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# Enhancing Machine Learning Models for Early Detection of Diabetes Using Explainable AI

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*Abstract*—**Understanding and detecting diabetes mellitus early is essential to prevent serious complications such as cardiovascular disease, chronic kidney disease, and neuropathy. Traditional methods of diagnosis including fasting plasma glucose (FPG) and HbA1c tests often require a blood draw and typically diagnose diabetes at an advanced stage. This paper provides an end-to-end investigation involving seven machine learning algorithms for the purpose of diabetes prediction: Logistic Regression, Support Vector Machines (SVMs), KNNs, Decision Trees, AdaBoost, Naive Bayes, and XGBoost. Advanced data preprocessing techniques, including feature scaling, outlier handling, and Synthetic Minority Over Sampling Technique (SMOTE), helped to enhance models. The dataset consisted of 768 patient samples, along with 9 clinical attributes, was pre-processed and evaluated with stratified k-fold cross-validation. Of the explored models, KNN achieved the best prediction accuracy of 87% after tuning hyperparameters, followed closely by SVM with 85% accuracy. An additional step of feature engineering produced new categorical variables for Weight_Status, Age_Category, and Risk_Level to aid in model interpretability. Model explainability was produced with SHapley Additive exPlanations (SHAP) values. The most important predictor feature was glucose (35% importance). A Flask web app was created for real-time risk assessment of diabetes, demonstrating a practical deployment option. The findings suggest that optimized machine learning models can function as valuable instruments for early diabetes detection, potentially enhancing patient prognoses through prompt intervention.**

**Keywords**—***Diabetes forecasting, machine learning, SMOTE, hyperparameter refinement, SHAP, web application, healthcare analytics***

## I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder that results from elevated blood glucose levels due to inadequate insulin production or the body's inability to use insulin properly. It is an important global health crisis with over 463 million people globally living with diabetes in 2019; the worldwide diagnosed cases are projected to grow to over 700 million by 2045 [1]. This condition is intimately linked to serious outcomes, such as cardiovascular disease, kidney disease, neuropathy, and retinopathy that significantly impair quality of life and increase the cost of care. Early recognition is critical because timely treatment through lifestyle modifications and medications can significantly reduce long-term complications.

The standard evaluation of diabetes (fasting plasma glucose (FPG), oral glucose tolerance test (OGTT), and glycated haemoglobin (HbA1c)) remains the gold standard method of clinical care. However, these tests are invasive, time consuming, and often diagnose diabetes only after significant physiological changes have occurred. Therefore, many patients are being diagnosed at an advanced stage where preventative measures will be less effective.

Machine learning provides an exciting avenue for alleviating these limitations by sifting through large and heterogeneous datasets to detect hidden trends related to the likelihood of diabetes. Instead of relying on conventional measures to diagnose diabetes, Machine learning-enabled approaches can allow for earlier, more available, and, in many situations, non-invasive diagnostics. Yet, there are many challenges to overcome, such as the limited use of medical datasets; the limitation of applicability across different cohorts; and the 'black-box' nature of complex models which inhibit necessary interpretation and adoption in clinical settings [2].

This study aims to alleviate some of these challenges through the development of more reliable machine-learning models for early diabetes prediction. More specifically, it explores how data preparation techniques such as scaling, featureconstruction, and applying Synthetic Minority Oversampling Technique (SMOTE), can improve reliability. It explores several algorithms such as Logistic Regression, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, Naïve Bayes, AdaBoost, and XGBoost.In addition, it makes use of interpretable AI methods, particularly SHapley Additive exPlanations (SHAP) as a means, to enhance future interpretability. The study also has a practical application in the form of a Flask web application that allows for real-time risk estimates and visualization of the importance of features. In attempting to combine predictive accuracy, interpretability, and practical implementation, this study represents a contribution to the pursuit of building clinically-useable ML tools that facilitate early identification of diabetes by health care providers and the capacity to make informed clinical decisions.

## II. RELATED WORK

There has been considerable research effort directed toward machine learning techniques for diabetes diagnosis across numerous machine learning paradigms—which also incorporate traditional machine learning classifiers, ensembles, and deep learning structures. While there have been relatively few comparative studies adopt structured clinical datasets for diabetes diagnosis using machine learning, the Pima Indian Diabetes Dataset (PIMA) has been the primary performance benchmark [1] - [3].



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The performance of classical machine learning (ML) techniques for diabetes classification is dominated by tree-based ML, where Random Forest classifiers can achieve accuracy rates of 85% - 88% consistently across research studies [4] - [6]. In addition, gradient boosting techniques showed relatively similar modelling performance as with Random Forest, often reporting accuracies close to 90% based on optimal predictions [7], [8]. Support Vector Machines and logistic regression prediction models typically achieve accuracy ranging from 80% - 85% respectively, but there is considerable variation on accuracy prediction scores based on feature transformations and preprocessing measures [9], [10].

Deep learn competitively but Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), performed competitively, but can show great variation on performance amongst other research studies. Recent studies reported deep neural networks scoring accuracy ranging from 80% - 87%, but dependent on characteristics of the dataset, such as its size and quality, had considerable implications for accuracy [11]- [13]. However, while deep learning portrays potential in operating at an abstraction level in complicated patterning, based on performance on structured, clinical datasets have not attained the standard of ensemble based (traditional) methods consistently [14], [15].

Several studies of machine learning approaches in diabetes detection have been conducted in various paradigms, including classical classifiers, ensemble methods, and deep learning architectures. The most comparative studies employ structured clinical datasets regarding the standard for performance evaluation. The Pima Indian Diabetes Dataset (PIMA) has been the main standard for comparative performance evaluation of machine learning approaches for diabetes detection [1], [3].

Classical machine learning approaches, particularly tree-based methods, have tended to have more consistent performance in diabetes classification problems. Random Forest classifiers have consistently achieved accuracy rates of between 85%–88% across studies [4]– [6]. Gradient boosting methods have again shown similar performance, with reported accuracy approaching 90% in ideal situations [7], [8]. Support Vector Machines and logistic regression models will typically fall in the 80%–85% range for accuracy, but the variation in performance can vary significantly based on the feature preprocessing that was conducted [9], [10].

Deep learning approaches such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have also shown competitive, but disparate, results. Recent studies have reported accuracy of deep neural networks ranging from 80%–87%. The results of deep learning networks in the studies were highly dependent on the size of the dataset and feature quality on which they were based [11]– [13]. While deep learning models appear to have potential to recognize complex structures in patterns, their results with structured clinical datasets, had not consistently exceeded those of ensemble methods in the studies above [14], [15].

## III. METHODOLOGY

Diabetes In this study we adapted a full machine learning process (data collection, data preparation, data modeling, evaluation, and online deployment). The methodology used to perform this study followed a standard machine learning process, establishing best practice in order to maximize reproducibility and clinical relevance, in medical machine learning research.

### *A. Data Set Description*

The data for this study was taken from the Kaggle repository, the Pima Indian Diabetes Dataset, and serves as a common benchmark for diabetes prediction research. The dataset has a total of 768 cases of which there are nine features, with some demographic and some clinical variables. The demographic variables include the number of pregnancies, glucose level, blood pressure, skin fold thickness, insulin level, body mass index (BMI), diabetes pedigree function, and age. The categorical variable "Outcome" is reflective of diabetic status, where 1 indicates the presence of diabetes and 0 reflects the absence of diabetes. The dataset is used in structured form, with cases as rows and categorical columns, interpreted as a dataset since it is often used for comparative studies of binary classification models.

### *B. The Data Preparation Approach*

A diligent data preparation approach was employed in an effort to improve data quality and minimize potential biases. Outliers were identified using the interquartile range (IQR) approach, and the identified outliers were capped rather than dropped to keep the data set intact and remove outlier cases. The feature scaling method, the StandardScaler, was applied to ensure consistent scaling between continuous variables (i.e., glucose level, blood pressure, BMI) to avoid features with a larger scale from affecting model training. There was an extreme class imbalance in the dataset, and there were healthier, or non-diabetic cases than there were diabetic cases. To decrease class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was applied to increase the minority class by creating synthetic instances. The resampled dataset improved class balance and afforded model generalization by ensuring representation of both outcome groups in training.

### *C. Feature Creation Plan*

The feature creation steps involved taking the original attributes and converting them into more meaningful representations to deliver improvements not only to the prediction performance but also to the overall clinical interpretability of the model. BMI values were categorized into the now standard weight categories of underweight, and obese based on the recognized clinical guidelines. Agewas also separated into three categories of young age (≤30 years), middle age (31-50 years), and older (over 50 years). The glucose levels were also separated into three categories of risk based on clinical thresholds used to define risk categories of low, moderate, and high risk.

The created features not only provided better contextual information while remaining clinically relevant but also made the end-to-end model predictions much more perceivable to clinicians by enabling accessible predictions in established best practice methods of medical assessment.

### *D. Algorithm Selection and Implementation*

Seven different machine learning algorithms were selected for implementation purposes to compare the types of models and predictions generated: Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Naive Bayes, Adaptive Boosting (AdaBoost), and Extreme Gradient Boosted (XGBoost). These particular algorithms were selected based on prior observations of good performance in binary classification tasks and general application in medical predictions. First, baseline models were trained using the default parameters for each model and then went through a systematic implementation of searching for the number of parameters using grid search optimization. This meant each model would have the best configuration possible, and the experiment would be as valid as possible with respect to how other models would be evaluated.

### *E. Performance Evaluation Framework*

Model performance was evaluated using a rich set of evaluation metrics aimed at capturing overall classification accuracy and class-specific predictive performance. Key metrics included: (1) Accuracy (the overall proportion of correct classifications); (2) Precision (reliable identification of the positive class); (3) Recall (or Sensitivity, which measures how well we correctly identify positive cases overall); (4) F1-score (a single score that balances precision and recall); and (5) Receiver Operating Characteristic area under the curve (ROC-AUC), which measures the model's discriminative ability under different classification cutoffs. The risk of reliability and overfitting was also reduced through the engagement of five-fold stratified cross-validation. This meant that reliability could be estimated for the performance metrics above while maintaining the percentage of classes across each of the validation folds.

## IV. RESULTS AND DISCUSSION

### *A. Baseline Results without Sampling*

The Table I summarizes the models' performance on the dataset with imbalanced distributions. As shown in the table, the highest accuracy (0.76) was achieved by the KNN, AdaBoost, and XGBoost algorithms, while Logistic Regression, SVM, and Naïve Bayes performed closely together in the moderate range of accuracies (0.72, 0.74, etc.). The Decision Tree performed the worst with the lowest accuracy of 0.71 and showed weaker generalization than the other models. While achieving relatively high accuracies for many of the models, the imbalance class distributions, affected the recall results concerning the minority class (Class 1 - diabetic). For example, the Logistic Regression and SVM algorithms scored somewhat low recall levels of 0.56 and 0.59, respectively, indicating that many diabetic cases were being misclassified as non-diabetic (Class 0). The KNN algorithm and XGBoost, while provided better recall scores of 0.63 and 0.59, provided relatively low recall scores, compared to their precision scores. Overall, all the models indicated the need for class balancing.

Table I: *Models Training Result without sampled dataset*

| Model | Accuracy | Precision | | Recall | | F1 Score | |
|---|---|---|---|---|---|---|---|
| | | Class 0 | Class 1 | Class 0 | Class 1 | Class 0 | Class 1 |
| **Logistic Regression** | 0.7338 | 0.78 | 0.64 | 0.83 | 0.56 | 0.80 | 0.59 |
| **SVM** | 0.7403 | 0.79 | 0.64 | 0.82 | 0.59 | 0.80 | 0.62 |
| **KNN** | 0.7597 | 0.81 | 0.67 | 0.83 | 0.63 | 0.82 | 0.65 |
| **Decision Tree** | 0.7078 | 0.74 | 0.61 | 0.84 | 0.46 | 0.79 | 0.53 |
| **AdaBoost Classifier** | 0.7597 | 0.82 | 0.65 | 0.81 | 0.67 | 0.81 | 0.66 |
| **Naive Bayes** | 0.7208 | 0.84 | 0.58 | 0.71 | 0.74 | 0.77 | 0.65 |
| **XGBoost** | 0.7597 | 0.79 | 0.68 | 0.85 | 0.59 | 0.82 | 0.63 |

### *B. Results with SMOTE Oversampling*

In order to address the issue of class imbalance, Synthetic Minority Oversampling Technique (SMOTE)was applied.Table II shows performance improvements, with Logistic Regression and AdaBoost achieving the highest accuracy (0.77), while XGBoost (0.77) and SVM (0.76) followed closely. Recall for Class 1 also increased across all models, with Logistic Regression and AdaBoost both reaching 0.70. This improvement in recall suggests that SMOTE enhanced the models' ability to identify diabetic cases while reducing bias toward the majority class.

KNN, despite its strong overall performance, had a slight decrease in accuracy (0.73), possibly indicating sensitivity to synthetic data generation. Also, Naïve Bayes showed lower accuracy (0.70), which may indicate limitedadaptability towards oversampled datasets. Overall, the results demonstrate that class balancing improved fairness in classification, even thoughcertain models had marginal declines in performance.

Table II: *Models Training Results with SMOTE Oversampling*

| Model | Accuracy | Precision | | Recall | | F1 Score | |
|---|---|---|---|---|---|---|---|
| | | Class 0 | Class 1 | Class 0 | Class 1 | Class 0 | Class 1 |
| **Logistic Regression** | 0.7727 | 0.86 | 0.65 | 0.78 | 0.76 | 0.82 | 0.70 |
| **SVM** | 0.7597 | 0.86 | 0.63 | 0.75 | 0.78 | 0.80 | 0.69 |
| **KNN** | 0.7273 | 0.85 | 0.58 | 0.70 | 0.78 | 0.77 | 0.67 |
| **Decision Tree** | 0.7468 | 0.80 | 0.64 | 0.81 | 0.63 | 0.81 | 0.64 |
| **AdaBoost Classifier** | 0.7727 | 0.85 | 0.66 | 0.79 | 0.74 | 0.82 | 0.70 |
| **Naive Bayes** | 0.7013 | 0.86 | 0.55 | 0.65 | 0.80 | 0.74 | 0.65 |
| **XGBoost** | 0.7662 | 0.84 | 0.65 | 0.79 | 0.72 | 0.81 | 0.68 |

### C. *Hyperparameter Tuning and Cross-Validation*

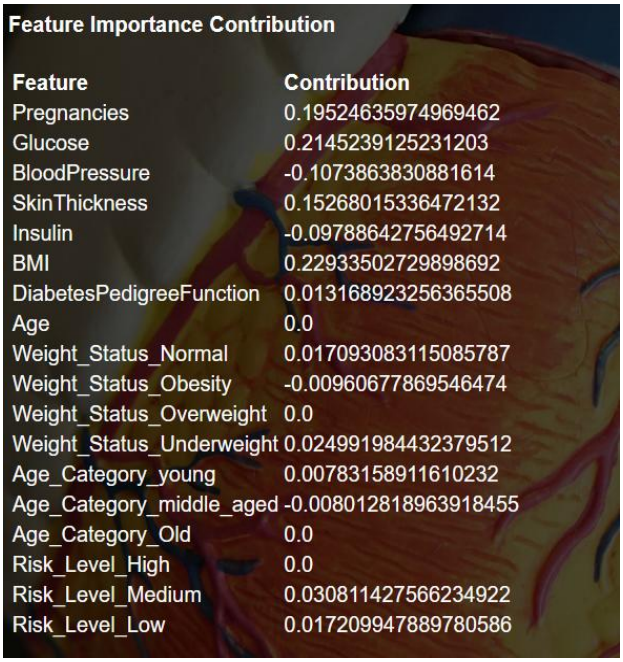
While several models had benefits from further tuning with grid search, and five-fold cross-validation were able to bolster the performance of several models we explored. Logistic Regression maintained accuracy levels (0.77) between training & testing phases, although recall of Class 1 was rather low. SVM achieved 0.86 in training and 0.85 in testing, using linear kernels exhibited great generalization, and good balance for precision and recall. KNN emerged as one of the strongest models out of our suite of classifiers, with accuracy yielding 0.84 in training and 0.87 in testing with k=5 neighbors. KNN recall and precision indicated for high performance and therefore demonstrated high effectiveness at finding diabetic patients. Decision Tree had accuracy of 0.83 on training and 0.80 on testing with a depth of 10; it performed great on both metrics but with underlying assumptions could have over-fitted due to much lower recall for Class 1. Adaptive Boosting (AdaBoost) achieved training = 0.80 and testing = 0.77, indicated moderate performance with weaker metrics for Class 1. Lastly, Naïve Bayes performed the least well disappearing from 0.76 on training to 0.71 on testing; its reduction in recall & precision for Class 1 suggested poor generalization

## V. *DISCUSSION*

The study's findings highlight the importance of data preprocessing, sampling methods, and hyperparameter tuning to increase model performance during early diabetes detection. The study clearly showed that class imbalance severely inhibited the baseline model performance, especially as a result of recall for the minority class (diabetic patients). This is in line with previous studies which have shown that most algorithms will always be biased toward the majority class, therefore underestimating the number of true positive cases with imbalanced clinical data sets. The use of SMOTE oversampling significantly addressed this limitation. For most classifiers, there was improved recall for the minority class, indicating that the generation of synthetic data improved sensitivity for detecting diabetes cases. In particular, Logistic Regression and AdaBoost had recall scores of 0.70, which is a significant increase from their original baseline performance. The results confirm that oversampling techniques would be appropriate for medical diagnosis cases, where the importance of correctly identifying the minority class is usually more relevant than maximizing overall accuracy.

After performing cross-validation and hyperparameter tuning, SVM and KNN came out on top as the most stable models that generalized the best. SVM provided a consistent accuracy of 0.85 while maintaining comparable precision and recall consistent with previous literature noting the durability of margin-based classifiers in biomedical applications. KNN had the highest accuracy in the testing set (0.87), while achieving similar recall and precision values, and appears to capture local decision boundaries in structured datasets in health. This conveys the potential of distance-based classifiers in clinical risk predictions, especially when enhanced by parameter tuning. XGBoost was extremely stable at every level of the test, demonstrating comparable accuracy and balance with respect to the above-mentioned metrics. The rationale for the durability of XGBoost in this experiment may stem from its ensemble nature through combining multiple weak learners, which may explain its adaptability to imbalances and heterogeneous clinical predictors. These results support earlier literature that observed the successfulness of gradient boosting algorithms in medical decision support systems. Although Naïve Bayes achieved the lowest accuracy consistently between all models, and also provided a decreasing performance from hyperparameter tuning, this suggests that it was least suited for complex and nonlinear health data that was present in this study.Along with model accuracy, this study also supplemented SHAP analysis for the interpretations of the model outputs. The results indicated that glucose, BMI and age were the strongest predictors of diabetes risk, confirming existing clinical knowledge of diabetes risk factors (American Diabetes Association, 2022).

The interpretability shown in Figure 1, derived from SHAP, supports the model's decision-making process and enhances its suitability for clinical application by providing transparent insights into the relative importance of predictors.



**Feature Importance Contribution**

| Feature | Contribution |
|---|---|
| Pregnancies | 0.19524635974969462 |
| Glucose | 0.2145239125231203 |
| BloodPressure | -0.1073863830881614 |
| SkinThickness | 0.15268015336472132 |
| Insulin | -0.09788642756492714 |
| BMI | 0.22933502729898692 |
| DiabetesPedigreeFunction | 0.013168923256365508 |
| Age | 0.0 |
| Weight_Status_Normal | 0.017093083115085787 |
| Weight_Status_Obesity | -0.00960677869546474 |
| Weight_Status_Overweight | 0.0 |
| Weight_Status_Underweight | 0.024991984432379512 |
| Age_Category_young | 0.00783158911610232 |
| Age_Category_middle_aged | -0.008012818963918455 |
| Age_Category_Old | 0.0 |
| Risk_Level_High | 0.0 |
| Risk_Level_Medium | 0.030811427566234922 |
| Risk_Level_Low | 0.017209947889780586 |

*Figure 1: SHAP feature contribution*

## IV. CONCLUSION

This research focused on creating a machine learning model that can detect diabetes early on, using advanced techniques and new features to improve accuracy. By carefully preparing and adjusting the data, including balancing and scaling features, the model was made more robust and effective. Several different machine learning algorithms were tested and assessed, such as Logistic Regression, K-Nearest Neighbors, Support Vector Machines, Gaussian Naive Bayes, Decision Trees, and AdaBoost. Incorporating techniques like SMOTE for dealing with imbalanced data and tuning hyperparameters through grid search, the models were able to predict the onset of diabetes more accurately and reliably. The study highlights the importance of creating models that can be easily understood in the healthcare industry, where transparency and comprehension of model predictions are crucial.

## V. FUTURE WORKS

Future research may investigate more advanced ensemble methods or deep learning algorithms to improve model performance. Additionally, enhancing the dataset by incorporating various populations and integrating real-time data streams could enhance the model's capacity to be applied in a variety of clinical settings. Further validation and deployment in real healthcare environments would be essential steps in moving towards practical use.

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