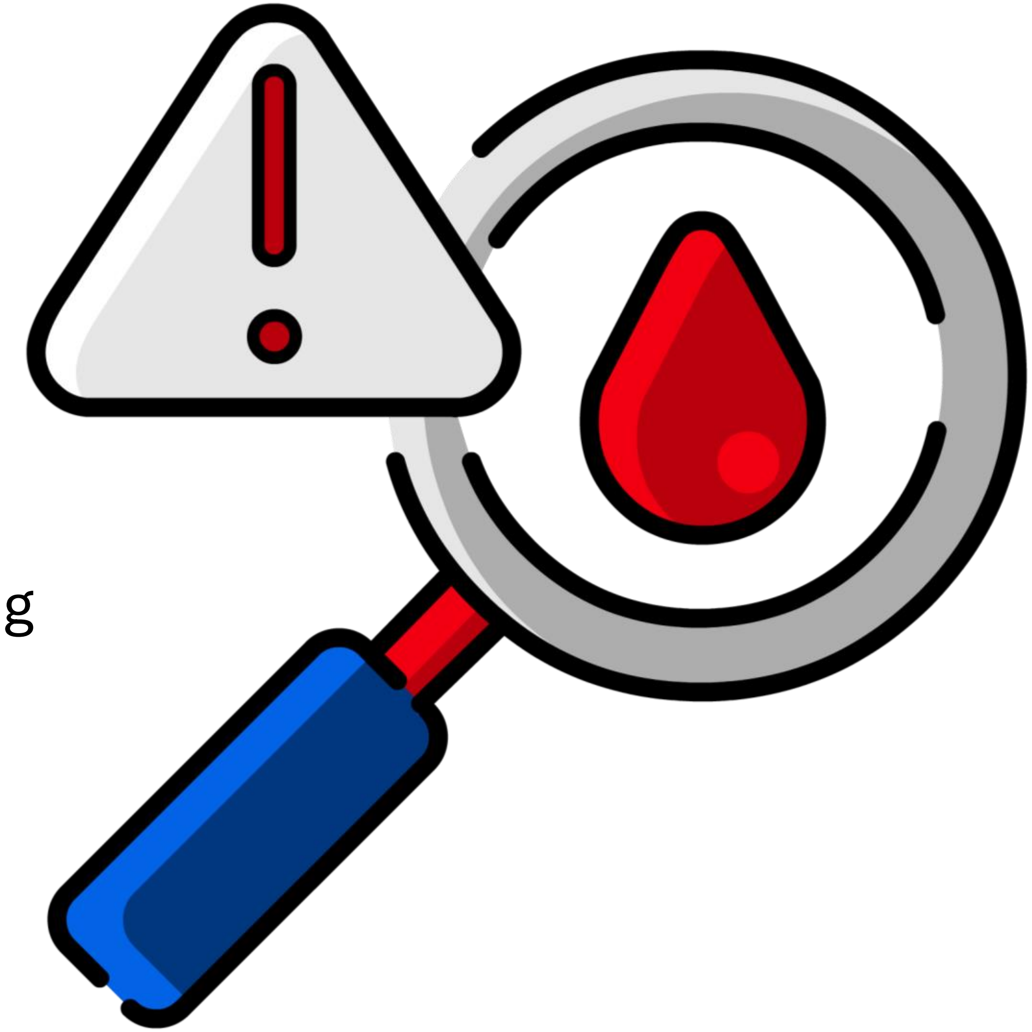
Decoding Diabetes



Predictive Models and Insights Using Machine Learning

Professor: 안용길

Presents

Braian Plaku (브라이언 플라쿠)

Introduction

Diabetes is one of the most prevalent **chronic diseases**, affecting millions globally. This project aims to **predict** the likelihood of an individual having diabetes using the Behavioral Risk Factor Surveillance System **(BRFSS)** dataset from Kaggle.

<u>The focus</u> will be on understanding which **factors contribute the most to diabetes risk** and developing machine learning models to predict diabetes **based on survey responses**.

Dependent Variable Y: Diabetes_012

- (0) no diabetes or only during pregnancy
- (1) prediabetes
- (2) diabetes

Dependent Variable X: 21 variables in the dataset

BMI, GenHlth
Age, Education
Income, Education
PhysHlth, MentHlth

HighBP, HighChol
Smoker, Veggies
Fruits, PhysActivity
Sex, DiffWalk

HeartDiseaseorAttack
NoDocbcCost
Stroke
AnyHealthcare, CholCheck

Digging deeper into the Data

Source:

CDC (Centers for Disease Control and Prevention) Behavioral Risk Factor Surveillance System, [LINK]

ANNUAL, uniform, state-specific data on preventive health practices and risk behaviors

Year 2011, extracted on Kaggle from CDC itself [LINK]

Original Data, in 'csv' format, 253,680 survey responses

Alex Teboul (Data Scientist), based on Building Risk Prediction Models for Type 2 Diabetes Using Machine Learning Techniques on Kaggle [LINK]

The data was **cleaned** into a useable format for machine learning alogrithms, reduction was made from **330 features** (dependent variables) onto **21 variables**

Link to his Notebook can be found here: [LINK]

Alex Teboul

Shaping the Data: Preprocessing & Preparation

Target Variable **Binarization**

Diabetes_012

- (0) no diabetes or only during pregnancy
- (1) prediabetes
- (2) diabetes

→ (0) no diabetes or only during pregnancy

→ (1) prediabetes or diabetes

allows the models to **focus** on a simpler task!

Perform **univariate logistic regression** for each feature

after **standardizing** the data

Feature selection based on their **p-values**

Shaping the Data: Preprocessing & Preparation

Feature selection based on their **p-values**

	coefficient	p-value	odds_ratio
HighBP	0.780275	<0.001	2.182072
Age	0.579303	<0.001	1.784794
DiffWalk	0.552433	<0.001	1.737476
PhysHlth	0.444809	<0.001	1.560193
GenHlth	0.914087	<0.001	2.494498

Cross-Validation

Using **5 splits**

Data Undersampling

Using the `RandomUnderSampler` from **imblearn-undersampling** Python Library

Key Traits of the three chosen Models

three models implemented

Random Forest

- Builds multiple **decision trees** and combines their predictions
- Provides **feature importance**, which tells us which factors are most important in predicting diabetes
- Better suited for capturing complex **patterns** and **interactions** between features

Logistic Regression

- Assigns **weights (coefficients)** to each feature, making it easy to interpret how each feature affects diabetes risk
- **Simple and more interpretable**, but may not capture complex patterns as well as Random Forest

Gradient Boosting

- Builds an ensemble of **weak learners**, each focusing on correcting errors made by previous models.
- Combines predictions in a sequential manner, leading to **higher accuracy over time**.
- More complex than Logistic Regression.

Key Traits of the three chosen Models

three models implemented

Random Forest

- Splitted Training and Testing Sets
- Built Random Forest Model
  - estimating **100** trees
- Fit & trained the model
- Predicted the data
- Evaluated the model
- Analyzed Feature Importance
- Plotted the results visually

Logistic Regression

- Splitted Training and Testing Sets
- Built Logic Regression Model
  - with **1000** iterations
- Fit & trained the model
- Predicted the data
- Evaluated the model
- Plotted the results visually

Gradient Boosting

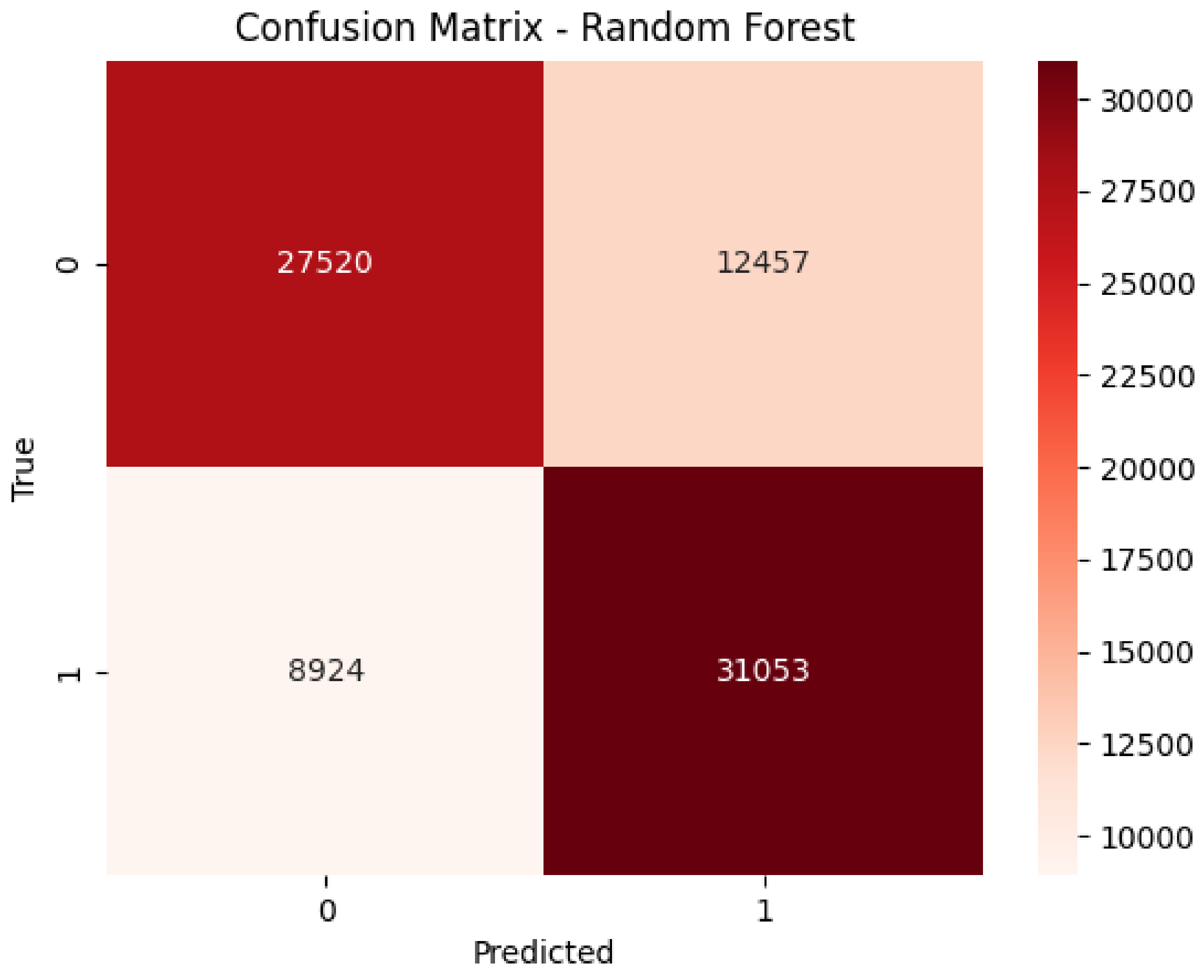
- Splitted Training and Testing Sets
- Built Gradient Boosting Model
  - using 100 estimators and a learning rate of 0.1
- Fit & trained the model
- Predicted the data
- Evaluated the model
- Analyzed Feature Importance
- Plotted the results visually

Outcome Review

Random Forest: Confusion Matrix

- Breakdown of true and false positives and negatives

- **Correctly predicted**
  - 27,520 negatives
  - 31,053 positives
- **Incorrectly flagged**
  - 8,924 negatives
  - 12,457 positives

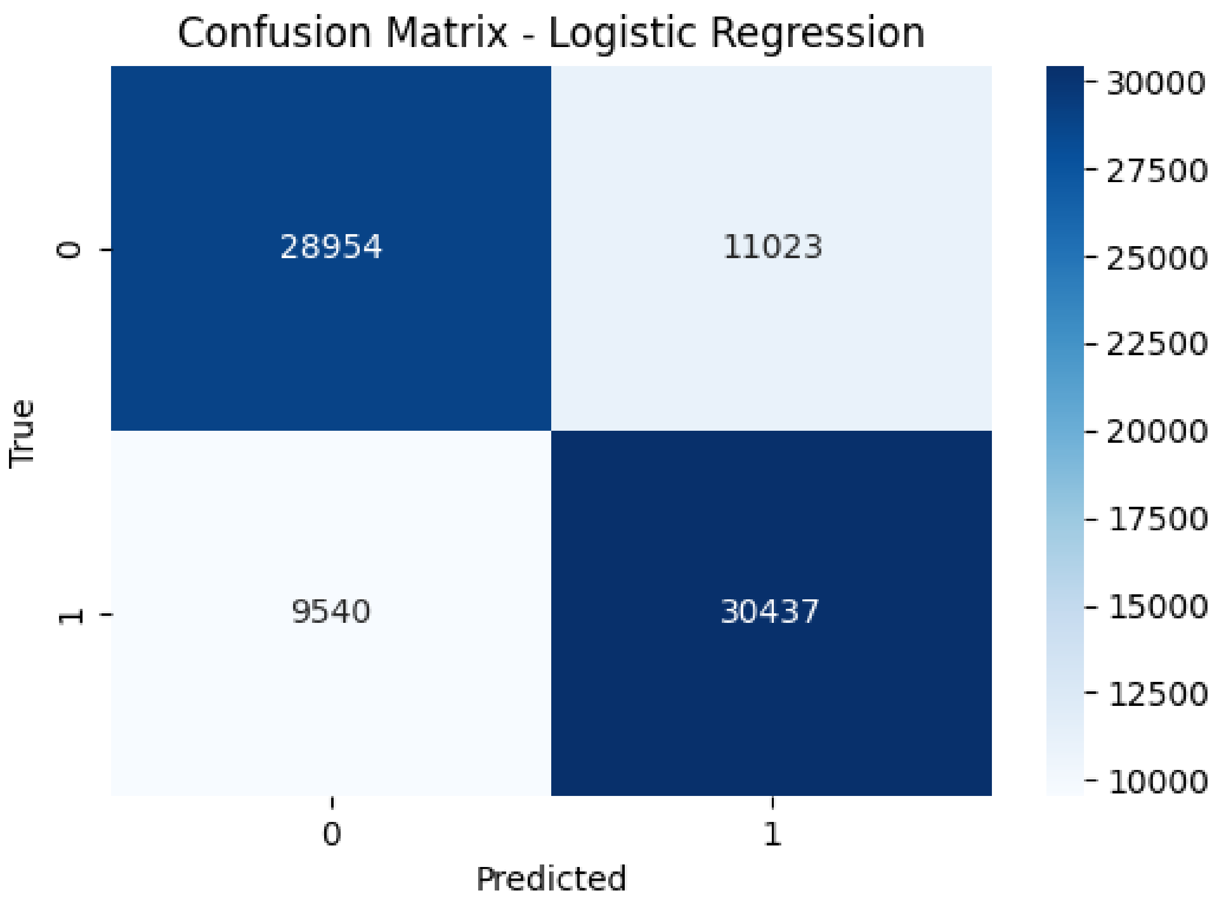


Outcome Review

Logistic Regression: Confusion Matrix

- Breakdown of true and false positives and negatives

- **Correctly predicted**
  - 28,954 negatives
  - 30,437 positives
- **Incorrectly flagged**
  - 9,540 negatives
  - 11,023 positives

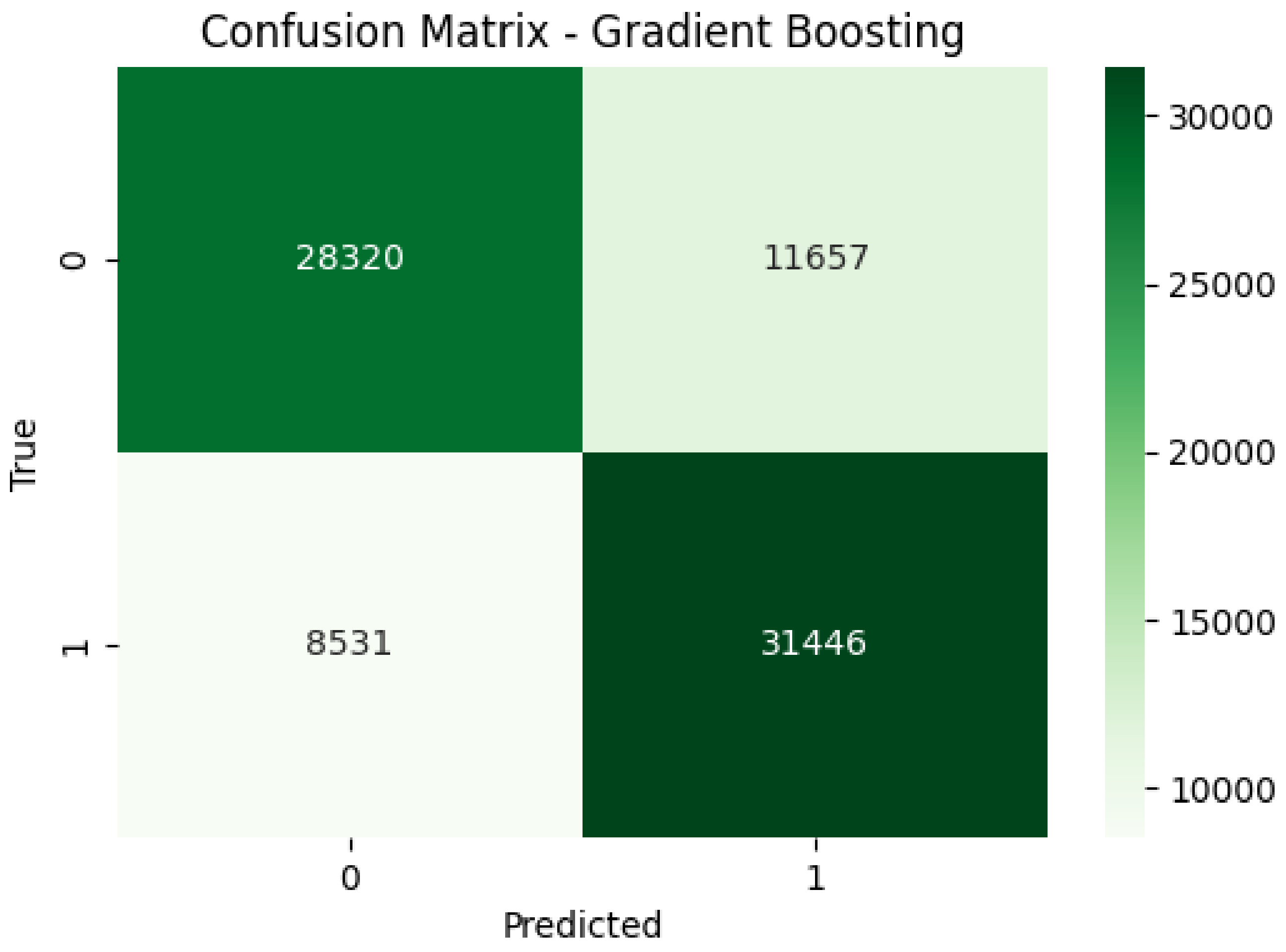


Outcome Review

Gradient Boosting: Confusion Matrix

- Breakdown of true and false positives and negatives

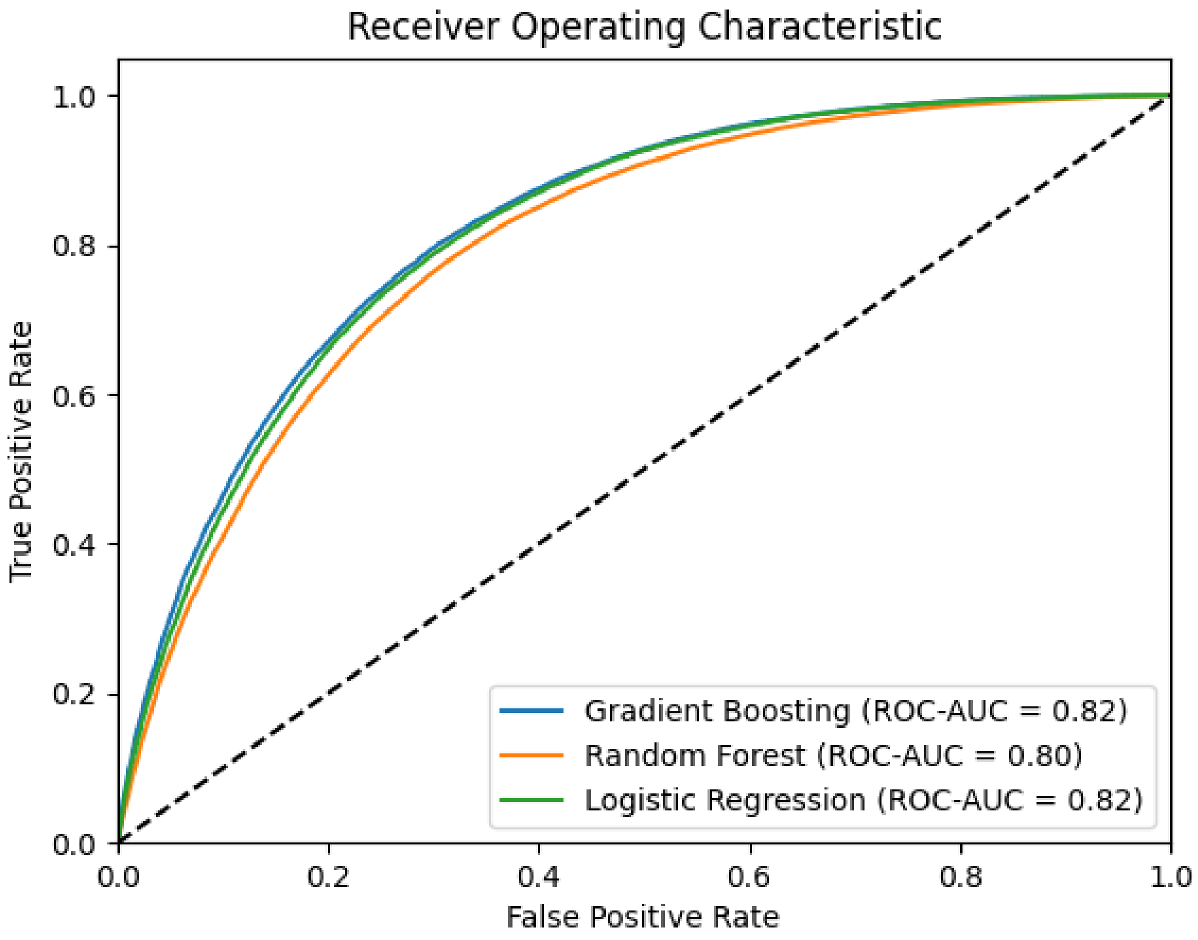
- **Correctly predicted**
  - 28,320 negatives
  - 31,446 positives
- **Incorrectly flagged**
  - 8,531 negatives
  - 11,657 positives



Outcome Review

Conclusion: Model Evaluation

- **Random Forest:**
  - **Lower accuracy (73.2%)**
  - **Good feature importance**
  - **Low precision (71.3%)**
- **Logistic Regression:**
  - **Higher accuracy (74.2%)**
  - **More interpretable**
  - **Slightly better precision (73.4%)**
- **Gradient Boosting:**
  - **Best accuracy (74.7%)**
  - **Best ROC-AUC (82.4%)**
  - **Good precision (73.0%)**



	Acccuracy	Precision	ROC-AUC
Random Forest	73,2%	71,3%	80,2%
Logistic Regression	74,2%	73,4%	81,8%
Gradient Boosting	74,7%	73,0%	82,4%

Literature

From the Web

Dataset:

Centers for Disease Control and Prevention:

- https://www.cdc.gov/brfss/annual_data/annual_data.htm

Kaggle Datasets:

- https://www.kaggle.com/datasets/cdc/behavioral-risk-factor-surveillance-system
- https://www.kaggle.com/datasets/alexteboul/diabetes-health-indicators-dataset

Material:

Statistical Learning with Python, Stanford Online

- https://www.youtube.com/playlist?list=PLoROMvodv4rPP6braWoRt5UCXYZ71GZIQ

Python Libraries:

- https://scikit-learn.org/
- https://imbalanced-learn.org/stable/under_sampling.html

More on Random Forest:

- https://www.geeksforgeeks.org/random-forest-algorithm-in-machine-learning/

Literature

Thank you

for your attention!