# Diabetic Retinopathy Screening

## BIS568 FINAL PROJECT

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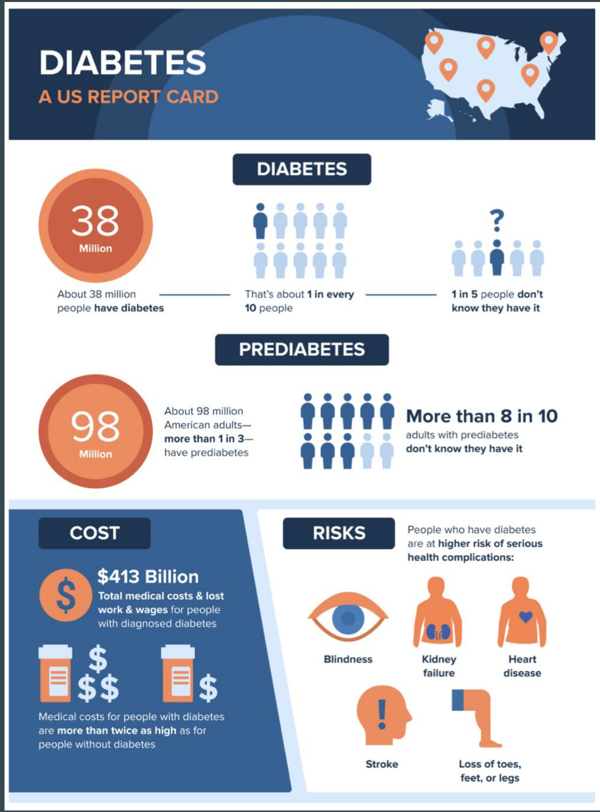
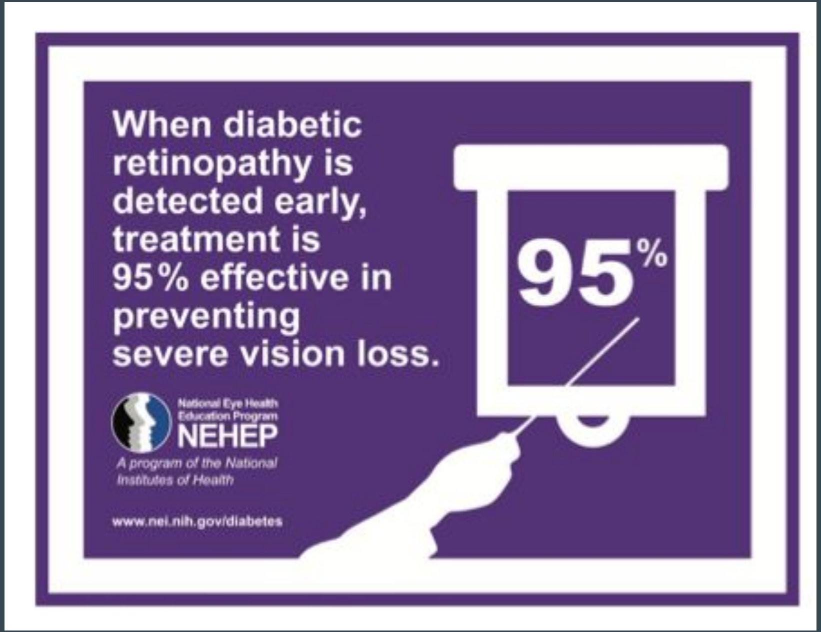
# Problem Specification - Background



# Problem Specification - Goal & Population

- **Goal of the Predictive Model**
  - Predict diabetic retinopathy(DR) in patients with diabetes

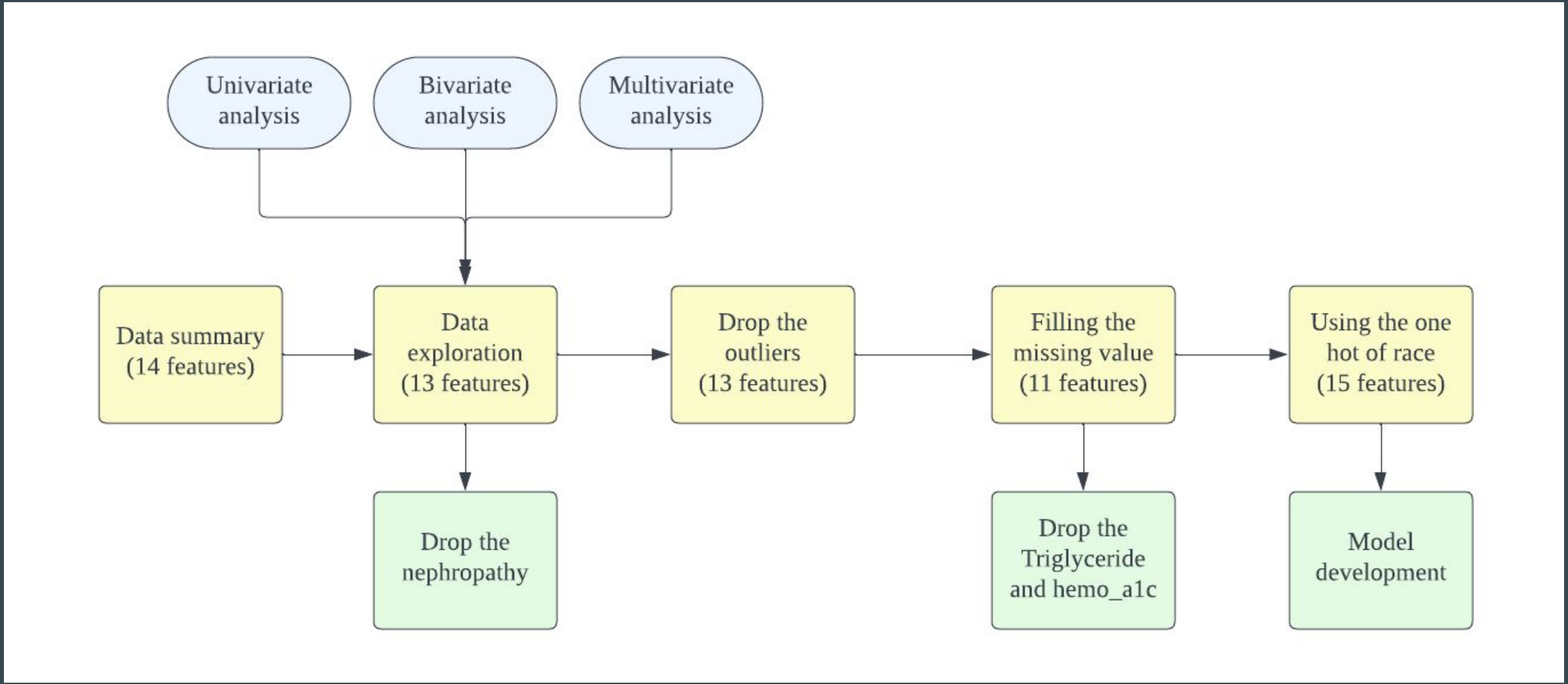
- **Patient Population**
  - Diabetic patients
    - with more than one record in MIMIC database

- **Target Cohort**
  - Diabetic patients with diabetic retinopathy(DR): 133
- **Control Cohort**
  - Diabetic patients without any complications: 1160

# Data Preparation

| | | |
|---|---|---|
| Demography | gender | Patient gender |
| | race | Patient race |
| | age | Patient age |
| Conditions | duration days | Diabetes/Diabetic retinopathy duration |
| | neuropathy | Neuropathy |
| | stroke | Stroke |
| | Insulin dependence | Insulin dependent diabetes mellitus |
| | nephropathy | Nephropathy |
| Clinical measurement | triglyceride | Triglycerides |
| | hemo | Hemoglobin |
| | hemo_a1c | Hemoglobin A1C |
| | bun | Blood urea nitrogen |
| | sbp | Systolic blood pressure |
| | dpb | Diastolic blood pressure |
| Predictor | predictor | Diabetes/Diabetic retinopathy |

# Data Preparation and Preprocessing



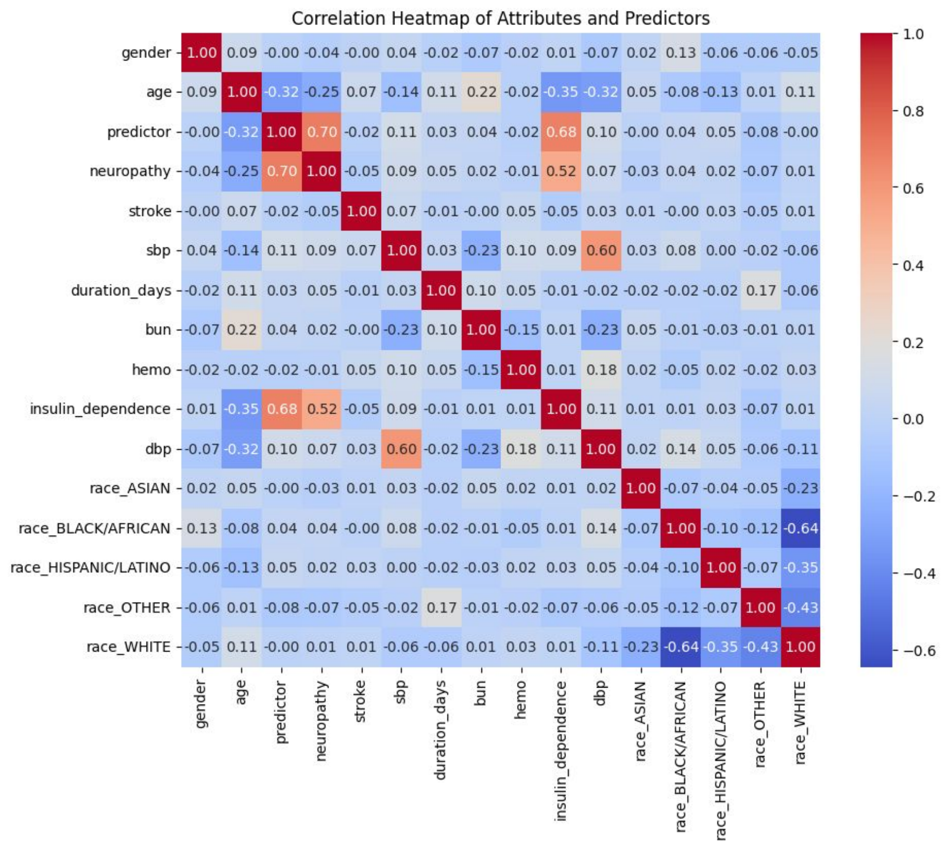
# Bias Assessment

- The data only reflects part of the patient in this area.
  - Our Prevalence based on MIMC dataset = 1.47%
  - 2021 Suffolk County Adjusted Prevalence of Any Diabetic Retinopathy (DR) or Vision Threatening DR from CDC = 4.04%
- Oversampling
  - Original cohort: 133 DR vs 1160 Non-DR
  - New cohort: 852 DR vs 1160 Non-DR

```
from imblearn.over_sampling import SMOTE
# Apply SMOTE to oversample the minority class (positive samples)
smote = SMOTE(sampling_strategy='auto')  # 'auto' adjusts to balance classes
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

- After implementing our model, we will continuously monitor of our ML model's performance.

# Correlation Matrix




- Predictor is strongly correlated with "neuropathy" (0.70) and "insulin_dependence" (0.68), suggesting that it is closely related to whether or not a person is having a insulin-dependent diabetes.
- Neuropathy is NOT a results from DR.

# Model Development

**Cleaned Data**

- 15 attributes
- 1 predictor
- 1293 patients

**Train-Test Splitting**

- 70 % Training
- 30% Testing
- Stratified Sampling

Resampling By SMOTE
Balance in neg- and pos+

**Inputted Data**

- From **1160** neg- and **133** pos+
- To **1160** neg- and **852** pos+

**Model Training**

- Logistic Regression
- Random Forest
- XGBoost

Parameter Tuning
by Grid Search

**Model Evaluation**

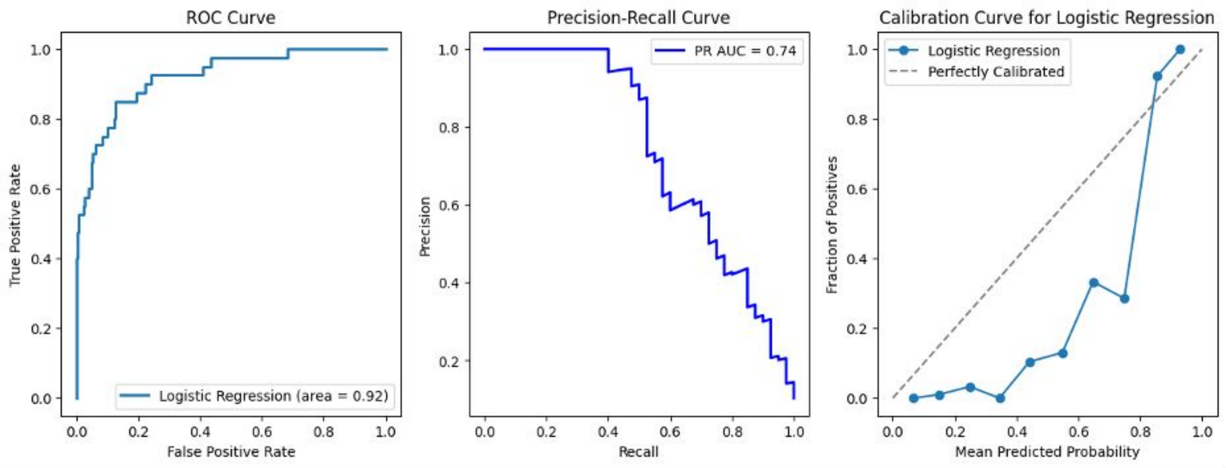
- ROC-AUC
- PR-AUC
- Confusion Matrix

**Interpretability Analysis**

- SHAP plots

# Model Performance and Evaluation

- **Logistic Regression**
  - ROC-AUC: 0.92
  - PR-AUC: 0.74
- Random Forest
  - ROC-AUC: 0.98
  - PR-AUC: 0.88
- XGBoost
  - ROC-AUC: 0.98
  - PR-AUC: 0.87




- Training and Cross-Validation
  - Best Model: **Random Forest**
  - Best Cross-Validation Accuracy: 0.961
  - Test Accuracy: 0.954

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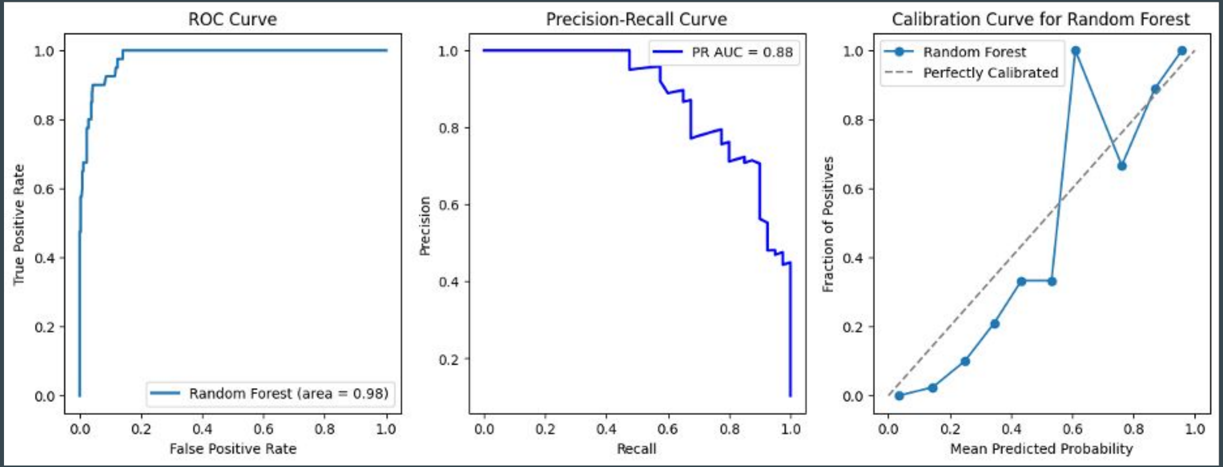


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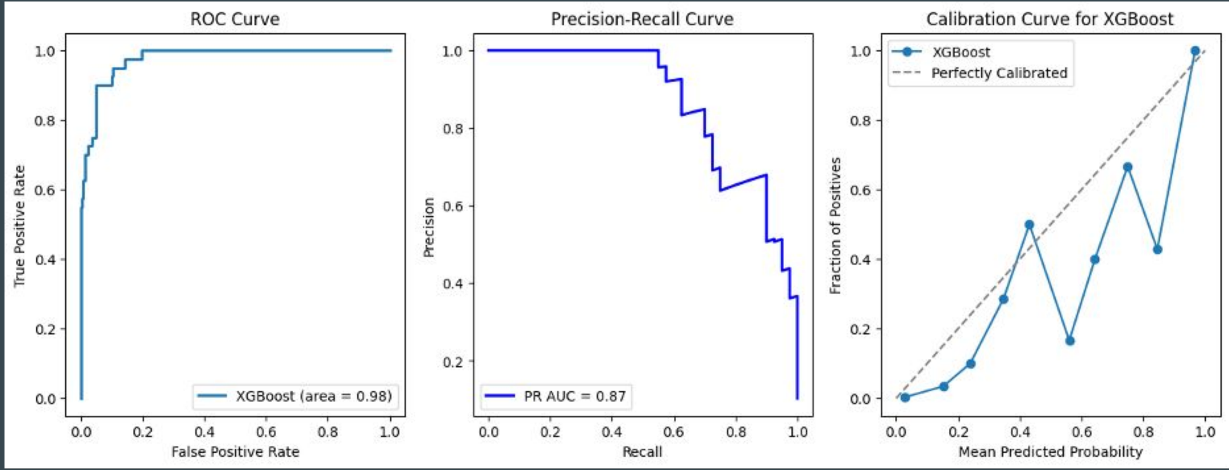


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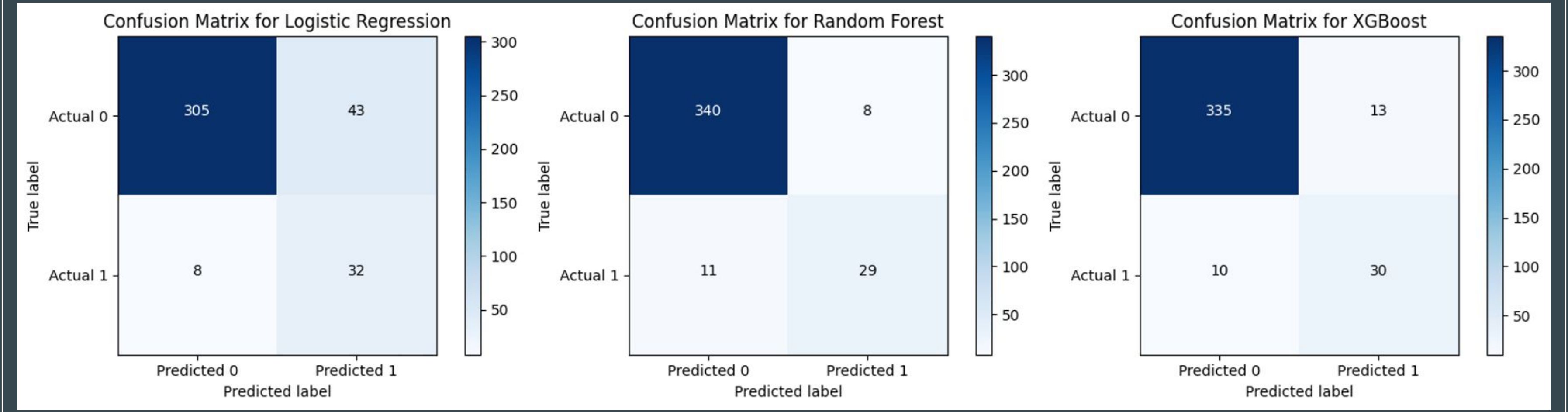
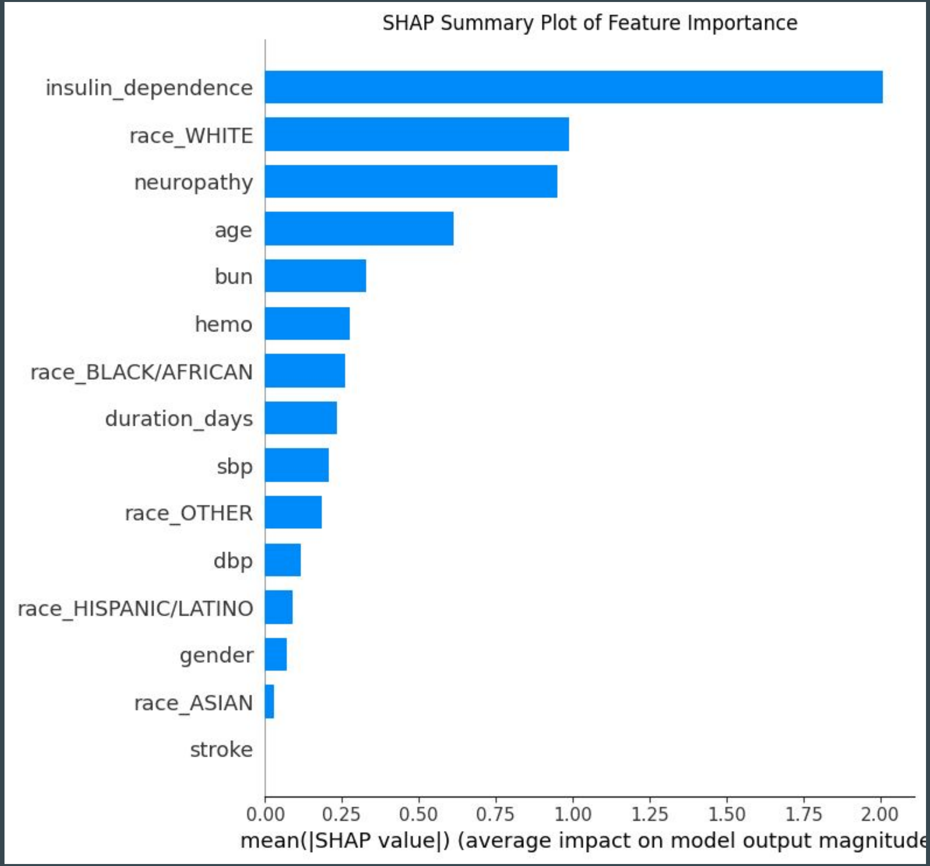
# Model Performance and Evaluation

- **Logistic Regression** outperforms in tolerating False Positive (FP)
- **XGBoost** outperforms Random Forest in minimizing False Negative (FN)



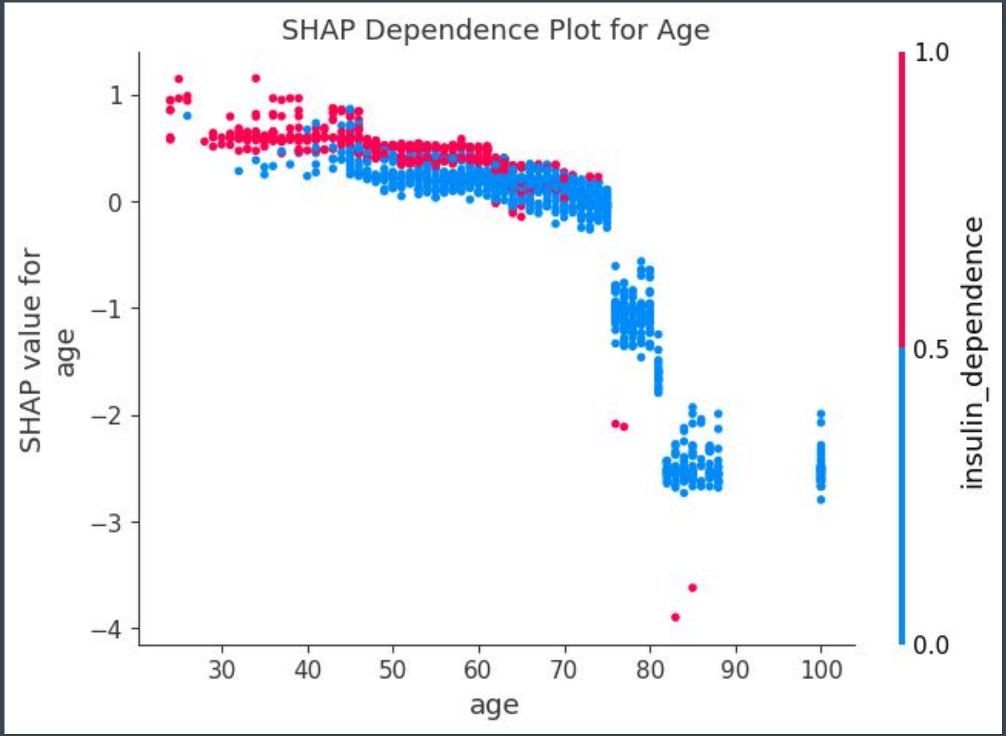
# Interpretability

- Insulin_dependenc show the most predictive power, followed by race_WHITE, and so on



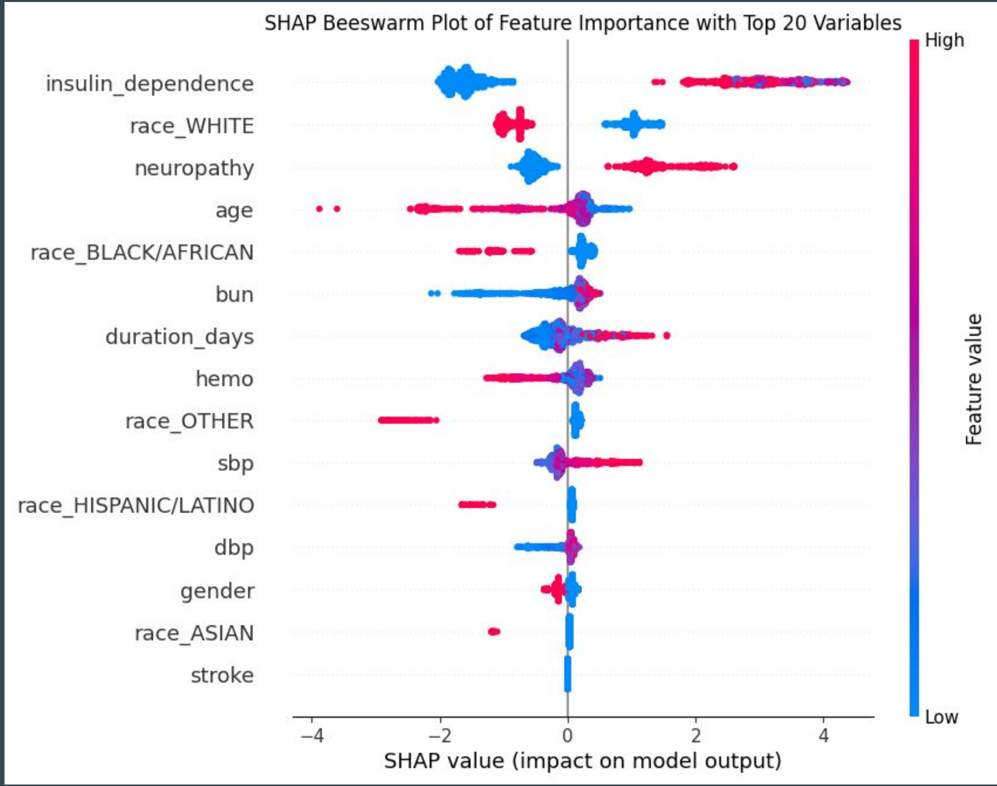
# Interpretability

- It is observed a downward trend in the SHAP dependence plot for the feature 'age,' indicating that smaller values of age contribute to higher SHAP values



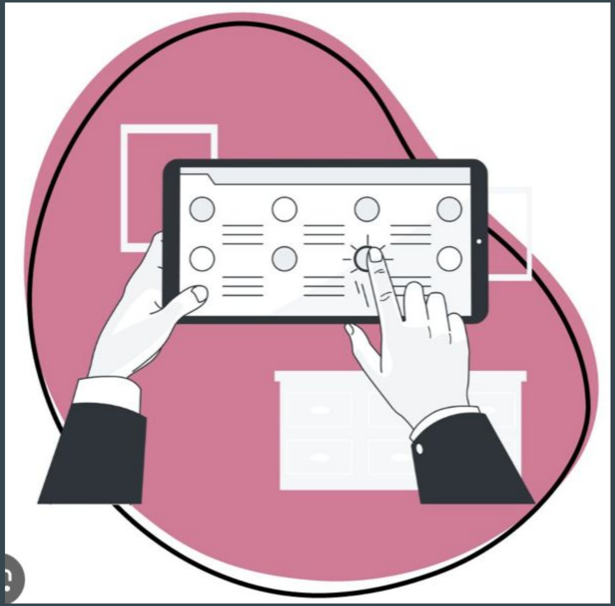
# Interpretability

- insulin_dependence not only has a significant impact on predictions (as indicated by the spread of dots along the x-axis) but also that higher values of insulin_dependence (red dots) are generally associated with an increase in the model's prediction value.



# Looking Forward

- Implementation Plan & Dissemination Strategy
    - User Interface
        - User-friendly Interface
    - Integration with Healthcare Systems
        - Electronic Health Records
        - Clinical Decision Support
        - Yale Health System



# References

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# Acknowledgement


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- Luning Yang: Data preparation, Model development and performance evaluation
- Mengmeng Du: Data preparation, Data preprocessing
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