

# Predicting Diabetes Risk from Smoking Dataset

A Machine Learning Approach

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Course: SCS\_3253

Source: Risk Factors for Type 2 Diabetes: A Guide

# Project Goal & Data



### Goal

Predict whether an individual is at risk for diabetes given dataset of health features.



### Dataset

15k initial rows. 23 features used.

could not use test.csv dataset from kaggle



### Target Variable

0: No Risk (FBS < 100 mg/dL). 1: At Risk (100-125 mg/dL).

2: Prediabetic (FBS >125 mg/dL).



Source: <u>Good news for those with type 2 diabetes: Healthy lifestyle matters (Harvard Health)</u>

# Data Exploration

#### Feature variables:

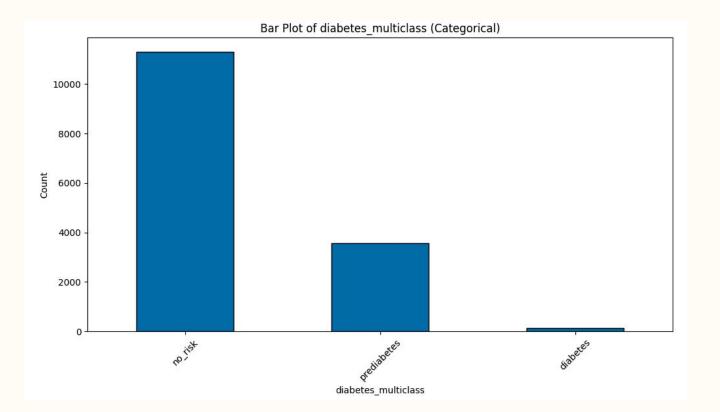
- 4 categorical features
- 18 numerical features

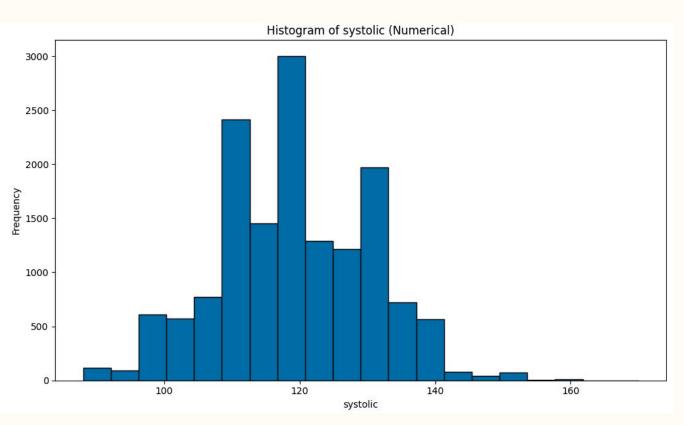
#### Labels:

diabetes\_multiclass

#### Observations:

- No missing value
- Some numerical features are skewly distributed. No apparent outliers found (Ex. Systolic blood pressure)





Age (5-year gap)

Height (cm)

Weight (kg)

Waist circumference (cm)

Eyesight (left)

Eyesight (right)

Hearing (left)

Hearing (right)

Systolic blood pressure

Diastolic blood pressure

(relaxation)

Total Cholesterol

Triglyceride

HDL cholesterol

LDL cholesterol

Hemoglobin

Urine protein

Serum creatinine

AST (glutamic oxaloacetic transaminase)

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GTP (y-GTP)

Dental caries

Smoking status



**6** Made with Gamma

# Challenges



- Significant class imbalance. 'Prediabetic' minority class (~0.92%) [138/15,000]
- Not removing Fasting Blood Sugar from training data (rule-based approach)

- SMOTE on entire dataset before splitting to training/testing
- Dataset was not intended for diabetes classification

- Feature Engineering did not provide any benefit to accuracy (Ex. BMI)

# Methodology

## Preprocessing

- SMOTE
- Feature Engineering (BMI calculation, height to weight ratio)
- Dropping unnecessary columns (ID, Fasting Blood Sugar)
- Handling Missing Data
- Label Encoding
- Feature Scaling (StandardScaler)
- Splitting training data into train/test (Kaggle had separate train/test)

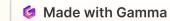
## Models Evaluated

- Logistic Regression (LR)
- Support Vector Classifier (SVC)
- Random Forest (RF)
- XGBoost (XGB) Often for imbalance dataset
- SGD Classifier
- Gradient Boost Classifier

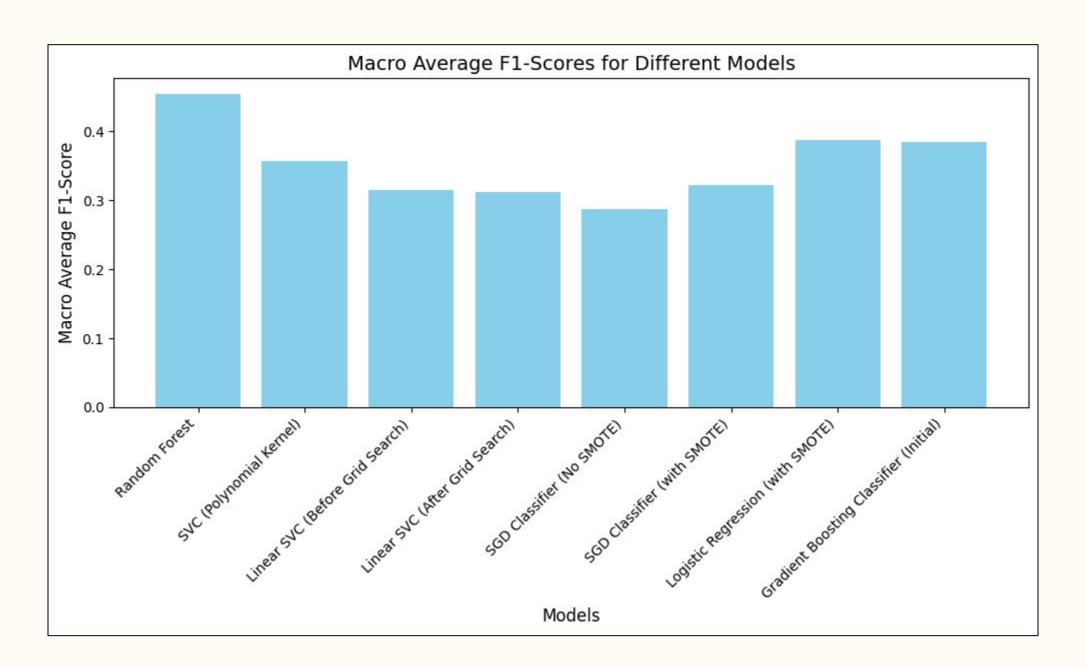
### **Imbalance Handling**

Auto Class Weighting

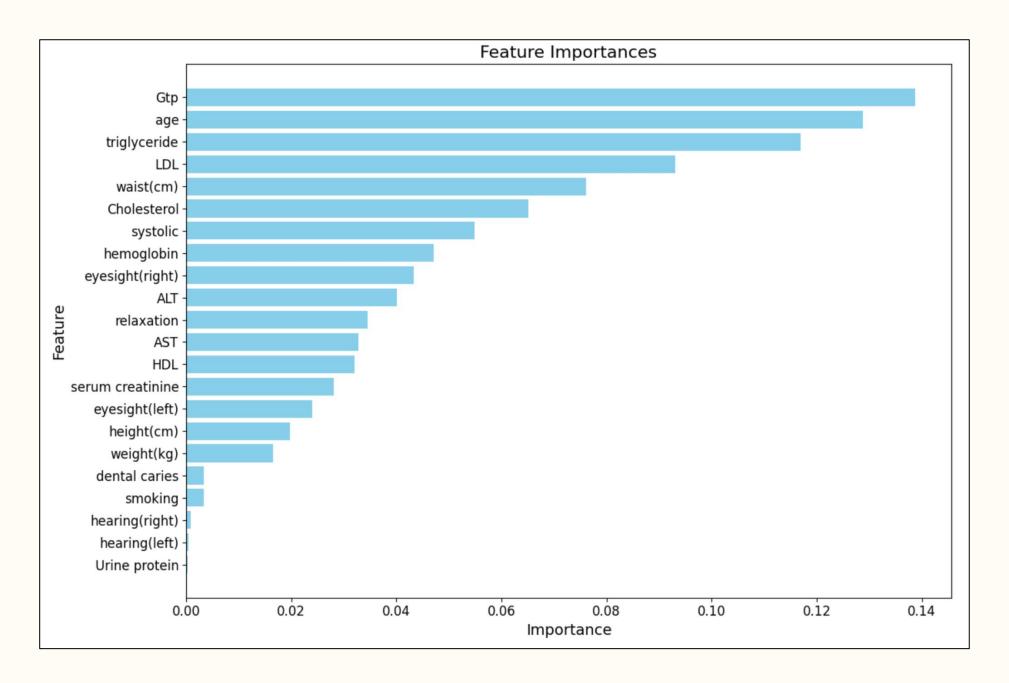
Model	<b>,</b> :	#	F1-Score (weighted) 🗸	#	Accuracy	<b>~</b>
XGBoost			0.328571		0.6807	69
Random Forest			0.370988		0.6865	38
SVC (RBF Kernel)			0.162983		0.6576	92
SVC (Polynomial Kernel)			0.365219		0.6923	80
Linear SVC			0.336727		0.6846	15
SGD Classifier (No SMOTE)			0.337317		0.6826	92
SGD Classifier (with SMOTE)			0.34966		0.6769	23
Logistic Regression (with SMOTE)			0.348107		0.6788	46
Gradient Boosting Classifier (Initial)			0.368829		0.6884	62
Gradient Boosting Classifier (with GridSearchC	V 8		0.369256		0.6884	62



# Macro Average Visualized



# Feature Importance - Random Forest



#### **Our Findings:**

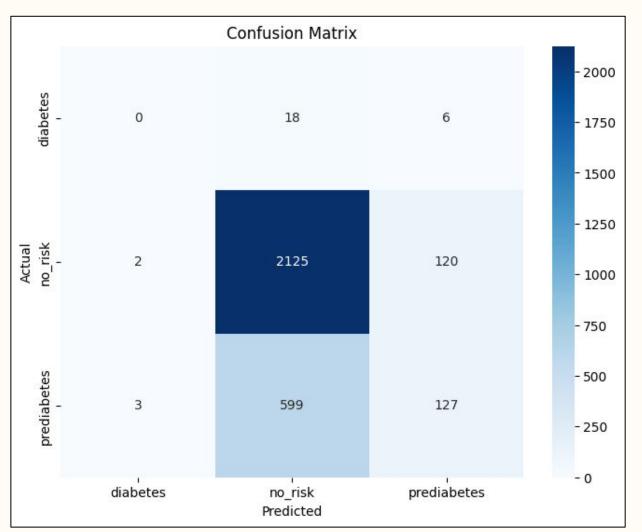
GTP stands for
Gamma-glutamyl transferase
(GGT). It's an enzyme that's
primarily found in the liver but is
also present in other organs like
the kidneys and pancreas.

High levels of GTP can indicate liver damage or disease.

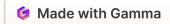
Our model rates GTP as of the highest importance.

## **XGBoost Results**

Classification Report:							
	precision	recall	f1-score	support			
diabetes no_risk prediabetes	0.00 0.77 0.50	0.00 0.95 0.17	0.00 0.85 0.26	24 2247 729			
accuracy macro avg weighted avg	0.43 0.70	0.37 0.75	0.75 0.37 0.70	3000 3000 3000			
Confusion Matrix:							
[[ 0 18 [ 2 2125 [ 3 599	6] 120] 127]]						

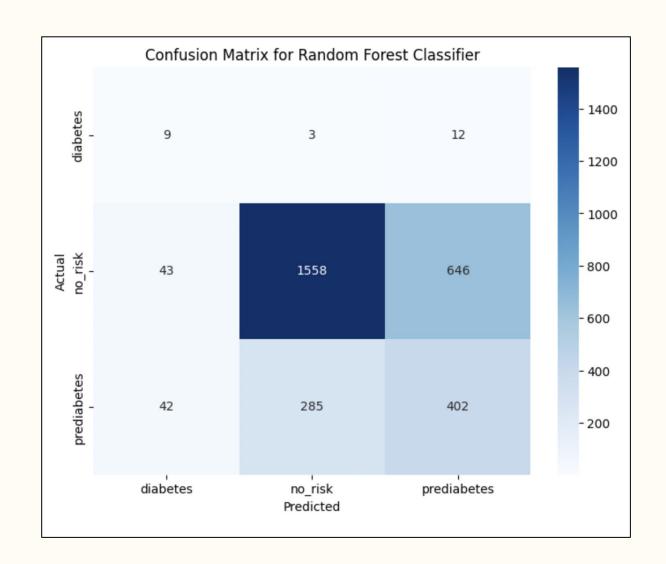


- Misleading Accuracy
- Adjusting Classes to only no\_risk and diabetes



## Random Forest Results

Classification Report:						
	precision	recall	f1-score	support		
diabetes no_risk prediabetes	0.10 0.84 0.38	0.38 0.69 0.55	0.15 0.76 0.45	24 2247 729		
accuracy macro avg weighted avg	0.44 0.73	0.54 0.66	0.66 0.45 0.68	3000 3000 3000		
Confusion Matrix:						
[[ 9 3 [ 43 1558 [ 42 285	12] 646] 402]]					



- Auto class weighting (class\_weight='balanced')



## Conclusion & Next Steps



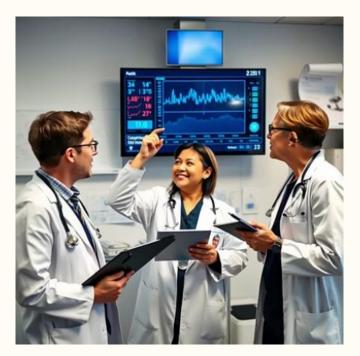
### **Next Steps**

- Explore other models for imbalanced dataset
- More Rigorous Hyperparameter Tuning
   (RandomizedSearchCV, Bayesian Optimization)
- A dataset related to diabetes with more balanced classes
- Other methods to correct for imbalance
- Selecting most important features
- More feature engineering

# Questions?









## References

- 1. Smoking dataset: <a href="https://www.kaggle.com/competitions/binary-smoke-detector">https://www.kaggle.com/competitions/binary-smoke-detector</a>
- 2. Gamma for Presentation template