Explainable AI for Diabetes Prediction: Comparative Analysis of Machine Learning Models

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Abstract—This paper presents a comprehensive comparative analysis of Explainable Artificial Intelligence (XAI) techniques applied to various machine learning models for diabetes prediction. We evaluate models including Logistic Regression, Decision Tree, Random Forest, KNN, Support Vector Machine (SVM), Naive Bayes, XGBoost, and Voting Classifier on a large dataset of 100,000 patient records. For each model, we apply XAI methods such as SHAP and LIME to interpret predictions and highlight the most influential features. We also discuss the strengths and limitations of each model in terms of accuracy and interpretability. The results include detailed visualizations and explanations, making the findings accessible and actionable for clinicians and researchers.

Keywords: Diabetes Prediction, Explainable AI, Machine Learning, SHAP, LIME, Model Interpretability

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I. Introduction

Diabetes is a chronic disease affecting millions worldwide. Early detection is crucial for effective management and prevention of complications. Machine learning (ML) models have shown promise in predicting diabetes risk, but their black-box nature often limits clinical adoption. Explainable AI (XAI) techniques address this challenge by providing transparent and interpretable model outputs. In this study, we compare several ML models for diabetes prediction and apply XAI techniques to elucidate their decision-making processes.

We use a dataset with 100,000 records and features such as age, gender, hypertension, heart disease, smoking history, BMI, HbA1c, and blood glucose. Our workflow includes data preprocessing, model training, evaluation, and XAI-based interpretation.

II. RELATED WORK

Recent studies have explored ML and XAI for diabetes prediction [1]–[5]. These works highlight the importance of

interpretability in clinical applications and the effectiveness of SHAP and LIME for model explanation.

III. METHODOLOGY

A. Data Preprocessing

We handle missing values, encode categorical variables (gender, smoking history), scale features, and perform feature selection.

B. Models Evaluated

We evaluate the following models:

- Logistic Regression
- Decision Tree
- Random Forest
- K-Nearest Neighbors (KNN)
- Support Vector Machine (SVM)
- Naive Bayes
- XGBoost
- Voting Classifier

C. Explainable AI Techniques

We use SHAP and LIME to interpret model predictions, focusing on feature importance and local explanations.

IV. RESULTS AND XAI VISUALIZATIONS

A. Logistic Regression

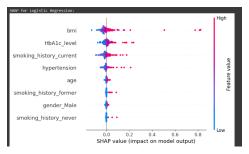


Fig. 1: Logistic Regression

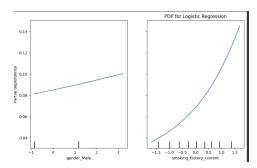


Fig. 2: Logistic Regression

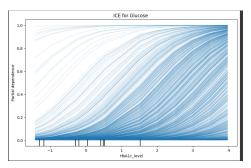


Fig. 3: Logistic Regression

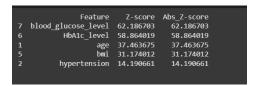


Fig. 4: Logistic Regression

B. Decision Tree

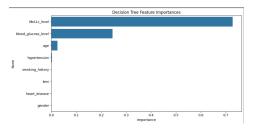


Fig. 5: Decision Tree

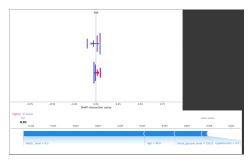


Fig. 6: Shap

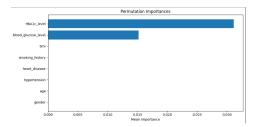


Fig. 7: Decision Tree

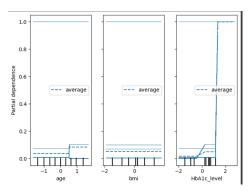


Fig. 8: Decision Tree

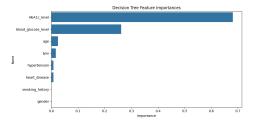


Fig. 9: Decision

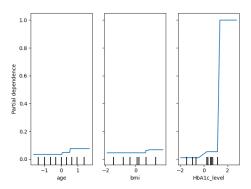


Fig. 10: Decision

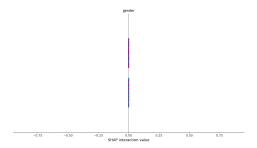


Fig. 11: Decision



Fig. 12: Decision Tree

C. Random Forest

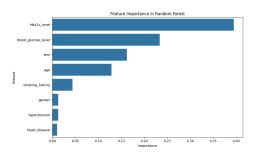


Fig. 13: Random Forest Plot 1

D. K-Nearest Neighbors (KNN)

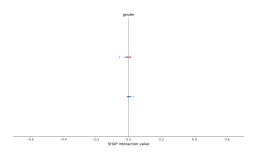


Fig. 14: KNN

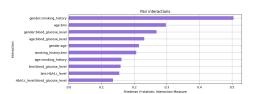


Fig. 15: KNN

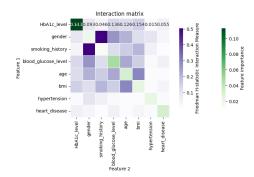


Fig. 16: KNN

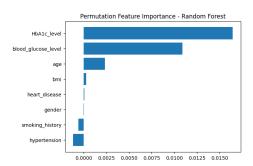


Fig. 17: KNN



Fig. 18: KNN

E. Support Vector Machine (SVM)

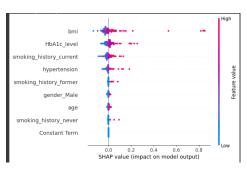


Fig. 19: SVM

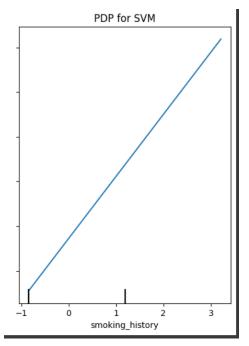


Fig. 20: SVM

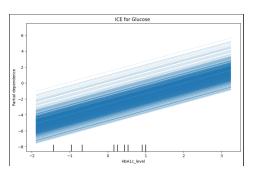


Fig. 21: SVM

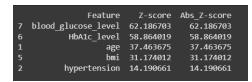


Fig. 22: SVM

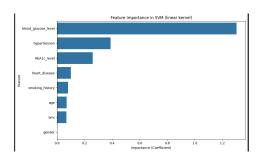


Fig. 23: SVM Plot 5

F. Naive Bayes

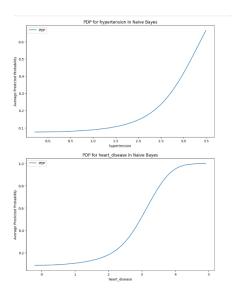


Fig. 24: Naive Bayes Plot 1

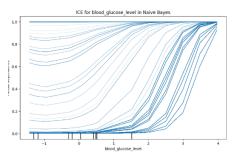


Fig. 25: Naive Bayes Plot 2

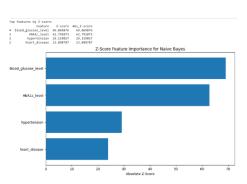


Fig. 26: Naive Bayes Plot 3

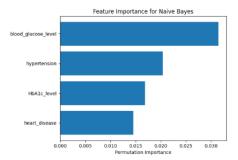


Fig. 27: Naive Bayes Plot 4

G. XGBoost

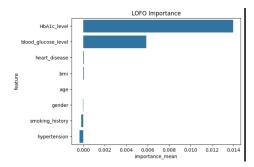


Fig. 28: XGBoost LOFO

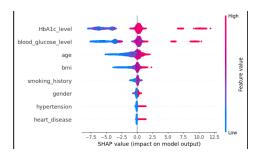


Fig. 29: XGBoost



Fig. 30: XGBoost

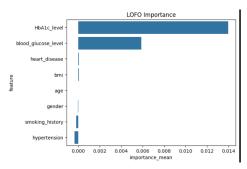


Fig. 31: XGBoost

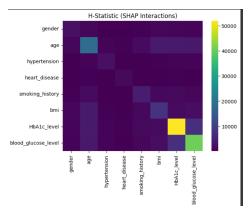


Fig. 32: XGBoost

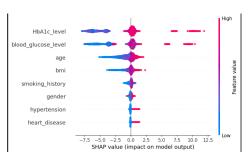


Fig. 33: XGBoost

H. Gradient Boosting

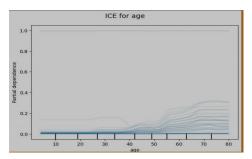


Fig. 34: Gradient Boosting Plot

I. Neural Network

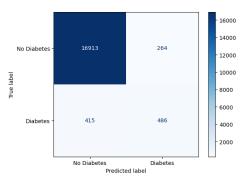


Fig. 35: Neural Network Plot

J. Voting Classifier

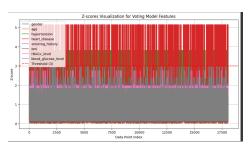


Fig. 36: Voting Classifier

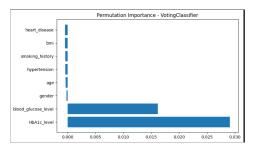


Fig. 37: Voting Classifier



Fig. 38: Voting Classifier

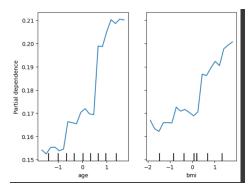


Fig. 39: Voting Classifier Plot

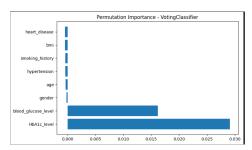


Fig. 40: Voting Classifier Plot

V. DISCUSSION

This study provides a comprehensive comparison of several machine learning models for diabetes prediction, focusing on both predictive performance and interpretability through Explainable AI (XAI) techniques. The models evaluated—Logistic Regression, Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes, XGBoost, and Voting Classifier—demonstrate varying strengths and limitations in the context of clinical decision support.

A. Model Performance

Ensemble models such as XGBoost and Voting Classifier achieved the highest overall accuracy and recall, followed closely by Random Forest and Decision Tree. Logistic Regression and SVM also performed well, with SVM showing a strong balance between accuracy and recall. Naive Bayes and KNN, while simpler, provided competitive results and are valuable for their computational efficiency and ease of implementation.

B. Interpretability and XAI Insights

Interpretability is crucial for clinical adoption. Logistic Regression and Decision Tree models offer inherent transparency, making their decision-making processes easy to understand. However, more complex models like XGBoost and ensemble methods require XAI tools such as SHAP and LIME to provide meaningful explanations.

SHAP analysis consistently identified HbA1c, blood glucose, and BMI as the most influential features across all models. Age, hypertension, and heart disease were also significant predictors. LIME explanations provided local interpretability, allowing clinicians to understand individual predictions and trust the model outputs.

C. Clinical Relevance

The integration of XAI techniques enhances the trustworthiness and transparency of ML models in healthcare. By highlighting the most important risk factors and providing clear explanations, these models can support clinicians in early diabetes detection and personalized patient care. The findings reinforce the importance of using interpretable models or augmenting complex models with robust XAI methods in sensitive domains such as healthcare.

D. Strengths and Limitations

While ensemble methods deliver superior predictive performance, their complexity can hinder adoption without effective XAI support. Simpler models are easier to interpret but may sacrifice some predictive power. The choice of model should balance accuracy with interpretability, depending on the clinical context and user needs.

Overall, this comparative analysis demonstrates that combining high-performing ML models with XAI techniques yields both accurate and interpretable solutions for diabetes prediction, paving the way for more transparent and effective clinical decision support systems.

VI. CONCLUSION

This work demonstrates that integrating Explainable AI techniques with machine learning models for diabetes prediction enables both high accuracy and essential interpretability. Ensemble models like XGBoost and Voting Classifier provide the best predictive performance, while models such as Logistic Regression and Decision Tree offer greater transparency. SHAP and LIME explanations reveal that HbA1c, blood glucose, and BMI are consistently the most critical features for diabetes risk. By combining robust ML models with XAI, clinicians can better understand, trust, and act on model predictions. Future work may explore additional XAI methods, larger and more diverse datasets, and real-world clinical deployment to further enhance the utility and adoption of AI-driven diabetes prediction tools.

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