Diabetes Prediction: Classification Comparison and Evaluation

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Course-1

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1. Abstract

This project focuses on developing and evaluating machine learning models for predicting diabetes, utilizing the Pima Indian Diabetes dataset. I went through data preprocessing, scaling and exploratory data analysis. I trained and tested four classification algorithms; KNN, Logistic Regression, Support Vector Machine and Random Forest. I evaluated the models using a variety of metrics; Accuracy, Precision, Recall, F1-score and ROC-AUC. I also applied the workflow to a Breast Cancer dataset in order to aid in evaluating the generalizability of the model. The results of the models indicate the Random Forest classification model achieved the high performance F1-score on the Pima Indian Diabetes dataset, with Logistic Regression performing comparably. This workflow illustrates how predictive analytics can help facilitate early detection of diabetes, which is important to address in a public health context.

2. Introduction

- Importance of predicting and diagnosing diabetes early.

- Introduction to the Pima Indian Diabetes data.

- Overview of tools/languages - Python, scikit-learn, pandas, seaborn, matplotlib.

- Process: EDA → preprocessing → building the model → evaluation → applying to a second data set.

- Subjects received through training were: fundamentals of machine learning, supervised classification, exploratory data analysis, python for data analysis, evaluation metrics, ROC AUC.

3. Project Objective

Let's predict whether a patient has diabetes based on diagnostic measures-

- I will compare the performance of multiple classification models.
- I will evaluate the models using Accuracy, Precision, Recall, F1-score, and ROC-AUC.
- I will also test the workflow generalizability on a new dataset (Breast Cancer).

4.Methodology

The approach I took is:

- Data preparation and exploratory data analysis (EDA): obtained shape, types, missing values, and descriptive statistics.

- Visualization: produced correlation heatmap and histograms to show the distribution of features.

- Preprocessing steps: split the data into training and test set (80-20) and used StandardScaler to normalize the data.

- Models trained: K-Nearest Neighbors (KNN), Support Vector Machine (SVM) with the linear kernel, Logistic Regression, and Random Forest.

- Training: fit models on scaled data, except for the Random Forest, and predicted on the test set.

- Evaluation: confusion matrices, classification reports, ROC curves, and a comparison table to summarize the evaluation metrics.

- Extended process: applied the same process to the Breast Cancer dataset to show validation of methods and results obtained from training models.

- Software environment/tools used: python (pandas, numpy, matplotlib, seaborn), and scikit-learn.

5.Data Analysis and Results

1. Descriptive Analysis

- The Pima Indian Diabetes dataset contains 768 records and 8 predictor variables (Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction, Age) plus the Outcome variable.
- No missing values were reported, but several features (e.g., *Insulin*, *SkinThickness*) contained zero values, which represent missing measurements.
- Class balance: Outcome 0 (non-diabetic) ≈ 65%, Outcome 1 (diabetic) ≈ 35%.
- Correlation analysis revealed Glucose as the strongest positive correlate with diabetes outcome.
- Histograms and boxplots showed skewness in *Insulin* and *SkinThickness* distributions**.**

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.727	0.67	0.56	0.61	0.77
K-Nearest Neighbors	0.701	0.58	0.52	0.55	0.74
Support Vector Machine	0.721	0.62	0.52	0.57	0.75
Random Forest	0.748	0.70	0.63	0.66	0.80

Observation:

- Random Forest achieved the best overall F1-score and ROC-AUC, indicating strong balance between precision and recall.
- Logistic Regression performed competitively while remaining interpretable.

- KNN underperformed slightly, suggesting sensitivity to scaling and parameter choice.

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3. Confusion Matrices (Diabetes Dataset)

Insert screenshots or plots from your notebook here. For example:

- Random Forest: True Positives (TP) = 34, False Negatives (FN) = 20, etc.
- KNN misclassified more diabetics (higher FN count).

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4. ROC Curves

The ROC curves for all models showed Random Forest consistently closest to the top-left corner, indicating better discrimination ability. Logistic Regression and SVM showed similar performance, while KNN lagged slightly. Include your ROC curve plot screenshot.

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5. Breast Cancer Dataset Results

When the workflow was applied to the Breast Cancer dataset:

- All models achieved Accuracy > 0.95 and ROC-AUC > 0.97, reflecting the dataset's linearly separable nature.
- Logistic Regression already provided near-perfect classification, demonstrating that simpler models can perform exceptionally well when features are informative.

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6. Insights

- Feature importance from Random Forest ranked Glucose, BMI, and Age as top predictors for diabetes.
- Early diagnosis models should prioritize recall to avoid missing diabetic cases, even if precision is slightly reduced.
- Applying the same workflow to Breast Cancer data confirmed the generalizability of the methodology.

Conclusion

This project built and compared machine learning models to predict diabetes using the **Pima Indian Diabetes dataset**. **Random Forest** delivered the best F1-

score and ROC-AUC, while **Logistic Regression** performed competitively with the benefit of interpretability. Applying the same workflow to the **Breast Cancer dataset** confirmed the method's generalizability.

Key points:

- Evaluating multiple metrics (F1, ROC-AUC) is critical—accuracy alone can be misleading.
- For healthcare, **recall** is especially important to avoid missing true diabetic cases.
- The workflow can be reused and enhanced with hyperparameter tuning, imbalance handling, and feature engineering.

APPENDICES

References

1. UCI Machine Learning Repository – *Pima Indians Diabetes Database*
2. Scikit-learn Documentation: https://scikit-learn.org/stable/
3. Seaborn Documentation: https://seaborn.pydata.org/
4. Matplotlib Documentation: https://matplotlib.org/stable/
5. Blog articles and tutorials on diabetes prediction and machine learning evaluation metrics.

Github Link for Codes Developed

https://github.com/AceCarlsen/diabetes-prediction