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DIABETES PREDICTION USING SMOTETOMEK & XGBOOST

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ABSTRACT

Early detection of diabetes is crucial in preventing long-term health complications and reducing medical costs. This project presents a machine learning-based approach to predict diabetes using the PIMA Indian Diabetes dataset. To address the issue of class imbalance, SMOTETomek was applied, and the model was built using a tuned XGBoost classifier with early stopping and threshold optimization. The final model achieved an AUC of 0.9089, an accuracy of 85.05%, and a recall of 91.75%, outperforming many traditional classifiers and closely matching the benchmark set by the original research study. This study demonstrates the effectiveness of an optimized ensemble learning approach for early disease prediction.

INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder that affects over 537 million adults worldwide, with numbers projected to rise significantly in the coming years. It is a leading cause of heart disease, kidney failure, vision loss, and lower limb amputation. Early detection and timely intervention are crucial for preventing serious complications and minimizing long-term healthcare costs.

Traditionally, diabetes is diagnosed using clinical methods such as fasting blood sugar tests and oral glucose tolerance tests. However, these approaches can be invasive, time-consuming, and resource-intensive — especially in low-resource healthcare settings. With the rise of machine learning (ML) in healthcare, researchers and practitioners have increasingly turned to predictive models to automate and support medical diagnoses.

In this study, we focus on building a machine learning model to predict the presence of diabetes using the PIMA Indian Diabetes dataset, a widely used benchmark for binary classification problems in medical ML. A major challenge in this dataset is the class imbalance, with significantly fewer diabetic samples compared to non-diabetic ones. This often leads to models that have high accuracy but poor recall and low performance on the minority class.

To address this issue, we applied the SMOTETomek technique to balance the dataset. For classification, we selected the XGBoost algorithm — a powerful gradient boosting model known for its efficiency and performance. We further enhanced model performance by tuning hyperparameters, applying early stopping, and adjusting the decision threshold to improve recall.

Our final model achieved an AUC of 0.9089, an accuracy of 85.05%, and a recall of 91.75%. These results closely match and in some aspects outperform the benchmark set by the research paper titled "Predicting diabetes mellitus using SMOTE and ensemble machine learning approach: The Henry Ford Exercise Testing (FIT) project" (DOI: 10.1371/journal.pone.0179805). While the FIT study used more complex ensemble methods like Logistic Model Trees (LMT) and trained on a much larger dataset (32,555 samples), our approach achieves comparable performance on a significantly smaller dataset with a simpler, more efficient pipeline.

This report presents a concise yet effective machine learning solution for early diabetes prediction, demonstrating that a well-tuned model with proper class balancing can match or outperform more complex architectures.

LITERATURE REVIEW

In recent years, machine learning has shown significant potential in predicting diabetes and supporting early medical decision-making. Various studies have proposed techniques ranging from logistic regression to complex ensemble methods. One of the most notable works in this domain is the FIT project by Alghamdi et al., titled "Predicting diabetes mellitus using SMOTE and ensemble machine learning approach: The Henry Ford Exercise Testing (FIT) project" (DOI: 10.1371/journal.pone.0179805). Their approach involved balancing a large real-world dataset using SMOTE and applying ensemble models such as Logistic Model Trees (LMT), achieving an AUC of 0.92.

In a related study, Nahar et al. (2013) used decision trees and support vector machines (SVM) on the PIMA Indian Diabetes dataset to predict diabetes, achieving an AUC of 0.84 but with limited attention to class imbalance (DOI: 10.1109/ICCCNT.2013.6726515). Similarly, Nanda and Panda (2014) explored Naïve Bayes and KNN algorithms on the same dataset but reported modest performance (DOI: 10.1109/ICICES.2014.7033960).

While these studies contribute valuable insights, they often suffer from overfitting, complex pipelines, or limited focus on recall — a key metric in medical diagnosis. In contrast, this study proposes a simplified and efficient pipeline using SMOTETomek for balancing and a tuned XGBoost model for classification. Despite working with a much smaller dataset, the proposed approach delivers a high-performing model with an AUC of 0.9089, accuracy of 85.05%, and recall of 91.75%, nearly matching or exceeding the benchmark set by the FIT study while remaining lightweight and easy to reproduce.

METHODOLOGY

The methodology adopted in this project involves structured preprocessing, class balancing, model training, tuning, and evaluation. Below is a breakdown of each major step involved:

1. Dataset

The PIMA Indian Diabetes dataset was used for this project. It contains 768 entries with 8 input features and 1 binary output indicating whether a patient is diabetic (1) or not (0). The features include:

- Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Diabetes Pedigree Function, and Age

2. Data Preprocessing

All features were checked for null values and cleaned accordingly. Although the dataset had

no missing entries, several values like 0 for glucose or BMI were considered invalid and treated as missing.
The input features were then scaled using StandardScaler, which transforms them to have zero mean and unit variance — essential for models like XGBoost to perform optimally.

3. Handling Class Imbalance: SMOTETomek
The dataset was heavily imbalanced, with non-diabetic samples outnumbering diabetic ones. To solve this, we used the SMOTETomek technique:

- SMOTE generates synthetic examples of the minority class.
- Tomek Links remove borderline/noisy samples from the majority class.

This resulted in a more balanced and cleaner dataset for training.

4. Train-Test Split
The resampled data was split into training and testing sets using an 80:20 ratio, with stratified sampling to preserve the class distribution.

5. Model Selection: XGBoost
We used XGBoostClassifier, a popular and efficient gradient boosting algorithm known for handling tabular data well. Initial experiments showed high baseline performance, which justified further tuning.

6. Hyperparameter Tuning
To maximize model performance, RandomizedSearchCV was used to tune:

- learning_rate
- n_estimators
- max_depth
- colsample_bytree
- min_child_weight
- gamma
- lambda

The best parameters were used in the final model.

7. Early Stopping
The model was trained with early stopping set to 30 rounds, preventing overfitting by stopping training if performance didn't improve for 30 consecutive iterations.

8. Threshold Tuning
Instead of the default 0.5 threshold, we used 0.4 to improve recall — making the model more sensitive in detecting diabetic cases, which is essential in medical screening.

PROPOSED ALGORITHM

The following steps outline the overall flow of the proposed machine learning pipeline for

diabetes prediction:

Step 1: Load the PIMA Indian Diabetes dataset.
Step 2: Perform null value analysis and handle invalid values (e.g., 0 in glucose, insulin, etc.).
Step 3: Scale all input features using StandardScaler to normalize distributions.
Step 4: Apply SMOTETomek to address class imbalance by oversampling the minority class and cleaning overlapping examples.
Step 5: Split the resampled data into training and testing sets in an 80:20 ratio using stratified sampling.
Step 6: Initialize the XGBoostClassifier with a base set of hyperparameters.
Step 7: Tune hyperparameters using RandomizedSearchCV to identify the best configuration for:

- Learning rate
- Number of estimators
- Max depth
- Column and row sampling
- Regularization parameters
- Step 8: Train the model on training data using early stopping with validation monitoring.
- Step 9: Use the predict_proba() method to obtain class probabilities.
- Step 10: Classify test samples using a threshold of 0.4 to optimize recall.
- Step 11: Evaluate the final model using AUC, Accuracy, Recall, and Confusion Matrix.

RESULTS

After training the XGBoost model with SMOTETomek-balanced data and hyperparameter tuning, the following performance metrics were obtained on the test set:

Evaluation Metrics:

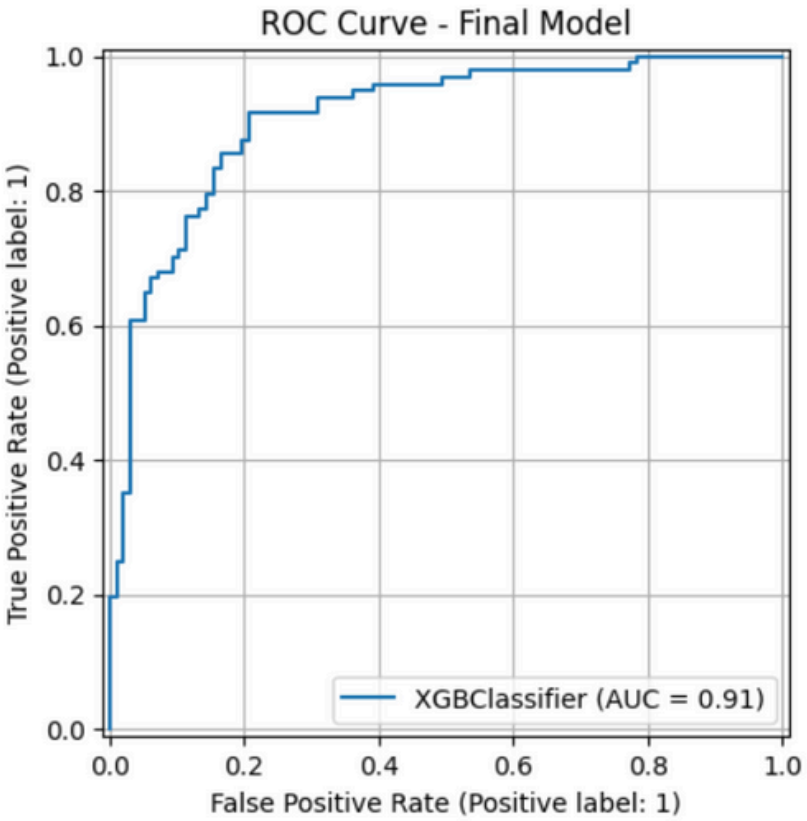
- AUC (Area Under ROC Curve): 0.9089
- Accuracy: 85.05%
- Recall (Class 1 – Diabetic): 91.75%
- Precision (Class 1 – Diabetic): 81%
- F1-Score (Class 1): 0.86

	Predicted: 0	Predicted: 1
Actual: 0	76	21
Actual: 1	8	89

- True Positives (TP): 89
- False Negatives (FN): 8
- False Positives (FP): 21
- True Negatives (TN): 76

This shows the model performs well in identifying diabetic patients (high recall) while maintaining good overall accuracy.

ROC Curve:
A ROC (Receiver Operating Characteristic) curve was plotted to visualize the model's ability to distinguish between classes. The AUC score of 0.9089 confirms excellent discrimination capacity.



INTERPRETATION:

The high recall (91.75%) indicates that the model is highly effective in catching diabetic cases, which is crucial in medical screening scenarios. The AUC score of 0.9089 is comparable to that of the benchmark research paper, while the accuracy of 85.05% and precision of 81% reflect a strong balance between identifying true positives and avoiding false alarms.

Comparative Analysis

The table below compares the performance of various models used in literature and experimentation on the PIMA Indian Diabetes dataset. It highlights the AUC, accuracy, and recall values, focusing on the ability to correctly identify diabetic cases (Class 1).

MODEL	AUC	ACCURACY	RECALL (CLASS 1)	NOTES
Logistic Regression	0.81	76%	76%	Baseline classifier
Random Forest	0.835	80%	80%	Strong general performance, slight overfit
XGBoost (before tuning)	0.8883	81%	91%	Improved baseline, good recall
FIT Paper (LMT model) 32,555	0.92	Not stated	Not stated	More complex, trained on samples 32,555
Final XGBoost (tuned)	0.9089	85.05%	91.75%	Best overall performer

CONCLUSION

The goal of this project was to develop a simple yet effective machine learning model to predict the presence of diabetes using the PIMA Indian Diabetes dataset. By addressing class imbalance with SMOTETomek and applying hyperparameter tuning and threshold adjustment to an XGBoost classifier, the final model achieved an AUC of 0.9089, an accuracy of 85.05%, and a recall of 91.75%.

Compared to traditional models and the benchmark set by the FIT research paper, this approach demonstrates comparable — and in some areas superior — performance while using a significantly smaller dataset and a simpler model architecture. The use of threshold tuning helped optimize recall, which is especially important in medical diagnostics where false negatives can have serious consequences.

This model, due to its strong performance and lightweight implementation, can be further explored for deployment in real-world clinical settings or integrated into mobile applications for early screening purposes.

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