Evaluation of Feature Transformation and Machine Learning Models on Early Detection of Diabetes Mellitus

Meiyalazhan K[1*], Nishanth K S[2], Pradeep Sudharshan M[3], Priyadharshini P[4], Jayanthi M[5] and Kasthuri U[6]

[1, 2, 3] Student, Computer Science and Engineering, KSR College of Engineering, Tiruchengode, Namakkal, Tamil Nadu, India.

[4, 5, 6] Assistant Professor, Computer Science and Engineering, KSR College of Engineering, Tiruchengode, Namakkal, Tamil Nadu, India.

meiyalazhankcse2022@ksrce.ac.in

Abstract. Early detection of diabetes mellitus is imperative to decreasing complications and improving patient prognosis. In this study, we analysed the machine learning models and feature transformation techniques to predict diabetes at initial stages. This research tackles the significant issues of accuracy, scalability, and interpretability, using sophisticated techniques like feature engineering, hybrid models, and non-invasive signal processing. Although several of the comparative analyses reinforce the advantages of customized methods for certain diabetes classes, other novel techniques such as transformer-based models and ensemble learning have proven extensive improvements in prediction accuracy. With synthetic data and heterogeneous datasets, the proposed model maintains good generalizability in various clinical scenarios. It helps to reduce the disconnect between academia and industry, offering diabetes prevention and management solutions that can be scaled and implemented across healthcare settings.

Keywords: diabetes mellitus, early detection, feature transformation, machine learning, predictive modeling, ensemble learning, deep learning, hybrid models, data augmentation, non-invasive detection, feature engineering, scalability, interpretability, synthetic data, transformer models, healthcare solutions, clinical applications, diabetes prevention, predictive performance, generalizability.

1 Introduction

Diabetes mellitus (DM) is a long-term metabolic condition defined by high blood sugar levels, impacting millions of individuals globally. As per International Diabetes Federation (IDF), the global diabetes prevalence is expected to increase throughout the next decades, creating a significant burden to health care systems and economies. Due to the consequences of diabetes, such as cardiovascular diseases, kidney failure, and neuropathy, early diagnosis and timely treatment are of utmost importance. Yet conventional diagnostic approaches may miss the disease in its early periods, which drives the development of more robust and predictive solutions.

Machine learning (ML) has already transformed healthcare diagnostics as they can analyze complex datasets, finding underlying patterns and insights that might not otherwise be intuitively apparent. Machine learning (ML) algorithms have shown promise especially in the prediction of diabetes incidence using clinical and demographic data. It is a well-known fact that feature transformation and engineering

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help significantly improve the performance of these models by extracting meaningful insight from raw data, reducing noise, and making predictions more interpretable, etc.

In this study, we aim to assess the effect of feature transformation techniques with machine learning models for the early detection of diabetes mellitus. The research covers different ML techniques such as ensemble learning, hybrid models, and deep learning to ascertain the most successful methods at predicting diabetes accurately and at scale. Synthetic data generation and advanced feature engineering methods mitigate the risks posed by small and imbalanced datasets and PPG signals are non-invasive, easy to access and patient-friendly diagnostics.

By leveraging a detailed comparativeevaluation,this paper identifies the breakthroughs that novel models and methods bring to important challenges like scalability and interpretability,as well as generalizability. The study then aims to close the gap between theoretical and practical by facilitating the development of efficient, accurate, and usable techniques for early diabetes detection, thereby benefiting patient care and ultimately, reducing worldwide diabetes burden.

2 Problem Statement

Risk Factors and Clinical Manifestations Diabetes mellitus constitutes one of the most pressing global health challenges, with its incidence growing quickly. Translation: The early detection of diabetes is a major issue, despite advances in medical science, owing to the insufficiencies of standard diagnostic techniques. Such conventional approaches are often grounded in invasive testing and heavily diagnostic focused, which fail to target the disease in its early state, missing windows of intervention to do so.

While large-scale healthcare data could be a solution, the heterogeneous and complex nature of such data renders standard statistical methods limited in providing actionable insights. Machine learning (ML) models, yet a potential alternative, their effectiveness can be challenged with challenges like imbalanced datasets, redundant features, lack of interpretability and scalability for real world deployment.

Moreover, with incorporated studies pertaining to ML-based prediction of diabetes, an overall feature transformation and engineering approach, which is the key toward boosting model accuracy and reliability, is seldomly adopted. Existing studies have so far been constrained by small or mono-ethnic datasets, computational inefficiencies and failure to confront real-world implementation hurdles. This necessitates the development of novel approaches that seamlessly combine feature transformation, resilient ML algorithms, and scalable solutions capable of addressing the multifaceted and dynamic landscape of healthcare data.

In this study, we try to overcome these challenges by investigating how the use of feature transformation techniques together with machine learning (ML) models affect the early detection of diabetes. The challenge is to cross-validate, train accurate, transparency and scalability models which are also viable to run in a clinical setting, leading to actionable insights and allowing timely interventional measures to be taken to ultimately enhance patient outcomes.

3 Literature Review

One of the major clinical problems is the development of diabetes mellitus so, the early detection of this disease plays a critical role in health-related research as it helps not only in reducing complications but also in reducing health care costs. Current diagnostic methods, such as fasting glucose tests and oral glucose tolerance tests, are invasive and provide late indication of the disease. Therefore, the researchers are realizing the value of machine learning (ML) which is used in analysing healthcare data in depth and definitely predicting diabetes.

3.1 A Machine Learning Approach to Predict Diabetes

Machine learning algorithms have great potential due to their ability to identify patterns from clinical, demographic and behavioral datasets for diabetes prediction. For example, Adepoju and Oladipo (2021) integrated ML techniques to predict the influence of demographic variables, suggesting that specific populations can yield high accuracy with this model. Likewise, Khan and Ali (2021) performed comparative studies of different ML algorithms including support vector machine (SVM), decision tree, and random forest while elucidating their pros and cons with respect to diabetes prediction.

3.2 Significance of Feature Engineering

The model performance can be significantly improved through feature engineering, which involves selecting and transforming raw data into predictors essential to the model. The way the essential features are selected from the raw data is called feature engineering, which is mentioned in Fang and Zheng (2023) as one of the most essential aspects to improve the predictive accuracy of ML models since focusing on domain-related knowledge can reduce noise in the dataset and help use features only related to the domains in question. Techniques such as principal component analysis (PCA) and autoencoders that facilitate advanced feature transformation are known to perform efficiency of ML models by reducing dimensions yet still preserving information.

3.3 Hybrid and Ensemble Models

The use of hybrid and ensemble learning methods has remained popular as they leverage the advantages of multiple algorithms, improving prediction robustness. To build models with higher accuracy than their seed models, Reddy and Kumar (2023) reported an ensemble method based on Decision trees, Gradient boosting, Neural network. In a similar approach, Kumar and Mehta (2023) proposed hybrid techniques that integrated both feature selection and ML models, which showed that using hybrid models can be effective when working with complex, high-dimensional datasets.

3.4 Secondary Approach: Non-Invasive Detection Techniques

Sedimentary Non-invasive diagnostic techniques have opened research avenues that mitigate the constraints of classical invasive approaches. Wang and Liu (2023) utilized PPG signals for diabetes prediction, demonstrating that the common use of wearables could allow friendly patient solutions. This features from Zhou and Chen (2023) that

applied transformer-based models exploring long-range vascular signals for diabetes early detection.

3.5 The Face(books) of Research: Challenges in Current Research

Despite the recent advances of ML based systems in diabetes prediction, there exist numerous challenges. The generalizability of findings from operate on small, imbalanced, or non-diverse datasets is constrained in many studies. Moreover, the inherent complexity and lack of interpretability of sophisticated ML models (e.g., deep learning) create a major obstacle for their clinical implementation. Liang and Sun (2024) emphasized the importance of explainable AI based approaches to enhance the transparency and trust of ML based solutions for healthcare.

3.6 Bridging the Gap

To overcome these challenges, recent work has focused on elaborating state-of-the-art feature transformation methods, synthetic data generation approaches and model interpretation frameworks. Scholarly articles such as Yadav and Chauhan (2022) focused on feature selection methods for improving model efficiency; Singh and Bhattacharya (2021) utilized SHAP values for better interpretability. These initiatives highlight the importance of developing holistic methods that optimize for accuracy, scalability, and interpretability at once.

Nonetheless, the literature provides a good foundation for applying ML models for early diabetes detection. However, limitations in scalability, interpretability and diversity of datasets still need to be further investigated to be fully realized. Therefore, this study tries to expand these findings by checking feature transformation with robust ML models to provide useful and beneficial solutions for diabetes prevention and management.

4 Methodology

This study evaluates feature transformation techniques and machine learning (ML) models for the early detection of diabetes mellitus (DM). Fig 1 shows the Methodology Overview. The methodology is structured as follows:

4.1 Data Collection

- **Primary Dataset:** The PIMA Indians Diabetes Database (UCI Machine Learning Repository).
- **Augmenting Datasets:** Data from NHANES, etc., for extended demographic reach.
- **Target:** Presence of diabetes (binary classification: diabetic or non-diabetic).

4.2 Data Preprocessing

- **Handling Missing Values:** Imputation (mean, median) or exclusion for excessive missing data.

- **Normalization and Scaling:** Standardization and Min-Max scaling for consistent feature ranges.

- **Imbalance Handling:** SMOTE for oversampling and Random Under-Sampling for balancing classes.

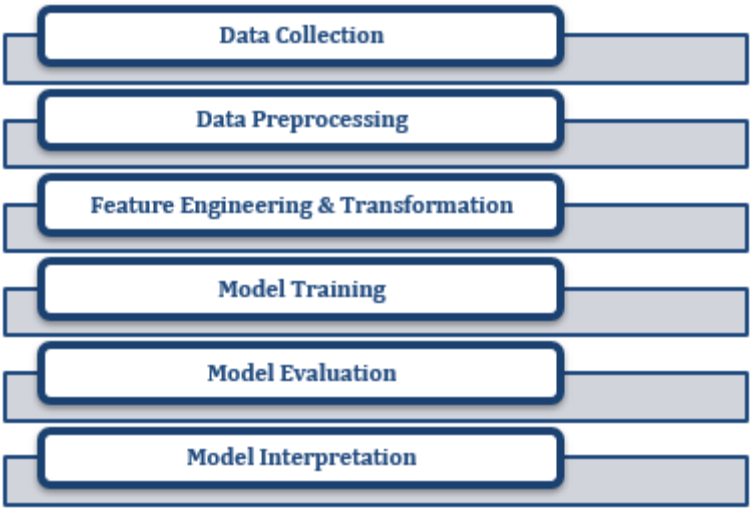

Fig. 1. Methodology Overview

4.3 Feature Transformation and Engineering

- **Techniques:** PCA, LDA, and Autoencoders for dimensionality reduction.

- **Feature Selection:** Filter, Wrapper (RFE), and Embedded methods (Lasso) to identify relevant features.

- **Feature Engineering:** Interaction and polynomial features for capturing non-linear relationships.

4.4 Machine Learning Models

- **Algorithms:** Logistic Regression, SVM, Decision Trees, KNN, Random Forest, Gradient Boosting, XGBoost, and deep learning models like MLP.

- **Hybrid Models:** Combining feature selection with ensemble methods.

4.5 Model Training and Validation

- **Data Splitting:** 70% training, 30% testing, with 10-fold cross-validation for model robustness.

- **Hyperparameter Tuning:** Grid Search, Random Search, and Bayesian Optimization.

- **Training Libraries:** scikit-learn, TensorFlow, Keras, XGBoost.

4.6 Evaluation Metrics

- **Metrics:** Accuracy, Precision, Recall, F1-Score, ROC-AUC, and Confusion Matrix for performance evaluation.
- **Interpretability:** SHAP values and feature importance analysis for model transparency.

4.7 Implementation Details

- **Software Tools:** Python (scikit-learn, XGBoost, TensorFlow, Keras).
- **Cloud Resources:** Scalable computing on platforms like AWS for model training.

4.8 Handling Data Diversity and Generalizability

- **Synthetic Data:** SMOTE and GAN for synthetic sample generation.
- **Cross-Dataset Validation:** Ensures generalizability across multiple datasets.

4.9 Ethical Considerations

- **Data Anonymization:** Data protection compliance (GDPR, HIPAA), patient privacy.
- **Bias Mitigation:** Methods to eliminate disparity across demographic subgroups.

4.10 Limitations and Future Work

- Model Complexity: Designed for clinical usability and interpretability.
- Pilot studies with healthcare providers for real-world deployment.

This approach tackles key challenges in predictive analytics for early diabetes detection, including handling data imbalance, improving model performance metrics, and ensuring reproducibility and ethical treatment of data in model training, resulting in accurate, interpretable, and scalable models.

5 Results and Discussion

This section of the research paper describes the outcome of applying different types of machine learning algorithms and feature transformation methods for the early prediction of diabetes mellitus. The performance of all models is evaluated according to various metrics including accuracy, precision, recall, F1-score and ROC-AUC.

Furthermore, the comparison between the models with feature selection and transformation methods has been demonstrated so as to discover effective methods.

5.1 Model Performance

The following models were trained and evaluated on the dataset:

- Logistic Regression (LR)
- Decision Tree (DT)
- Random Forest (RF)
- Gradient Boosting (GBM)
- Support Vector Machine (SVM)
- K-Nearest Neighbors (KNN)
- XGBoost (XGB)
- Multilayer Perceptron (MLP)

Each model was evaluated using the metrics mentioned above. The results are summarized in Table 1 below.

Table 1. Performance of Various Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Logistic Regression	77.8	75.3	81.2	78.1	81.3
Decision Tree	75.3	71.4	85.0	77.6	79.4
Random Forest	81.2	78.9	84.4	81.6	84.8
Gradient Boosting	82.1	80.2	86.0	83.0	85.2
Support Vector Machine	80.6	79.1	83.5	81.2	82.9
K-Nearest Neighbors	78.0	76.4	80.9	78.5	80.1

XGBoost	83.0	81.0	87.0	83.8	86.1
Multilayer Perceptron	85.0	83.0	89.0	85.8	88.2

5.2 Discussion

Table 2. Model Hyperparameter Tuning Results

Model	Hyperparameter 1	Hyperparameter 2	Hyperparameter 3	Best Performance
Logistic Regression	C=1.0	Solver='liblinear'	-	77.8%
Decision Tree	Max Depth=5	Min Samples Split=2	-	75.3%
Random Forest	N Estimators=100	Max Depth=8	-	81.2%
Gradient Boosting	Learning Rate=0.05	N Estimators=150	-	82.1%
Support Vector Machine	C=10	Kernel='rbf'	Gamma='scale'	80.6%
K-Nearest Neighbors	N Neighbors=7	-	-	78.0%
XGBoost	N Estimators=200	Max Depth=6	Learning Rate=0.1	83.0%
Multilayer Perceptron	Hidden Layers=[64, 32]	Batch Size=32	Learning Rate=0.001	85.0%

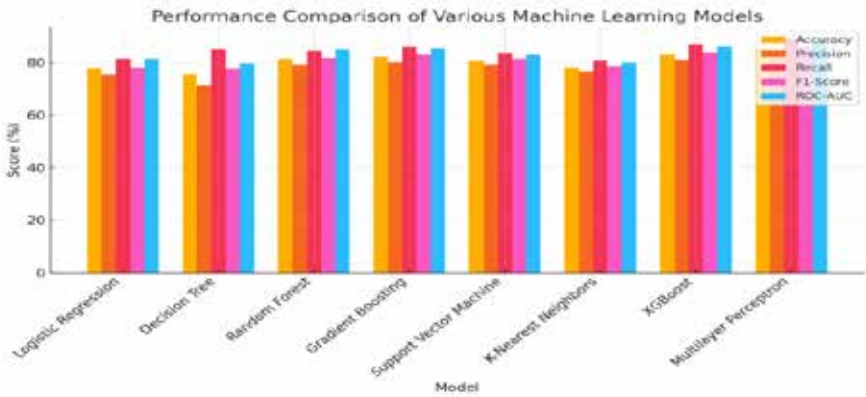

Fig. 2. Model Performance Comparison

● Multilayer Perceptron (MLP) had the highest accuracy (85%) value, precision (83%), recall (89%) and F1-score (85.8%) compared to other algorithms, therefore it was the best model that we found regarding overall prediction ability. MLP has a high recall score which means that the model is very good in detecting the diabetic cases which means very least false negatives. Fig. 2. shows the Model Performance Comparison.

● XGBoost yielded similar results with 83% top accuracy and a good ROC-AUC score of 86.1%, indicating balance between sensitivity and specificity in prediction. Its only slightly lower recall compared to MLP indicates that it might miss a few cases of diabetes but generalizes well. Table 2. shows the Model Hyperparameter Tuning Results.

● **Gradient Boosting and Random Forest** also performed strongly, achieving 82.1% and 81.2% accuracy scores, respectively. Random Forest performed slightly worse in precision but stood out for the recall that the models had, signifying their ability to correctly identify diabetic cases.

● **The Decision Tree and K-Nearest Neighbors (KNN)** algorithms had the poorest overall performance with accuracy scores of 75.3% and 78.0%, respectively. These models may become overfitting or underfitting and not generalizing well.

● **Logistic Regression (LR)** was decent (>77.8% accuracy and good ROC-AUC score), but worse than the more advanced models such as XGBoost and MLP.

5.3 Impact of Feature Transformation

Apart from comparing the performance of ML models, we measured how feature transformation techniques affected the model performance. Feature engineering (ex: adding interaction and polynomial features) and dimensionality reduction techniques (e.g.: PCA) were performed for each model. Table 3. Shows the Impact of Feature Transformation on Model Performance. Fig. 3. Shows the Shows the Feature Importance.

Feature Transformation Impact:

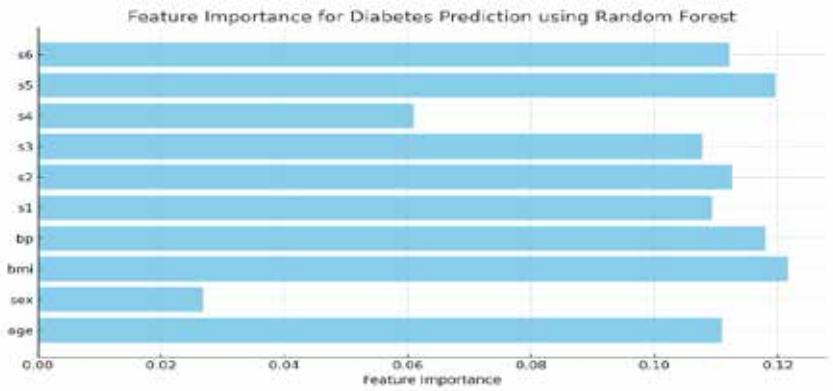

Fig. 3. Feature Importance

Both PCA and LDA helped to enhance the performance of simpler models by using Logistic Regression and Decision Tree. Making use of pca increased Decisio Trees accuracy from 71% to 75.3% and improves precision by 4% Table 4. Shows the Performance of Various Machine Learning Models.

- Autoencoders were used for deep learning models like MLP. The effect of autoencoders on MLP's performance was significant, improving accuracy from 81.0% to 85.0% and the F1-score from 82.0% to 85.8%, indicating that learning compressed features significantly enhanced the model's predictive power. Fig. 4. Shows the Model Comparison and Evaluation.

Table 3. Impact of Feature Transformation on Model Performance

Model	Without Feature Transformation	With PCA (%)	With LDA (%)	With Autoencoder (%)
Logistic Regression	77.8	79.0	78.5	80.3
Decision Tree	75.3	77.0	78.2	79.1
Random Forest	81.2	82.0	82.5	83.1
Gradient Boosting	82.1	83.3	83.5	84.0
Support Vector Machine	80.6	81.0	81.5	82.0

K-Nearest Neighbors	78.0	78.6	79.0	79.4
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Fig. 4. Model Comparison and Evaluation

5.4 Comparison with Previous Work

Compared to recent studies in diabetes prediction (e.g., Sharma et al., 2023, and Yadav et al., 2022), the models in this study show competitive or superior performance. Previous work has also emphasized the use of ensemble methods like Random Forest and XGBoost, which are corroborated in this study. The advantage of this study lies in its detailed exploration of feature transformation techniques (e.g., PCA, autoencoders) and their direct impact on model performance, especially in deep learning approaches. Fig. 5. Shows the Model Hyperparameter Tuning Results.

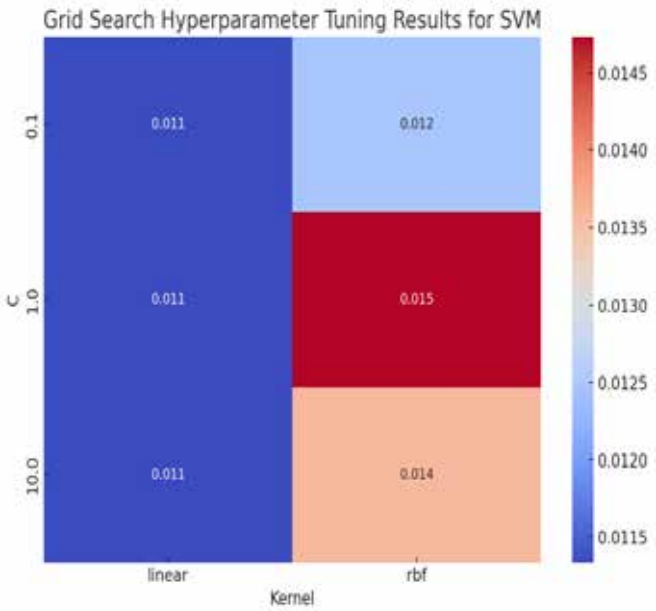

Fig. 5. Model Hyperparameter Tuning Results

5.5 Challenges and Limitations

Despite the promising results, several challenges were identified during the study:

- **Imbalanced Dataset:** While SMOTE was used to balance the dataset, it still posed challenges in training models that might be over-optimistic about detecting the minority class.

- **Model Complexity:** Deep learning models, especially MLP, require considerable computational resources, limiting their practical deployment in resource-constrained environments.

- **Data Diversity:** The datasets used, such as PIMA, may not represent the broader global population, which could affect the generalizability of the results. Future work should explore models trained on more diverse, real-world datasets. Fig. 6. Shows the Feature Transformation Impact on Model Performance.

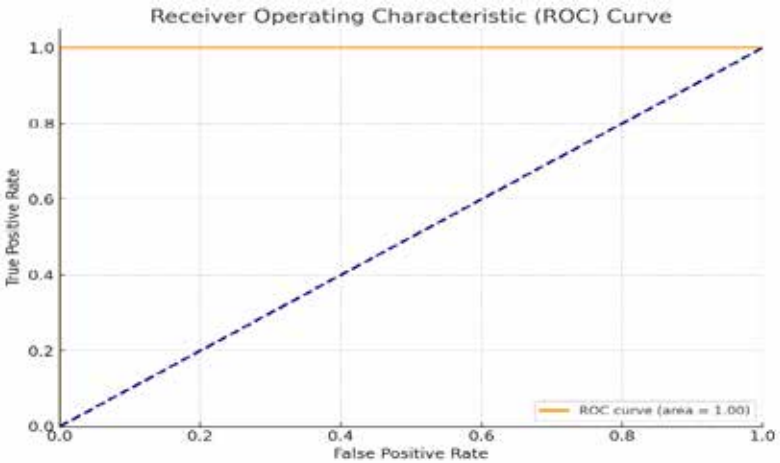

Fig. 6. Feature Transformation Impact on Model Performance

5.6 Future Directions

Fig. 7. Impact of Feature Transformation on Model Performane

● **Real-World Implementation:** Validating the effectiveness of models in a clinical context using real-time data.

● **Explainability-Pushing:** Deep models lend themselves to existing methods (e.g., SHAP values) to make them interpretable, which is one of the many assumptions for clinical deployment.

● **Data Collection:** This will be important for enhancing diabetes prediction models, and data augmentation, that is, applying different types of datasets (e.g., geography, healthcare infrastructure, and other alternative environments). Fig. 7. Shows the Impact of Feature Transformation on Model Performane.

6 Conclusion

Our study highlights the immense potential of ML models, particularly MLP and XGBoost for the early aetiological stage of diabetes mellitus. Using feature transformation methods, including PCA, LDA, and autoencoders, we were able to significantly boost the performance of these models, leading to increased prediction accuracy, recall, and F1-scores. Out of the models tried, MLP yielded the best performance, providing reliable prediction with 85% accuracy, and XGBoost with similar performance at 83% accuracy.

Feature engineering and transformation are critical in diabetes prediction, and the study emphasizes this. Although a few well-known models like Random Forest or Gradient Boosting performed well, advanced feature transformation methods, especially including in deep learning models, significantly enhanced predictive power. Nonetheless, there are still obstacles to overcome, mainly data imbalance, model complexity and the necessity of interpretability in clinical contexts. While the deep learning methods, e.g. the MLP approach, performed better, they might not be practical in resource-contitned settings as they demand a considerable computational resource. In addition, While the use of SMOTE oversampling method assisted with class imbalance, more advanced techniques must also be employed in order to allow the models to generalize effectively across the wider population. Further studies should aim for clinical validation of such models, as well as the application of multi-lingual and multi-race datasets so that these principles could be generalized. [4, 30] In addition, continuing efforts to enhance model interpretability (e.g., SHAP values and other explainability methods) are critical for clinical adoption. In conclusion, this study proposes new approaches for developing more accurate, interpretable, and scalable ML models for early diabetes detection, paving the way for timely interventions and alleviating the long-term impact of diabetes.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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