Smart Diagnosis

Predicting Diabetes using Logistic Regression

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Why is Diabetic Study Important?

- Affects millions globally
- Identifying predictors helps:
  - Focus on preventive measures
  - Reduce healthcare costs
  - Improve the quality of life

Focus of Study:

- Use logistic regression model to evaluate diabetes prediction

Previous Research

- Use of Neural Networks (Jack W Smith, et. al)
- Logistic Regression (UCI Machine Learning)
- Random Forestion (Quan Zou, et. al)

What is unique about our study?

- Use Logistic Regression for easier interpretation
- Use of Data Validation for better accuracy

Why use a Logistic Regression model?

- Study is based on Binary Classification
- Feature coefficients directly reflect importance
- Focus is on probabilities:
  - More insight than just classifications
  - Helps determine confidence level of diagnosis

Dataset Scope

- Total 768 female patients
- Pima Indian heritage
- All at least 21 years old

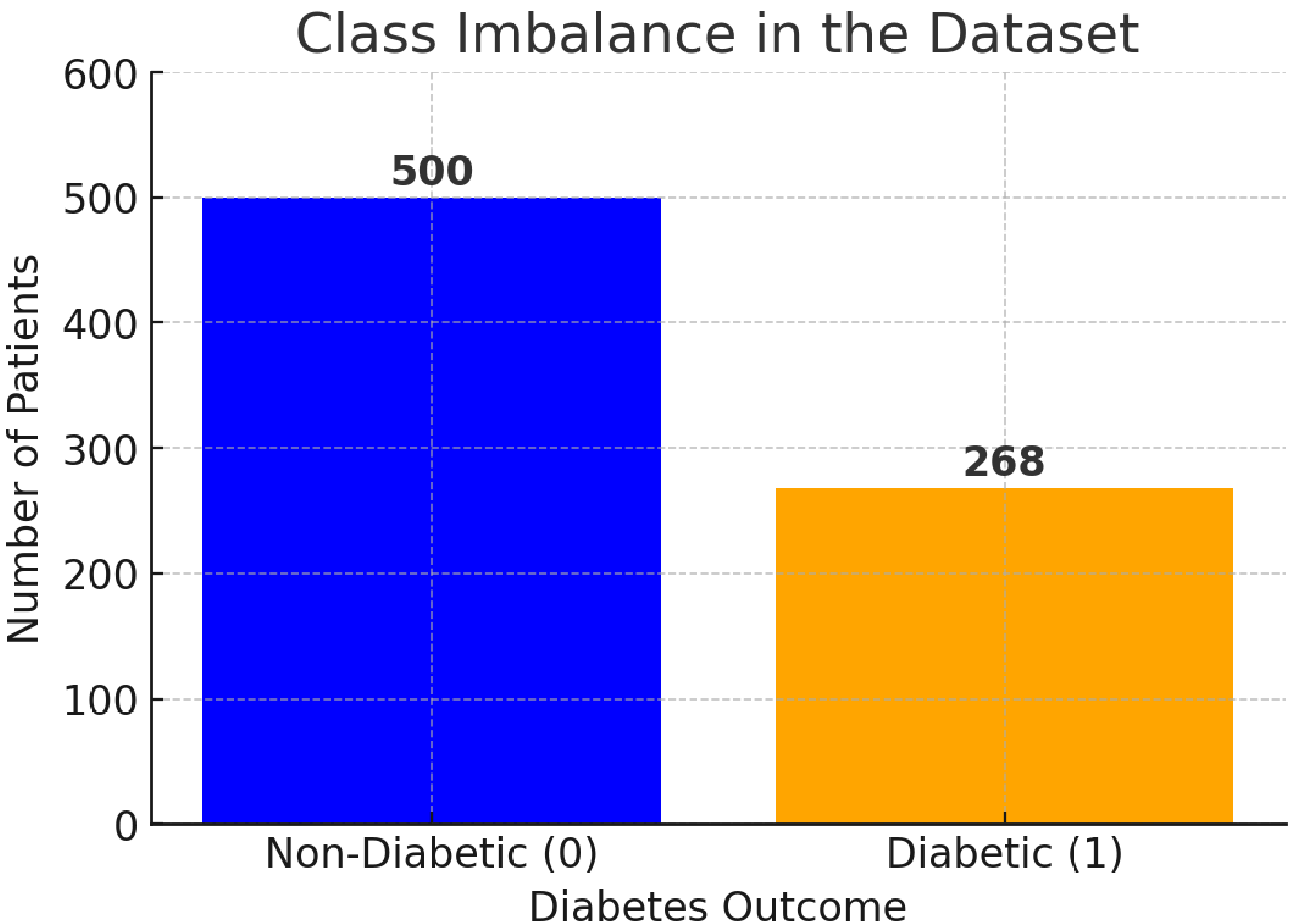
NIH National Institute of Diabetes and Digestive and Kidney Diseases

Feature Descriptions

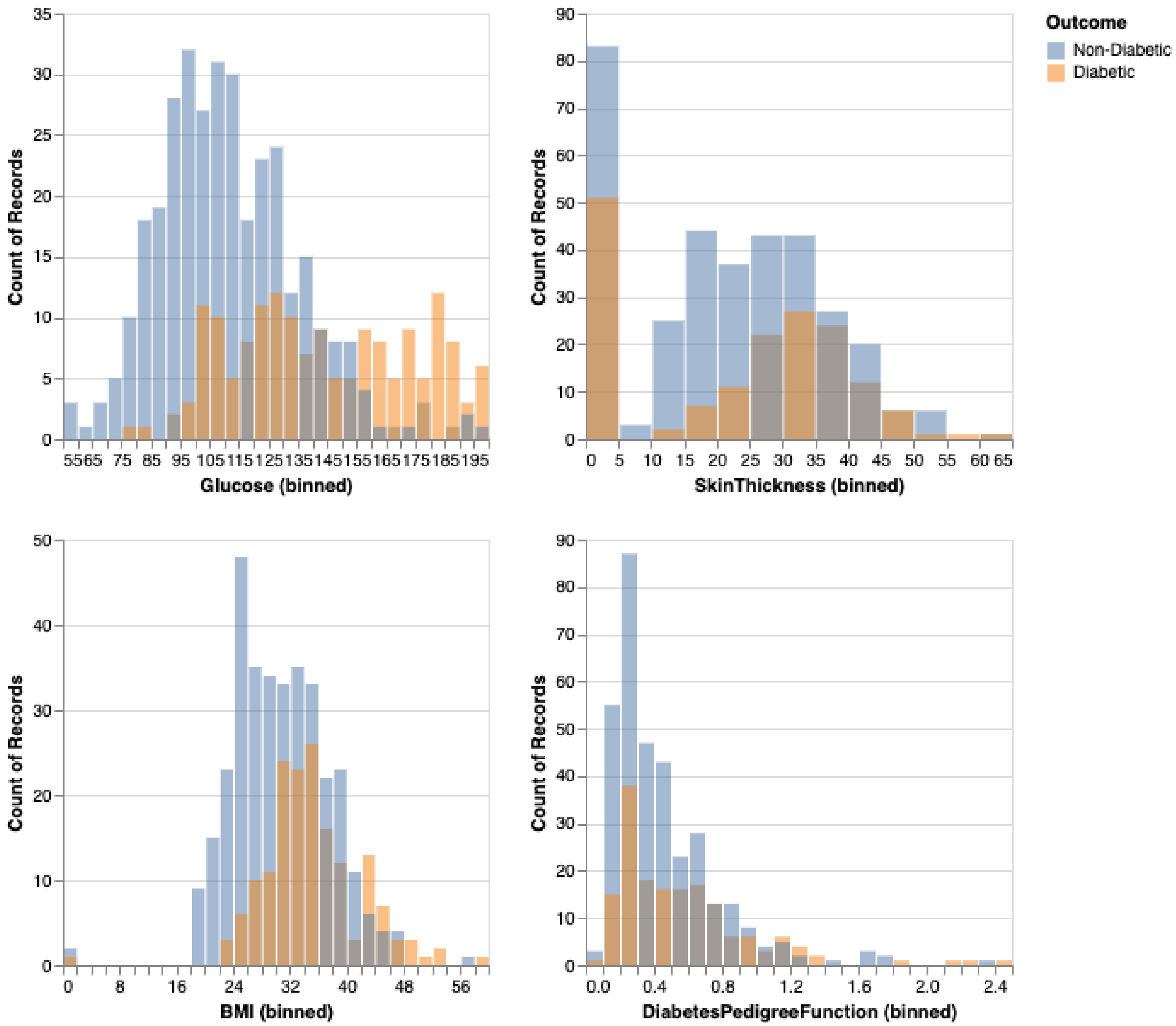
Feature	Type	Units/Description
Pregnancies	Numerical	Number of pregnancies
Age	Numerical	Age in years
Glucose	Numerical	Plasma glucose concentration in mg/dL
BloodPressure	Numerical	Diastolic blood pressure measurement in mm Hg
Insulin	Numerical	Insulin level in mu U/ml
SkinThickness	Numerical	Triceps skin fold thickness in mm (estimates body fat)
BMI	Numerical	Body Mass Index in kg/m^2 (indicates body fat)
DiabetesPedigreeFunction	Numerical	Diabetes likelihood score based on family history
Outcome	Categorical	Diabetic / Non-Diabetic

- Direct Health measurements
- Calculated health metrics

Exploratory Data Analysis

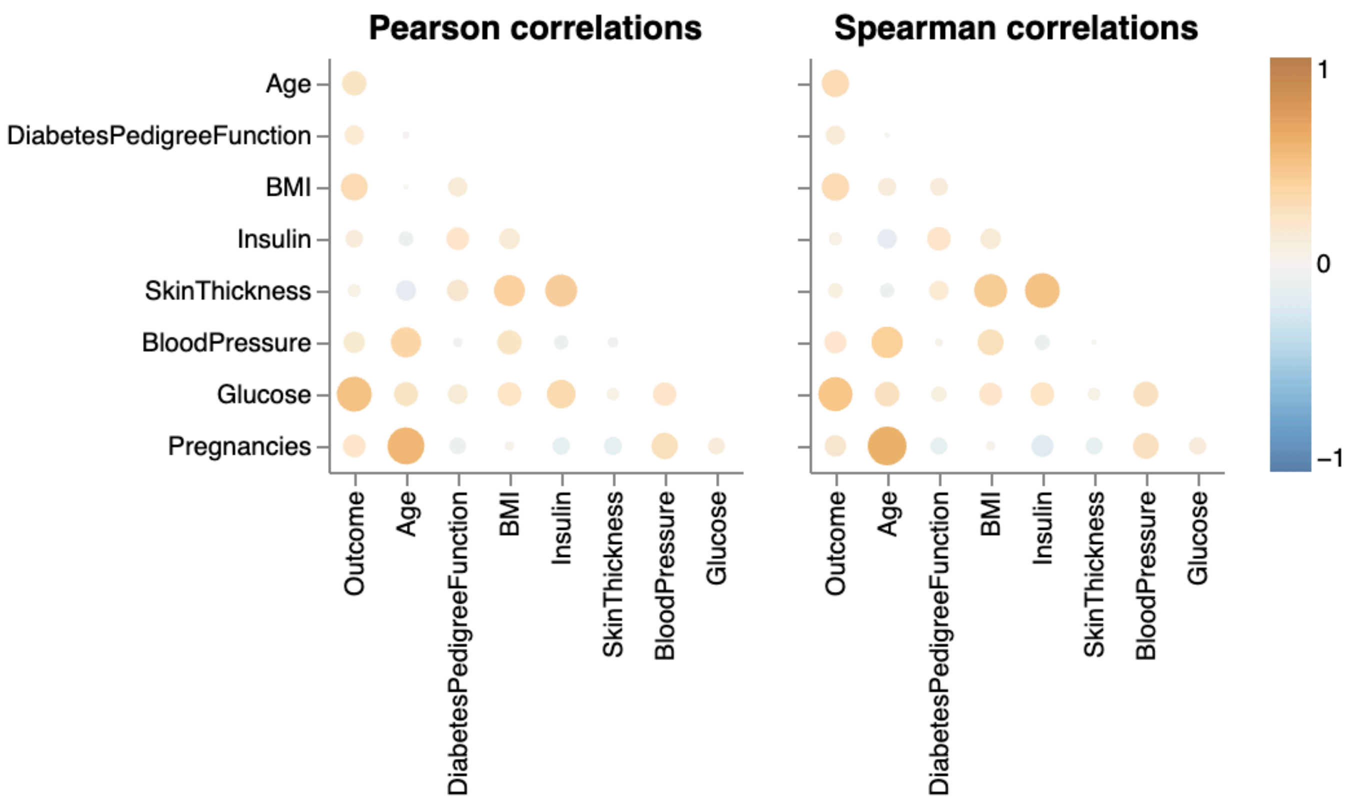


Exploratory Data Analysis



Data Validation

Data Validation (cont'd)



- Identify potential multicollinearity
- Ensure feature correlation does not pass 0.7 threshold

Analysis Methodology

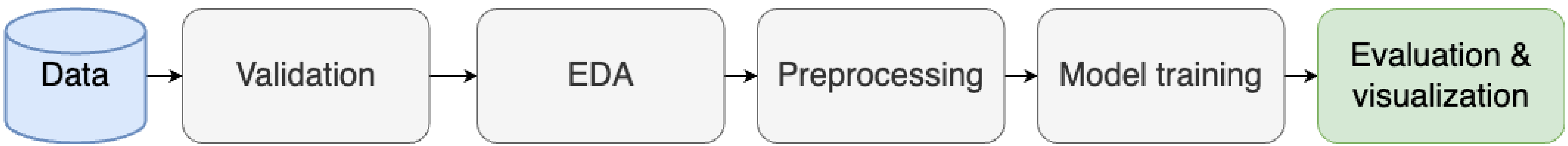
- Data split: 70% training, 30% testing
- Features:
  - Structured numeric data
  - No missing values
- Preprocessing:
  - Standardization through `StandardScaler()`

Analysis Methodology (cont'd)

- Model evaluation metric: Accuracy
- Baseline model: `DummyClassifer`
- Choosen model: `LogisticRegression`
- Hyperparameter tuning:
  - Optimize regularization strength `C` between 10^{-5} and 10^{5}
  - Use method `RandomizedSearchCV()`

Reproducible Data Pipeline

- The pipeline followed a **modular structure**, ensuring:
- **Reusability**
- **Interdependency**
- **Automation**



Results - Feature Importance

- Feature importance measured by coefficients

Features	Coefficients
Glucose	0.724
BMI	0.389
Pregnancies	0.229
Age	0.194
DiabetesPedigreeFunction	0.161
BloodPressure	0.048
SkinThickness	-0.007
Insulin	0.002

Results - Model Evaluation

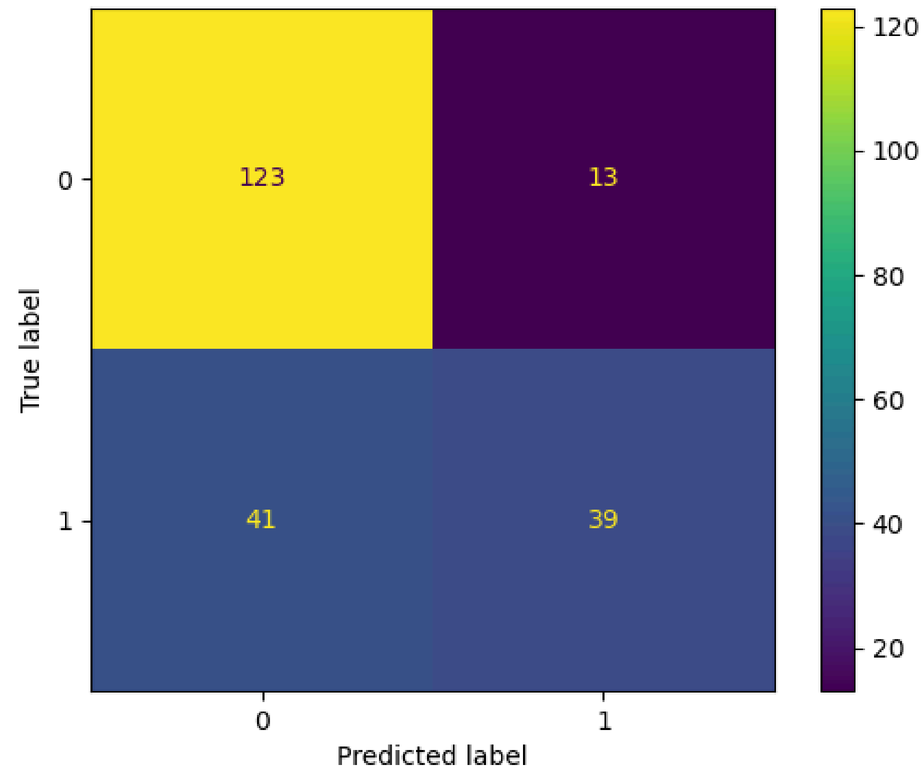
- Dummy Classifier:
  - **Cross validation accuracy = 0.672**
- Logistic Regression:
  - Best hyperparameter C $\approx$ 0.027
  - Cross validation:
    - Training accuracy = 0.786
    - Validation accuracy = 0.781
  - **Test set accuracy = 0.750**

Results - Confusion Matrix

216 total test cases

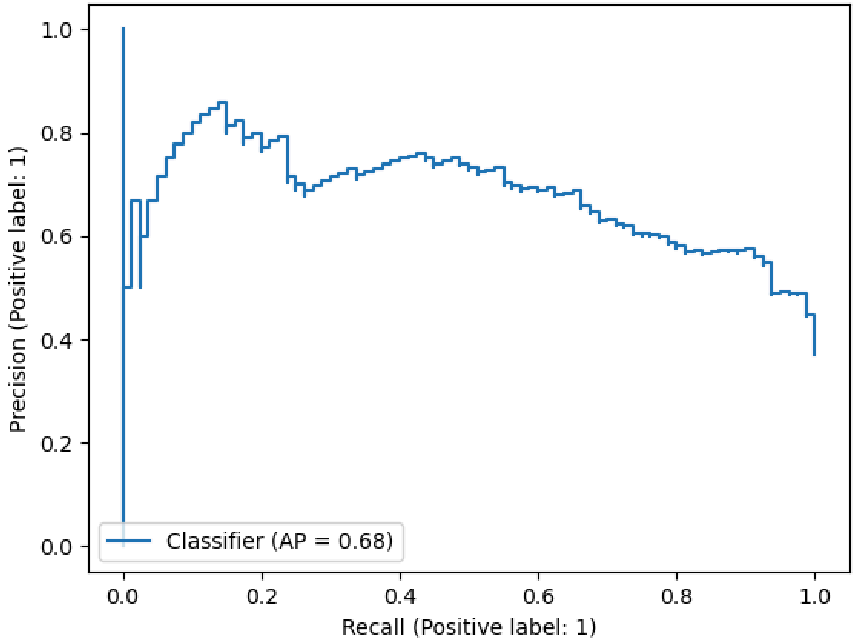
54 misclassifications

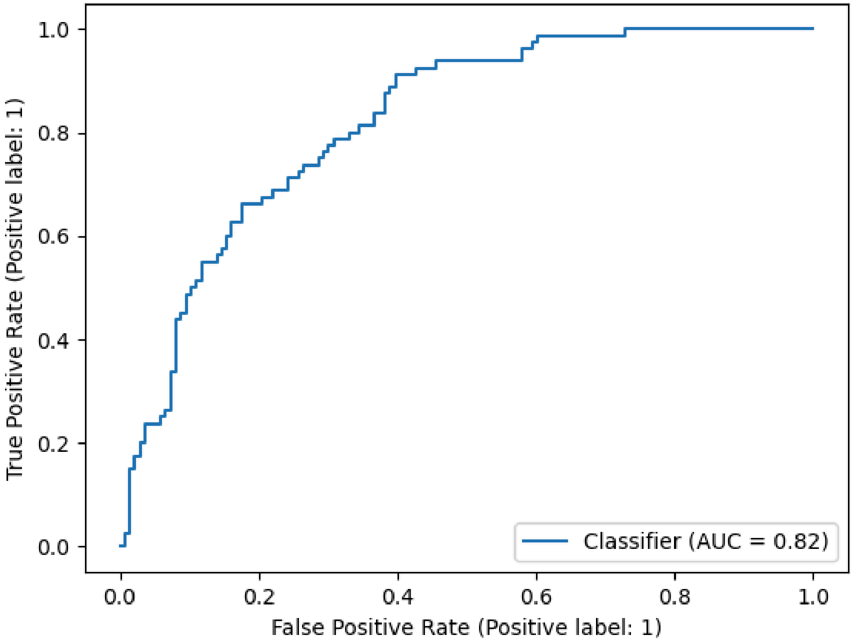
- *41 false negatives*
- *13 false positives*



Results - PR and ROC Curve

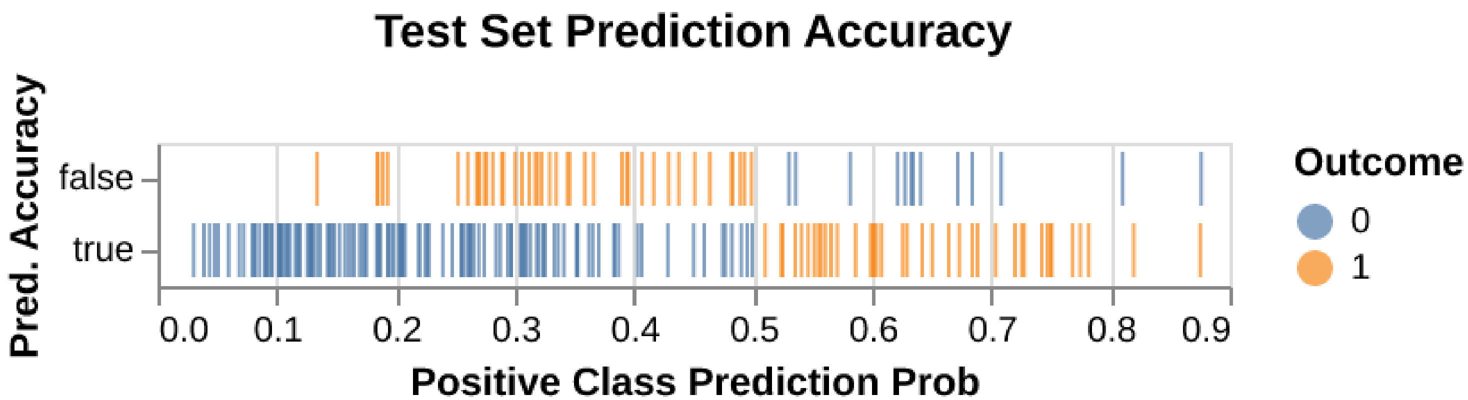
- Model performance does not achieve optimal trade-off across all thresholds.





Results - Clinical Utility

- Visualizing predicted probabilities to help clinicians assess model confidence.



Discussion - Model Performance

- Clinical Relevance: effective screening tool
- Enhancement Approaches:
  - Examine misclassified observations

Discussion - Enhancement Opportunities

- Explore feature engineering
- Alternative classifiers:
  - Random Forest
  - k-Nearest Neighbours (k-NN)
  - Support Vector Classifier (SVC)

Limitations & Future Directions

- Dataset Limitations
- Future Data Exploration
  - Collaborate with data collectors
  - Combine with external datasets
    - Broaden demographic coverage
    - Enable comprehensive insights and greater applicabilit

Conclusion - Key Findings

- Logistic regression vs. Dummy Classifier.
- Key predictors/features: Glucose (most influential) BMI, pregnancies.
- Challenges: 54 misclassifications, including 41 false negatives, highlight risks of undiagnosed cases.
- Clinical Potential: initial screening tool, data-driven approach to improve outcomes and reduce complications.

Conclusion - Recommendations

- Recommendations for Improvement:
  - Feature engineering
  - Test alternative ML models
  - Incorporate additional data (e.g. Lifestyle factors, Genetic information etc.)

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