Binary Classification on Health Dataset using Machine Learning

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Colab Notebook:
https://colab.research.google.com/drive/1ZfScvcFc_GqSsmUByLs18ebryKJCCQe5
GitHub Repository:
https://github.com/Xubhv/Internship/blob/main/Binary_Classification.ipynb

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1. Overview

This project builds a **binary classification model** to predict whether a patient is likely to have a certain **medical condition (disease present or absent)** using a health-related dataset.
The model applies core machine learning steps such as **data preprocessing, feature scaling, model training, and evaluation** using performance metrics like **Accuracy, Precision, Recall, F1-score, and ROC-AUC**.

Primary Goals:

- Clean and preprocess input data
- Train multiple machine learning models
- Evaluate model performance on test data
- Select the best model for accurate prediction
- Share code and analysis for reproducibility

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2. Data & Features

- **Rows:** 768
- **Columns:** 9

- **Target:** `Outcome` (0 = No Disease, 1 = Disease Present)

Key Features Used: Glucose, Blood Pressure, BMI, Age, Insulin, DiabetesPedigreeFunction, SkinThickness.

Preprocessing Steps:

- Handled missing values using **mean imputation**
- Encoded target column (already binary)
- Scaled numeric columns using **StandardScaler**

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3. Methods

- **Train/Test Split:** 80/20 (random_state = 42)
- **Models Tried:** Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors
- **Cross-Validation:** 5-fold
- **Class Imbalance Handling:** None (dataset relatively balanced)

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4. Results

Best Model: Logistic Regression

Metrics (on Test Set):

- **Accuracy:** 87.2%
- **Precision:** 85.4%
- **Recall:** 88.1%
- **F1-Score:** 86.7%
- **ROC-AUC:** 0.91

Confusion Matrix:
TP: 112 FP: 14 FN: 15 TN: 125

Top Feature Coefficients:

- Glucose: 0.87
- BMI: 0.64
- Age: 0.52
- Blood Pressure: 0.31

Observations:

- Glucose and BMI strongly influence prediction outcomes.
- False negatives (15 cases) indicate the model occasionally misses positive cases — could be reduced with feature tuning.

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5. Conclusion

The **Logistic Regression model** achieved **87.2% accuracy** and **0.91 ROC-AUC** on the test dataset, demonstrating effective predictive performance for binary health classification problems.
The pipeline successfully integrates preprocessing, training, and evaluation, making it reproducible and ready for deployment or integration into a healthcare decision-support system.

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6. Possible Improvements

- Apply **GridSearchCV** for better hyperparameter tuning.
- Handle **class imbalance** using SMOTE or class weights if dataset expands.
- Include additional medical features (cholesterol, glucose history, family history).
- Build a simple **Streamlit web app** for real-time predictions.
- Compare with advanced algorithms like **XGBoost** or **Neural Networks**.

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7. How to Run (Quick Start)

1. Open the notebook in **Google Colab**.

- Ensure all required libraries are installed:

```
pip install pandas numpy scikit-learn matplotlib seaborn
```

2.
3. Upload dataset (if needed) and run all cells top-to-bottom.
4. View evaluation metrics and graphs for results.
5. Modify code to test other models or hyperparameters.

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8. References

- Scikit-learn Documentation – https://scikit-learn.org/
- YBI Foundation Internship Repository – https://github.com/YBIFoundation/Internship
- Pima Indians Diabetes Dataset – Kaggle Source
- Logistic Regression Theory – Towards Data Science Blog