Predicting Diabetes Risk Based on Health and Lifestyle Factors

An Analysis Using Machine Learning Techniques

Problem Definition

- Project Goal: Predict who might have diabetes based on their health and lifestyle habits.
- Why This Matters: Early prediction can help doctors catch diabetes sooner and give better care.
- Methods:
 - Used two different models to predict diabetes: K-Nearest Neighbors (KNN) and Logistic Regression.

Data Overview

- Source: Easiest Diabetes Classification Dataset from Kaggle.
- Key Features:
 - Age: How old the person is.
 - Gender: Male or Female.
 - BMI: A measure of body fat based on height and weight.
 - Blood Pressure: Measurement of blood pressure levels.
 - FBS: Blood sugar level after fasting.
 - HbA1c: Average blood sugar over the past few months.
 - Family History: Whether diabetes runs in the family.
 - Smoking: Whether the person smokes.
 - Diet: Eating habits (Healthy or Poor).
 - Exercise: Activity level (Regular or Not).
 - Diagnosis: Whether the person has diabetes or not.

Data Preparation and Cleaning

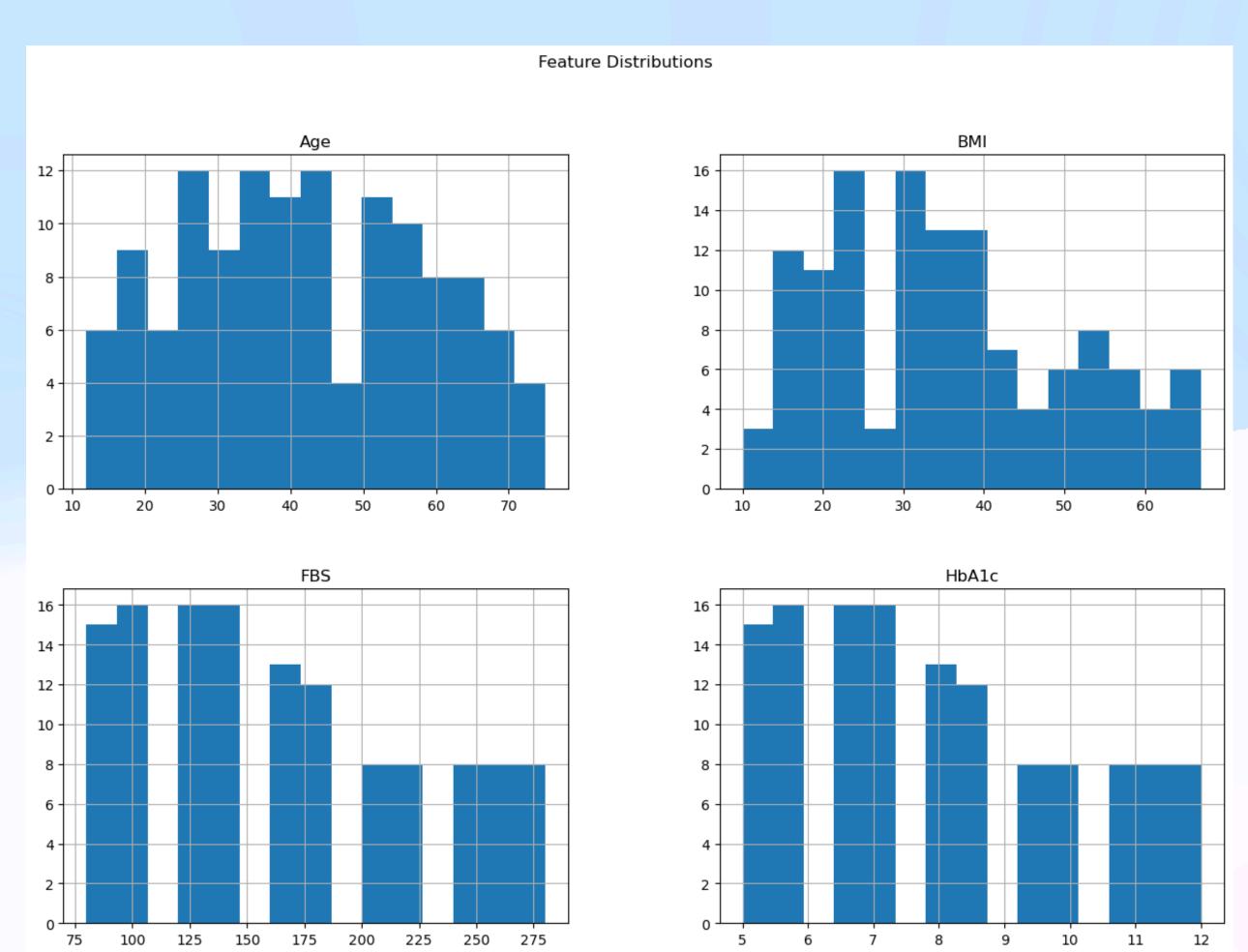
- Converted Categorical Data: Changed text data (like Male/Female) to numbers so the models could use them.
- Created New Columns: Split categories (like Blood Pressure) into separate columns.
- Standardized the Data:
 - Why: Scaling features (like Age and BMI) to have similar ranges helps models perform better.
- Goal: Make the data ready for accurate model training.

Exploring the Data

• Feature Distributions: Show graphs to see how values like Age, BMI, and HbA1c are spread out.

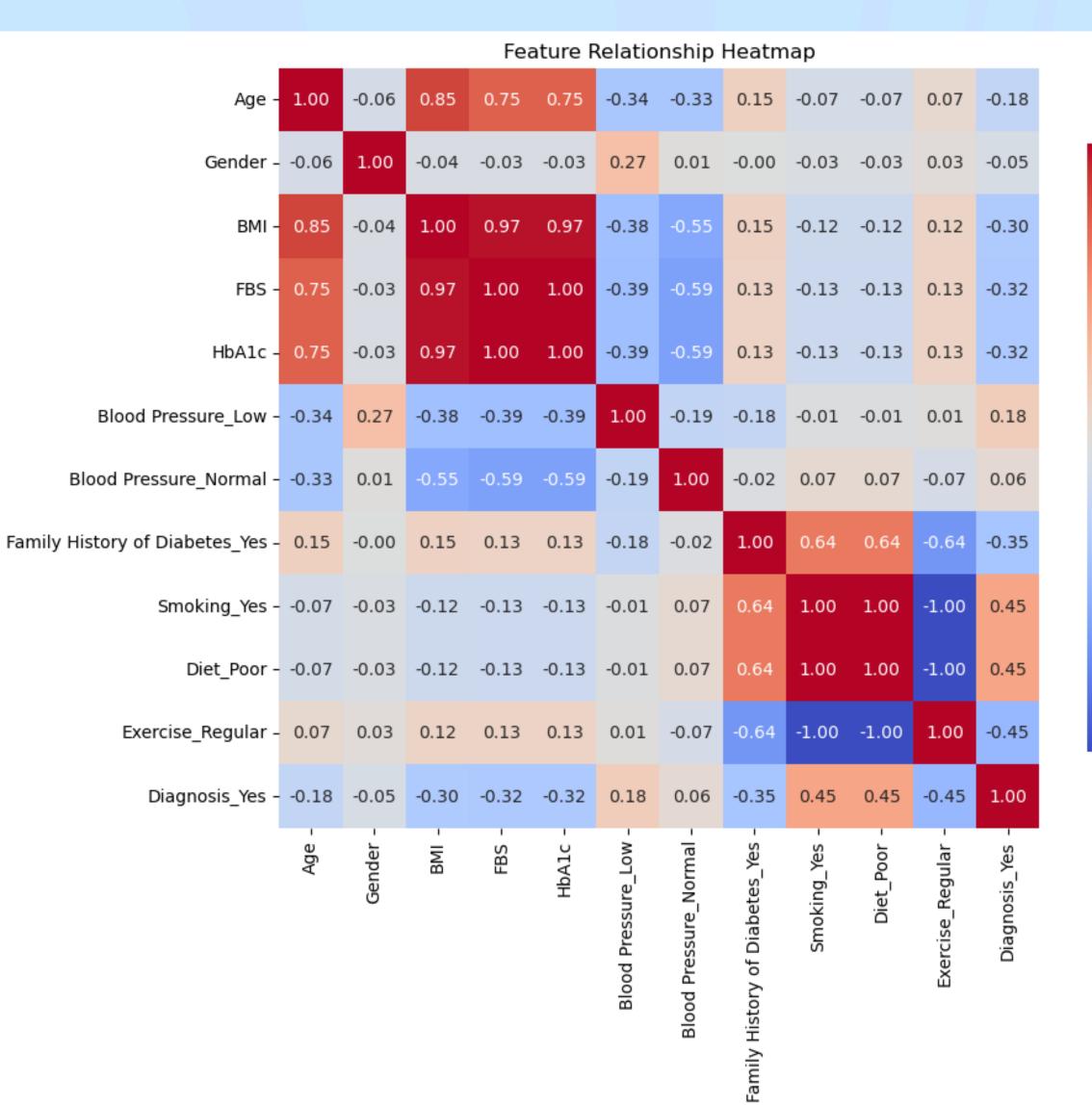
Observations:

- Are most people in certain age or BMI ranges?
- Do HbA1c levels show patterns for people with and without diabetes?
- Why It's Useful: Helps us understand the data before modeling.



Relationships Between Features

- Heatmap: Shows how features (like Age, BMI, FBS, etc.) relate to each other.
- Key Patterns:
 - Stronger relationships between some features can hint at how diabetes is connected to these factors.
- Why It's Important: Knowing which features are related helps us focus on the most useful ones.



- 0.50

- 0.25

- 0.00

- -0.25

- -0.75

Splitting the Data into Training and Testing Sets

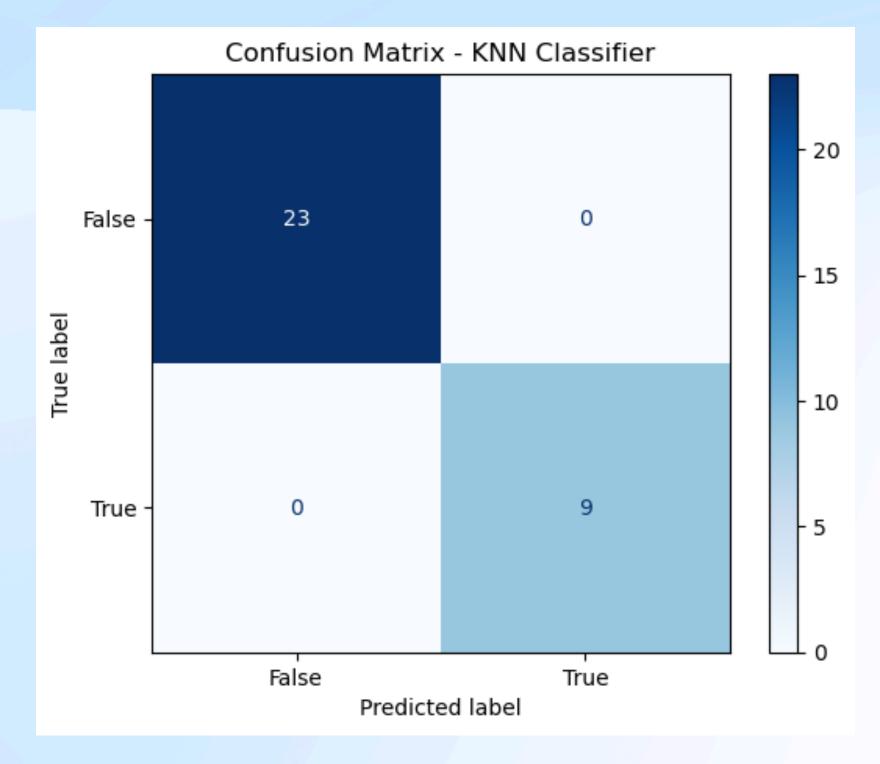
- Purpose: To check if the model can predict diabetes accurately on new, unseen data.
- Data Split:
 - Training Set (75%): Used to train the model.
 - Testing Set (25%): Used to test the model's accuracy.

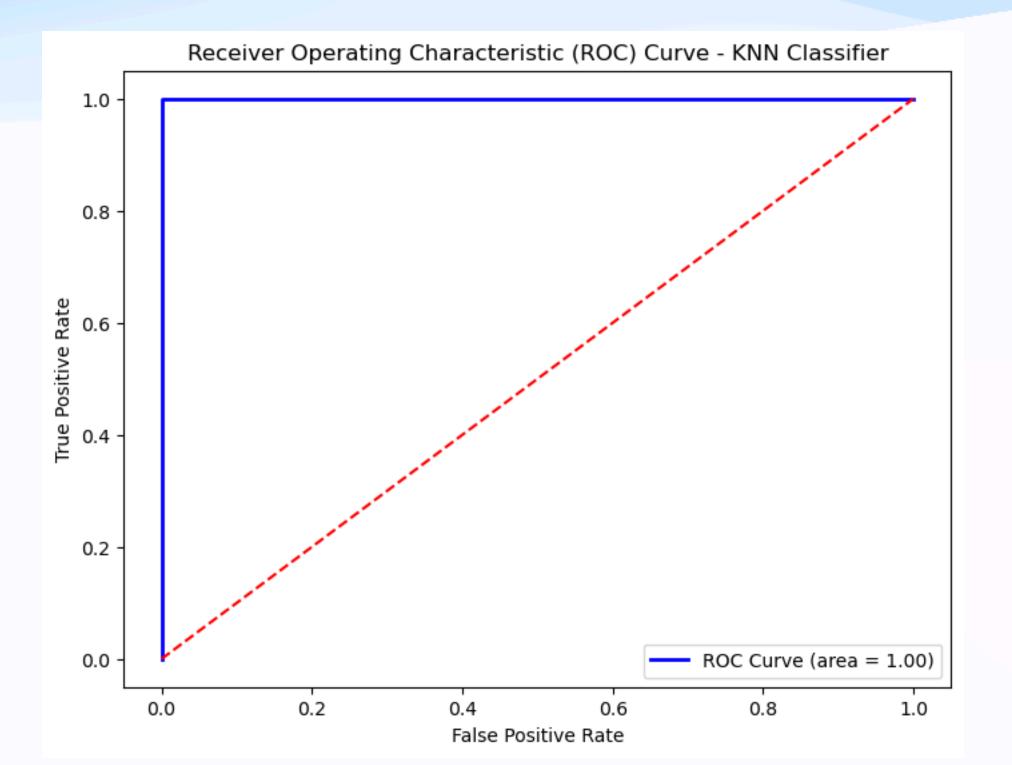
Choosing K-Nearest Neighbors (KNN) Model

- Goal: Find the best number of neighbors (k) for the highest accuracy.
- Process: Tested different values of "k" to see how each affected accuracy.
- **Results:** Found that k=11 (11 neighbors) gave the best balance for accurate predictions.

KNN Model Results

- Accuracy on Test Data: Achieved 100% accuracy with k=11.
- Confusion Matrix: Shows how many predictions were correct vs. incorrect.
- ROC Curve: Measures the model's ability to correctly identify diabetes cases.
 The area under the curve (AUC) shows how well the model performs.





Using Logistic Regression for Comparison

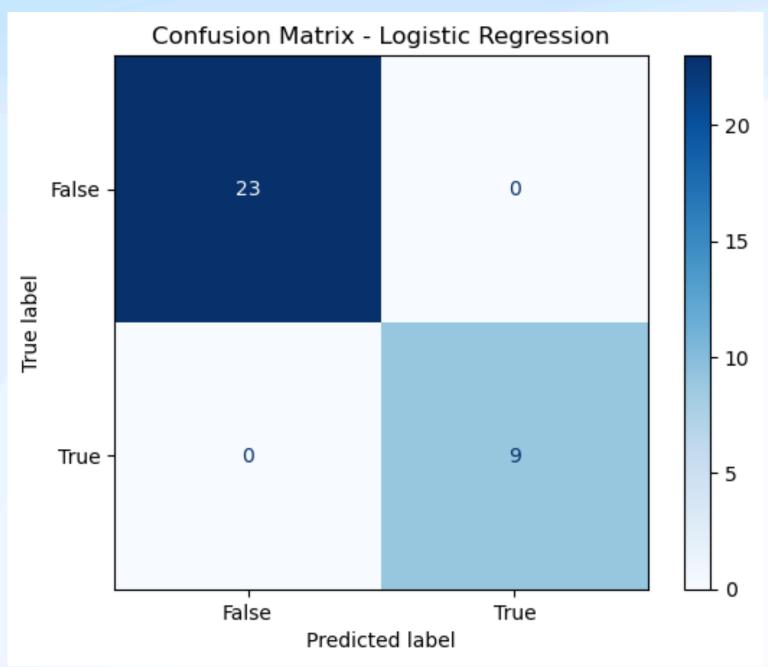
- Purpose: Use another model type to see if it also performs well.
- Training: Used the same training data to fit the model.
- Testing: Checked accuracy on the test data for comparison with KNN.

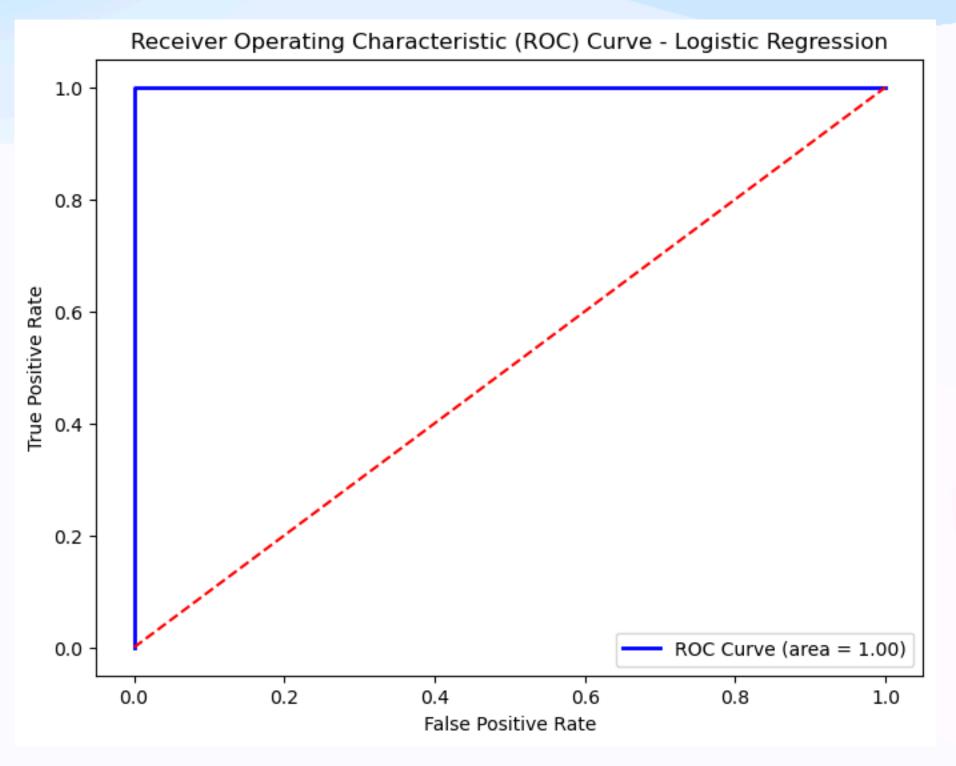
Logistic Regression Results

- Accuracy on Test Data: Also achieved 100% accuracy.
- Confusion Matrix: Shows correct vs. incorrect predictions.

• ROC Curve: Similar to KNN, the ROC Curve shows how well Logistic Regression can predict diabetes cases. High AUC again suggests good

model performance.





Comparing the Models

- Both Models Showed High Accuracy: Both KNN and Logistic Regression predicted perfectly on the test data.
- Key Takeaway: Both models are effective in predicting diabetes in this dataset. High accuracy suggests they can be useful tools for doctors to identify at-risk individuals.

Summary and Next Steps

Project Summary:

- Developed two models (KNN and Logistic Regression) to predict diabetes using health and lifestyle data.
- Both models showed 100% accuracy on test data.
- Implications: These models could help doctors spot diabetes early and plan better care.

Next Steps:

- Try models on a larger dataset to confirm accuracy.
- Experiment with other algorithms for better insights.