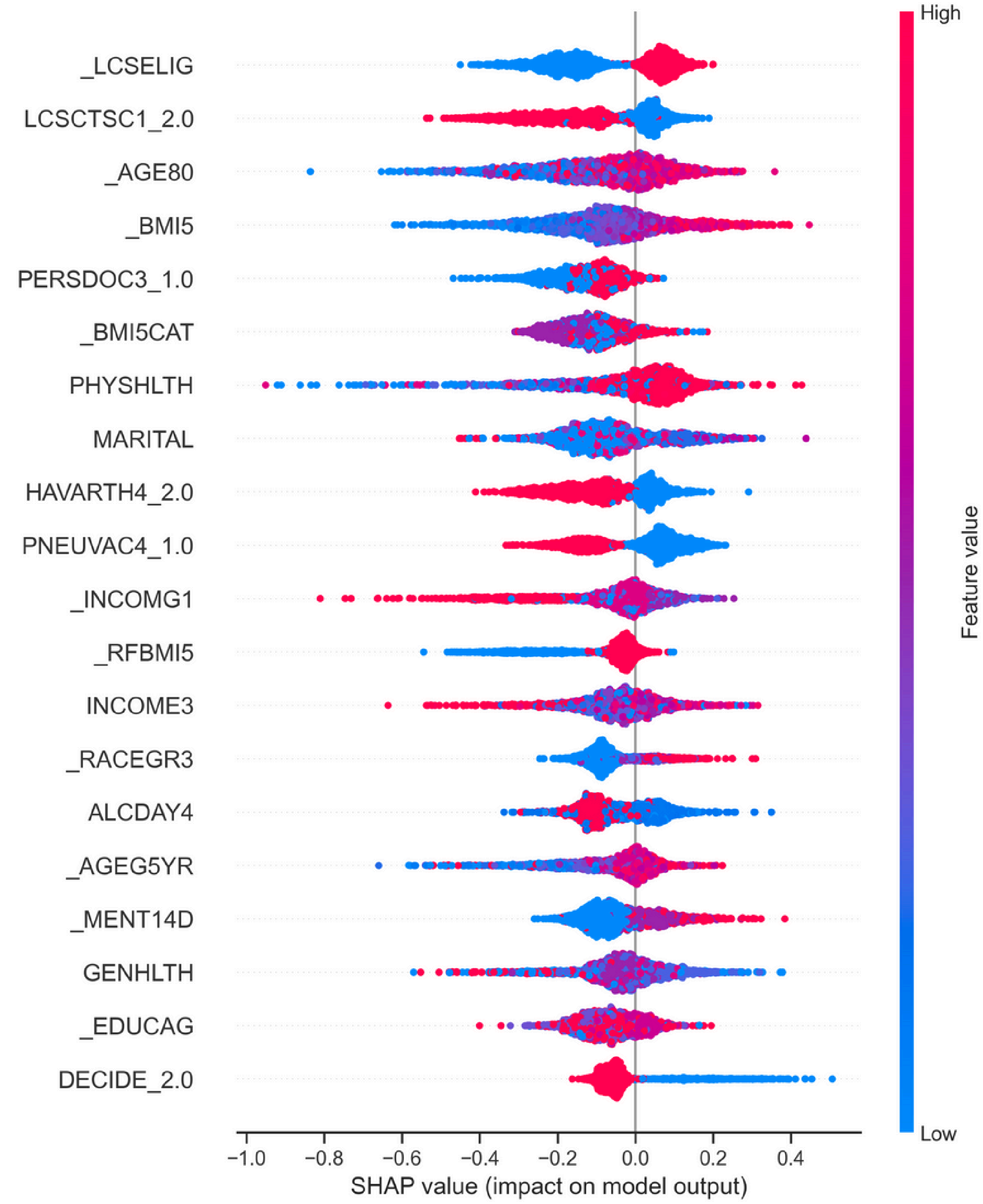




[Interactive LR Probability Visualization]

MODEL VISUALIZATIONS

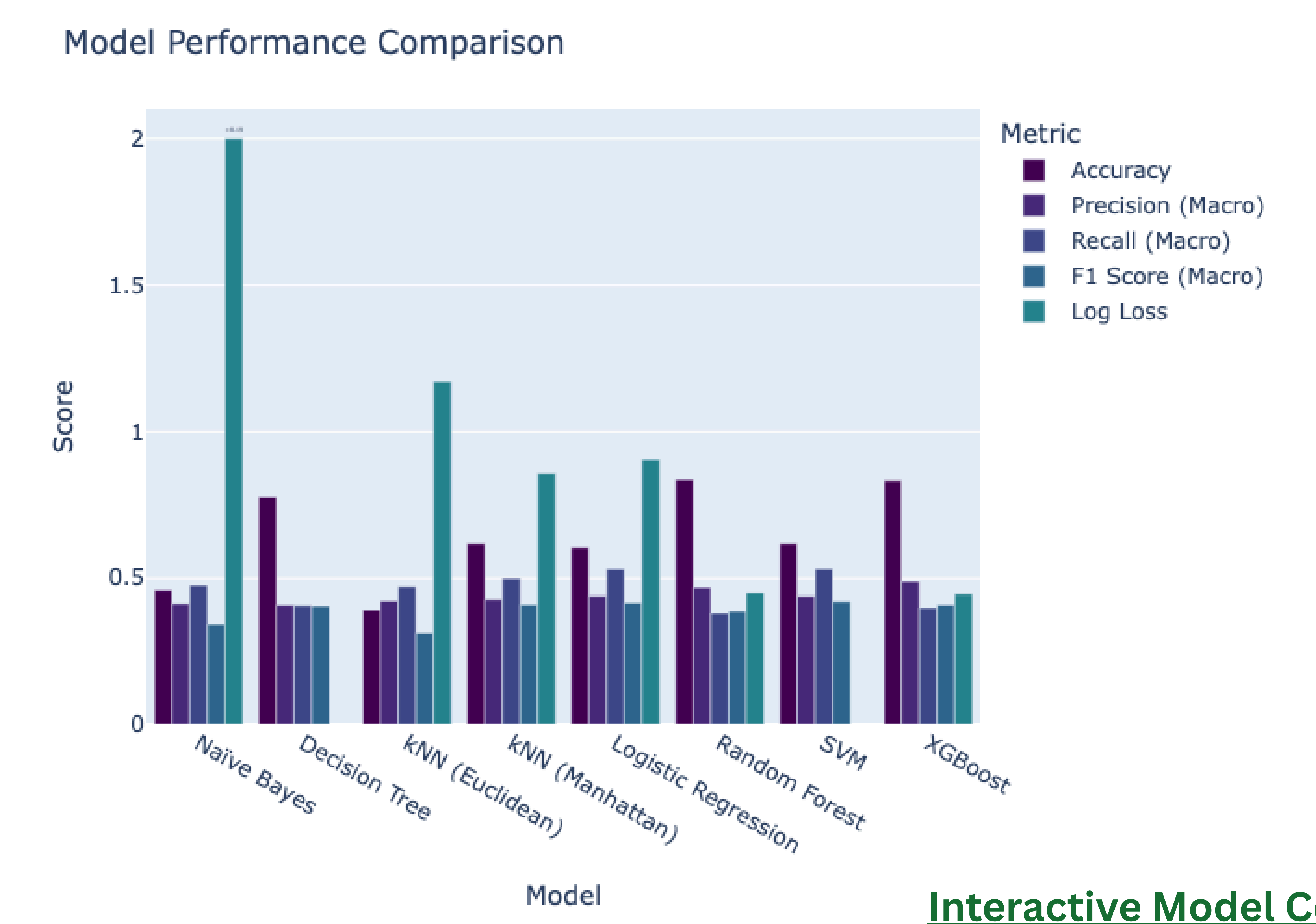




Interactive PCA

Interactive SHAP

MODEL PERFORMANCE COMPARISON



- Random Forest and XGBoost deliver the highest overall performance across most metrics.
- Logistic Regression and SVM achieve strong, balanced results, especially in precision and recall.
- Naïve Bayes performs weaker overall, with higher log loss due to modeling assumptions.
- KNN models show moderate performance, with Manhattan distance slightly outperforming Euclidean.
- Tree-based methods show better robustness on imbalanced classes, reflected in higher F1 and accuracy.

Interactive Model Comparison here

CONCLUSION

END-TO-END PIPELINE & KEY MODELING FINDINGS

- Built a full, reproducible pipeline from raw ASCII BRFSS data → cleaned, engineered dataset ready for large-scale modeling.
- Reduced 300+ raw variables to a focused set of meaningful predictors; raised valid response rate from ~48% → ~89%.
- Exploratory analysis showed diabetes clusters around: older age, higher BMI, lower income/education, limited physical activity, and multiple chronic conditions.
- Severe class imbalance (≈83% non-diabetic) required ADASYN oversampling and class weighting to train stable models.
- Logistic Regression, Manhattan kNN, and Linear SVM provided the strongest macro F1 scores (~0.41–0.42), balancing minority-class detection with interpretability.
- Random Forest and XGBoost delivered the highest accuracy (~0.83–0.84) and best probability calibration, especially for distinguishing diabetic vs. non-diabetic respondents.

PRACTICAL INSIGHTS & FUTURE IMPLICATIONS

- Reinforces public-health knowledge: diabetes risk is shaped by behavioral, metabolic, and socioeconomic factors together, not in isolation.
- Highlights the challenge of reliably identifying pre-diabetic individuals, even with oversampling—important for early intervention programs.
- Demonstrates which features consistently matter: general health, BMI, age, preventive-care indicators, and income/education.
- Shows that ensemble models excel in accuracy and risk ranking, while linear models excel in minority-class sensitivity.
- Provides a reusable ML pipeline for future BRFSS analyses, policy evaluation, and population-level risk modeling.
- Opens doors for next steps: cost-sensitive learning, fairness evaluations across demographic groups, and larger hyperparameter searches.

THANK YOU FOR YOUR ATTENTION