

Supervised Learning – Pima Indians Diabetes: Comparative Analysis of Tabular Models

Introduction.....	1
Dataset Distribution.....	1
Hyperparameters.....	2
Relevant Libraries.....	2
XGBoost, LightGBM, and CatBoost Numerical Results.....	2
ROC Curves.....	3
Youden's J Plots.....	4
References.....	5

Introduction

Developed learning pipeline using three tabular supervised learning models, (XGBoost, LightGBM, and Catboost), to predict diabetes risk using the famous Pima Native Indian Diabetes Database from UCI.

- The pretrained models take in eight medical/physical features (e.g. BMI, blood glucose, insulin), and output a binary prediction of a patient's diabetes diagnosis.
- Implemented data preprocessing and data cleaning using the Pandas library. Used a 60-20-20 training, validation, test split for robust model evaluation (done using train_test_split from scikit-learn)
- To display a performance evaluation for each model, I used matplotlib and generated ROC curves, AUC scores, and Youden's J plots, which helped visualize how well the models distinguish between diabetic and non-diabetic test cases.
- Compared binary cross-entropy loss data, testing accuracy, and evaluation via ROC curves to assess optimal decision thresholds and classification performance across models.
- Demonstrated a need for generalization in supervised learning through the drastic differences in training and testing accuracy for low-performing models.
- Identified the best-performing model based on test accuracy, achieving the highest predictive performance for diabetes classification (CatBoost)

Dataset Distribution

- **Train Set:** 60%
- **Validation Set:** 20%
- **Test Set:** 20%

The dataset is loaded from an online CSV and split into training, validation, and test sets using scikit-learn's train_test_split.

Dataset Reference: <https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database>

Hyperparameters

- **XGBoost / LightGBM / CatBoost:**
 - Default parameters are used, with random seed set for result reproducibility
 - For CatBoost, early stopping rounds are 10 (special parameter)

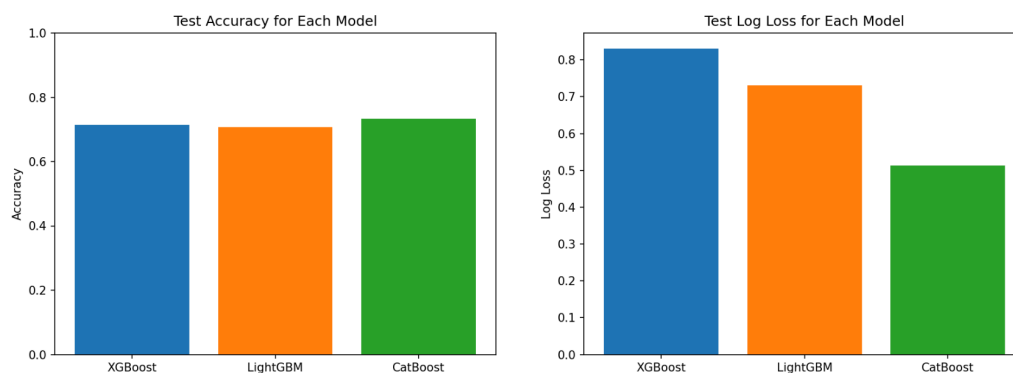
The models were trained using entire feature set (8 numeric features) w/ out image conversion

Implemented this project to apply my ML knowledge to structured tabular data

Relevant Libraries

- Pandas (Structured Data Parse)
- Numpy
- XGBoost (Tabular Model 1)
- LightGBM (Tabular Model 2)
- CatBoost (Tabular Model 3)
- SKLearn (ROC, AUC, StandardScaler, TrainTestSplit)
- Matplotlib

XGBoost, LightGBM, and CatBoost Numerical Results

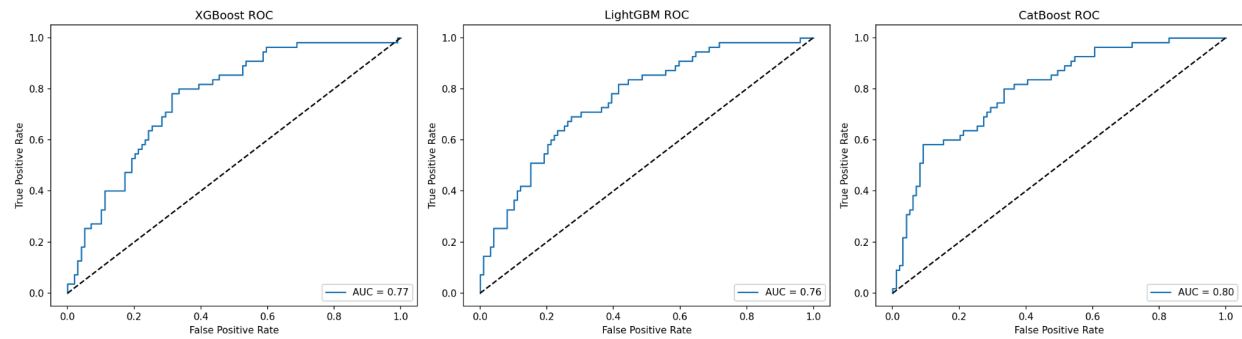


XGBoost Test Accuracy: 0.7143, Log Loss: 0.8313

LightGBM Test Accuracy: 0.7078, Log Loss: 0.7309

CatBoost Test Accuracy: 0.7338, Log Loss: 0.5137

ROC Curves

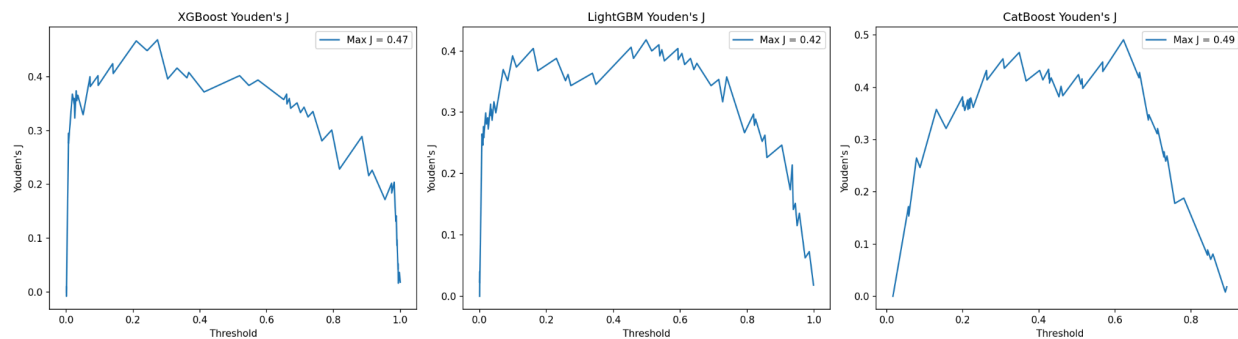


AUC XGBoost - 0.77

AUC LightGBM - 0.76

AUC CatBoost - 0.80

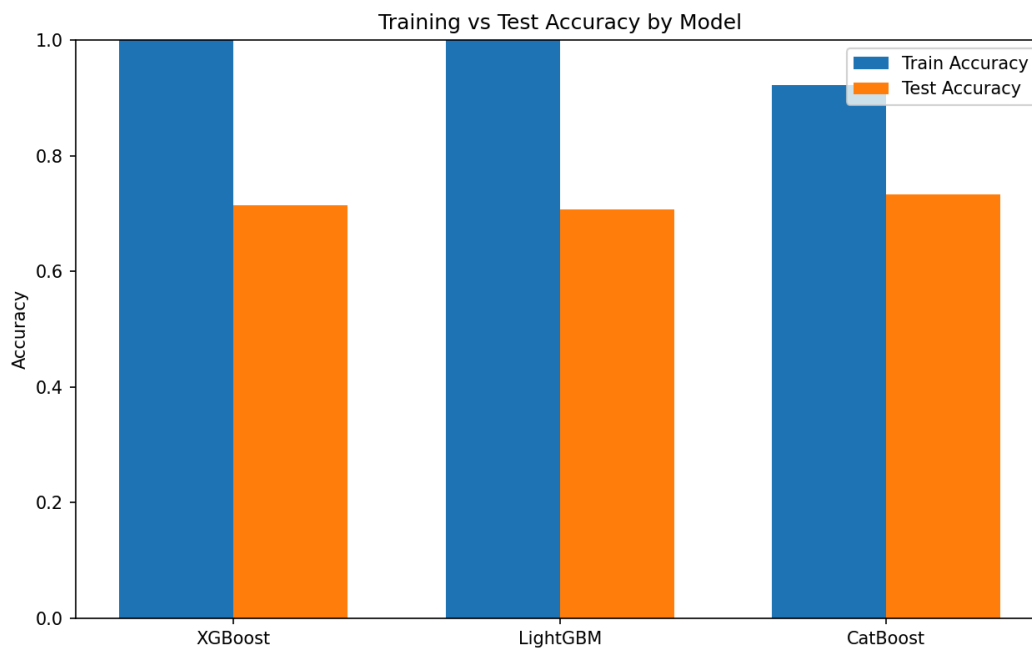
Youden's J Plots

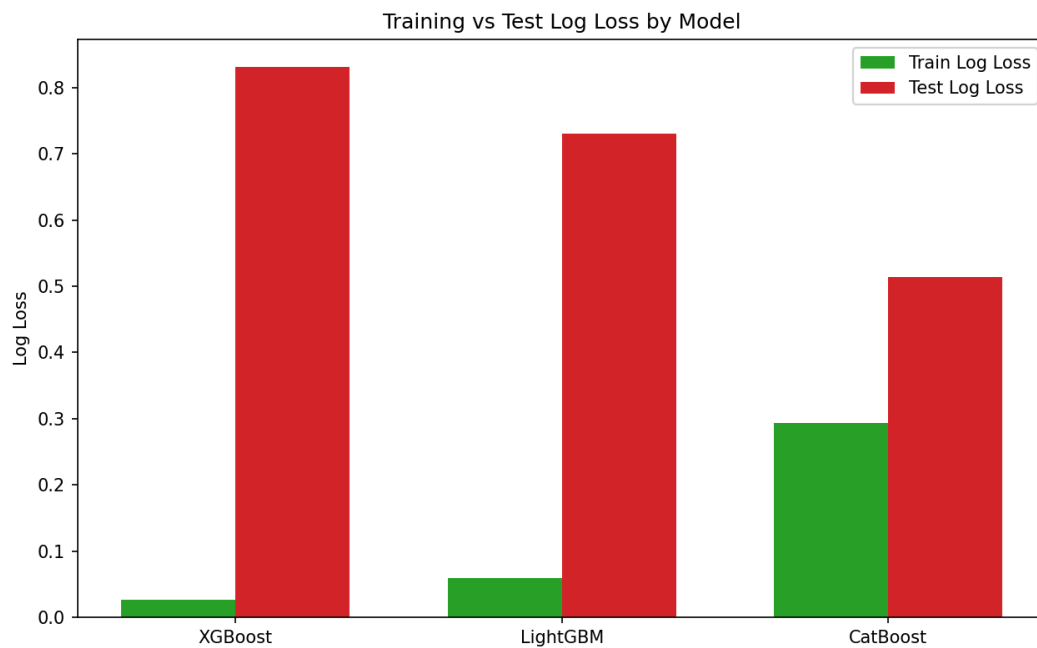


Max J XGBoost - 0.47

Max J LightGBM - 0.42

Max J CatBoost - 0.49





Best model based on test accuracy: **CatBoost**

References

1. **Git repository:**
<https://github.com/akshat-git/Pima-Indian-Diabetes-Inference-Supervised-Learning>
2. **Dataset:**
<https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database>