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Review

Machine Learning and Deep Learning Approaches for Prediction of Diabetes Health Outcomes: A Comparative Analysis

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Abstract: The increasing prevalence of diabetes has made early detection and accurate diagnosis essential. Traditional diagnostic methods often suffer from human errors, leading to a growing reliance on artificial intelligence (AI) for improved screening techniques. Machine learning (ML) and deep learning (DL) models have been extensively explored to enhance predictive accuracy. This study compares ML models, DL models and their ensemble methods based on key evaluation metrics, including accuracy, precision, recall, AUC-ROC and computational efficiency. The findings highlight the potential for improved methodologies to refine diagnostic accuracy, providing valuable insights into future advancements in AI-driven healthcare solutions.

Keywords: Diabetes; Machine Learning; Deep Learning; Ensemble methods

1. Introduction

Diabetes mellitus (DM) is a chronic metabolic disorder characterised by elevated blood glucose levels due to the body's inability to produce or effectively utilise insulin. It is one of the most prevalent diseases worldwide, with type 2 diabetes accounting for nearly 90% of all cases. The rapid increase in diabetes cases has been linked to factors such as obesity, lifestyle changes, and genetic predisposition. If left untreated or poorly managed, diabetes can lead to severe complications, including cardiovascular diseases, kidney failure, and neuropathy. Given its growing burden on healthcare systems, early detection and accurate diabetes prediction are crucial for timely intervention and improved patient outcomes.

Machine learning (ML) and deep learning (DL) have emerged as powerful medical diagnosis and prediction tools, offering automated, data-driven insights that can enhance clinical decision-making. Various ML models, including decision trees, logistic regression, and support vector machines, have been widely used for diabetes prediction, while DL models such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) provide advanced feature extraction capabilities. However, the comparative performance of these models in terms of accuracy, reliability, and computational efficiency remains an area of active research. This study aims to address two key research questions: (1) What are the differences in accuracy and reliability between ML and DL models in predicting diabetic patient outcomes across various healthcare settings? (2) How do ML, DL, and ensemble models compare in terms of processing time and computational efficiency when applied to selected datasets for diabetes mellitus personalised medicine? By analysing multiple datasets and evaluating various predictive models, this study seeks to provide insights into the effectiveness of different AI-based approaches in diabetes diagnosis and management.

Received:
Accepted:
Published:

Citation: Lastname, F.; Lastname, F.; Lastname, F. Title. *Journal Not Specified* **2025**, *1*, 0. https://doi.org/

The rest of the paper is structured as follows: Section 2 reviews previous studies addressing diabetes prediction. Section 3 provides a detailed overview of the datasets used, including data preprocessing steps to make them suitable for the models and a description of the algorithms used. Section 4 presents the results of each technique, highlighting their respective metrics and time efficiency. Finally, Section 5 concludes the study with key findings and insights.

2. Related Work - 2 pages

Previous work on diabetes prediction can be taken from any other review paper.

3. Experimentation

3.1. Methodologies

This subsection provides a comprehensive overview of the methods and algorithms utilised in the experimentation. It primarily focuses on defining the techniques employed and offering a brief explanation of their working principles. It is divided into five parts: (i) oversampling techniques used to address class imbalance by generating synthetic samples, (ii) undersampling techniques aimed at reducing data imbalance while preserving critical patterns, (iii) machine learning algorithms applied for classification, (iv) hyperparameter tuning, and (v) evaluation metrics. Each of them outlines the fundamental concepts behind the methods, ensuring a clear understanding of their role in the study.

3.1.1. Oversampling Techniques

1. SMOTE (Synthetic Minority Oversampling Technique): It is a synthetic minority oversampling technique that balances class distribution by generating artificial samples for the minority class. Instead of simple duplication, SMOTE creates new instances by interpolating between existing minority class samples. For each minority class observation, it selects k nearest neighbours and generates synthetic points along the line segments connecting them. A random interpolation factor between 0 and 1 is applied to ensure diversity. This approach helps mitigate overfitting compared to random oversampling while improving model performance on imbalanced datasets.
2. SMOTE-ENN: It combines SMOTE with Edited Nearest Neighbours (ENN) to enhance data quality. First, SMOTE generates synthetic minority samples to balance the dataset. Then, ENN removes noisy instances—both original and synthetic—where the majority of their nearest neighbours belong to the opposite class. This two-step process ensures cleaner decision boundaries by eliminating misclassified or ambiguous samples, leading to better generalisation in classification tasks.
3. Random Oversampling: It addresses class imbalance by randomly replicating minority class samples until the desired balance is achieved. Unlike SMOTE, this method duplicates existing observations without creating synthetic data. While simple and effective, it risks overfitting if the same samples are repeated excessively. To reduce this risk, subsets of minority instances can be resampled with replacement, ensuring diversity in the augmented dataset.
4. ADASYN (Adaptive Synthetic Sampling): It is an adaptive extension of SMOTE that focuses on challenging minority class samples. ADASYN assigns higher weights to minority instances near the decision boundary or surrounded by majority class samples. More synthetic data is generated for these "hard-to-learn" cases, shifting the classifier's attention to ambiguous regions. This adaptiveness improves model robustness by reducing bias and refining the decision boundary in imbalanced datasets.

3.1.2. Undersampling Techniques

1. Clustering Centroids: It reduces majority class samples by replacing clusters with their centroids. Using K-means clustering, groups of majority instances are condensed into single representative points. This preserves the overall distribution while significantly reducing computational overhead. The minority class remains untouched, ensuring its patterns are retained. This method is particularly useful for large-scale datasets where brute-force undersampling is impractical.
2. NearMiss-3: It selects majority class samples based on their distance to minority instances. In its first phase, it identifies the M nearest neighbours of each minority observation. Then, it retains majority samples with the largest average distance to these neighbours, effectively removing redundant or overlapping points. This approach prioritises majority instances farthest from the minority class, improving class separability.
3. Random Undersampling: It randomly discards majority class samples to balance the dataset. Though computationally efficient, this method may remove informative instances, increasing model variance. To mitigate this, stratified sampling or controlled undersampling rates can be applied. Despite its simplicity, it remains a baseline technique for quick imbalance correction.
4. Random Undersampling with Tomek Links: It first applies random undersampling to reduce the majority class size. Then, it removes Tomek Links—pairs of opposing class instances that are mutual nearest neighbours. By deleting majority samples from these pairs, it clarifies the decision boundary and reduces noise. This hybrid approach balances efficiency with improved classifier performance.
5. Neighbourhood Cleaning: It refines undersampling by removing noisy majority samples. Using a k-NN classifier, it flags misclassified majority instances and eliminates them. This targeted cleaning reduces overlap between classes while preserving critical data structures. It is often paired with other undersampling methods for optimal results.
6. One-Sided Selection (OSS): It combines Tomek Links removal and Condensed Nearest Neighbour (CNN) to prune redundant majority samples. First, Tomek Links are cleared to eliminate borderline cases. Then, CNN retains a minimal subset of majority instances that accurately represent the original distribution. This two-step process ensures a compact yet representative majority class, enhancing model efficiency and accuracy.

3.1.3. Machine Learning Algorithms

1. Logistic Regression: It is a statistical and machine learning algorithm used for binary classification tasks. It models the relationship between input features and the probability of a class label using the sigmoid (logistic) function, which maps real-valued inputs to a range between 0 and 1. The model is trained by optimising the log-likelihood function using techniques like Gradient Descent. It assumes a linear relationship between the independent variables and the log-odds of the dependent variable. Computation is efficient, making it suitable for large datasets. However, it struggles with complex relationships unless feature transformations or polynomial terms are introduced.
2. Naïve Bayes: It is a probabilistic classification algorithm based on Bayes' theorem, assuming that all features are conditionally independent given the class label. Despite this strong independence assumption, it performs well in many real-world applications like text classification and spam filtering. It calculates the posterior probability of a class using prior knowledge and observed data. Variants include Gaussian Naïve

Bayes (for continuous data), Multinomial Naïve Bayes (for text data), and Bernoulli Naïve Bayes (for binary features). Proper feature selection and data preprocessing significantly impact its effectiveness. It is computationally efficient and works well with high-dimensional datasets.

3. KNN (K-Nearest Neighbors): It is a non-parametric, instance-based learning algorithm that classifies data points based on the majority class of their k nearest neighbours. The distance between points is typically measured using Euclidean, Manhattan, or Minkowski distance. KNN does not require explicit training, making it computationally efficient during training but computationally expensive during inference, as it requires storing and searching through the entire dataset. The choice of k affects model performance—small values may lead to overfitting, while large values can cause underfitting. Feature scaling, such as Min-Max normalisation or standardisation, is often necessary to ensure meaningful distance calculations.
4. Decision Tree: It is a supervised learning algorithm that recursively splits data into subsets based on feature conditions to make predictions. It consists of nodes (decision points), branches (outcomes), and leaves (final predictions). The splitting criteria are based on impurity measures such as Gini Index or Entropy (Information Gain) for classification and Mean Squared Error (MSE) for regression. The tree grows by selecting the best feature at each step to minimise impurity until a stopping condition is met. While Decision Trees are interpretable and easy to implement, they are prone to overfitting, which can be mitigated by pruning or ensemble methods like Random Forest and Gradient Boosting. Decision Trees can handle both numerical and categorical data, but they tend to be sensitive to small variations in the dataset, leading to high variance if not properly regularised.
5. Random Forest: It is an ensemble learning algorithm that constructs multiple decision trees during training and combines their outputs for more accurate predictions. Each tree is trained on a randomly sampled subset of the data (bagging) and uses a randomly selected subset of features at each split, reducing overfitting and improving generalisation. The final prediction is determined by majority voting (classification) or averaging (regression) across all trees. Random Forest handles both numerical and categorical data, is resistant to noise, and provides feature importance scores. However, it can be computationally expensive for large datasets due to the need to build and store multiple trees. Random Forest reduces variance by averaging multiple decision trees, but it may still struggle with highly imbalanced datasets and require hyperparameter tuning for optimal performance.
6. SVM (Support Vector Machine): It is a supervised learning algorithm that finds an optimal hyperplane to separate data points by maximising the margin between different classes. It relies on support vectors, which are the most critical data points defining the decision boundary. SVM employs kernel functions (e.g., linear, polynomial, RBF) to map non-linearly separable data into a higher-dimensional space where separation becomes feasible. It is highly effective in handling high-dimensional data and avoids overfitting by focusing only on key boundary points. The proper selection of the kernel and hyperparameters is crucial for achieving optimal model performance. The linear kernel SVM is computationally efficient, making it suitable for large datasets with linearly separable classes.
7. AdaBoost: It is an ensemble learning algorithm that combines multiple weak learners (typically decision stumps) to create a strong classifier. It works iteratively by assigning higher weights to misclassified samples, forcing subsequent weak learners to focus on harder cases. The final prediction is obtained through a weighted majority vote of all weak classifiers. AdaBoost minimises an exponential loss function and adjusts

sample importance dynamically to improve model performance. It is resistant to overfitting in moderate-sized datasets and performs well in classification tasks. However, it is sensitive to noisy data and outliers due to its emphasis on hard-to-classify samples.

8. XGBoost (Extreme Gradient Boosting): It is an advanced gradient boosting algorithm optimised for efficiency and accuracy. It employs a second-order Taylor expansion to approximate the loss function, enabling more precise updates during training. The algorithm improves computational performance through parallelised execution, histogram-based split finding, and cache-aware access patterns. Regularisation techniques, including L1 and L2 penalties, help control model complexity and mitigate overfitting. XGBoost also incorporates shrinkage (learning rate tuning) and column subsampling to enhance generalisation. Additionally, it efficiently handles missing values and sparse data using a default direction method. Its ability to optimise both speed and accuracy makes it a powerful tool for large-scale machine learning tasks.
9. DNN (Deep Neural Network): It is a type of artificial neural network (ANN) with multiple hidden layers between the input and output layers. Each layer consists of interconnected neurons that apply nonlinear activation functions, allowing the model to learn complex patterns. Training is performed using backpropagation and optimisation algorithms like Stochastic Gradient Descent (SGD) or Adam. DNNs excel at feature extraction and representation learning, making them highly effective for tasks such as image recognition, natural language processing, and time-series forecasting. Regularisation techniques like dropout and batch normalisation help improve generalisation and prevent overfitting.
10. RNN (Recurrent Neural Network): It is a type of neural network designed for processing sequential data by maintaining a memory of previous inputs through its hidden states. Unlike feedforward networks, RNNs share parameters across time steps, allowing them to capture temporal dependencies. They are widely used in tasks like speech recognition, time-series forecasting, and natural language processing. However, standard RNNs face challenges like vanishing and exploding gradients, making it difficult to learn long-term dependencies. This limitation is addressed by advanced variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks. The proper tuning of hyperparameters and sequence length is essential for optimal performance.
11. GRU (Gated Recurrent Unit): It is an advanced type of Recurrent Neural Network (RNN) designed to handle sequential data while addressing the vanishing gradient problem. It introduces gating mechanisms that regulate information flow, allowing the network to retain relevant past information and discard unnecessary details. Unlike LSTMs, GRUs have a reset gate and an update gate, making them computationally simpler while achieving similar performance. GRUs are widely used in tasks like speech recognition, time-series forecasting, and machine translation. Their ability to adaptively control memory retention makes them efficient for capturing long-term dependencies in sequences. Proper tuning of gate thresholds and network depth impacts their effectiveness.
12. LSTM (Long Short-Term Memory): It is an advanced type of Recurrent Neural Network (RNN) designed to effectively capture long-term dependencies in sequential data. It overcomes the vanishing gradient problem by introducing gates—the forget gate, input gate, and output gate—which regulate the flow of information. These gates allow LSTMs to selectively retain or discard information, making them highly effective for tasks like speech recognition, language modelling, and time-series forecasting. Unlike standard RNNs, LSTMs can learn long-range dependencies without

significant loss of information. The proper tuning of gate activations and sequence lengths is crucial for optimal performance.

13. CNN (Convolutional Neural Network): It is a type of deep learning model designed for processing grid-like data, such as images and time-series. It consists of convolutional layers that apply filters to detect spatial features, pooling layers that reduce dimensionality while retaining essential information, and fully connected layers that perform classification or regression. CNNs leverage local connectivity and weight sharing, making them highly effective in feature extraction. Activation functions like ReLU introduce non-linearity, enhancing learning capability. Proper architecture design, including the number of layers, filter sizes, and pooling strategies, is crucial for achieving optimal performance.
14. KNN-Autoencoders (KNN + autoencoders): It is a hybrid model that combines Autoencoders (AEs) for feature extraction with K-Nearest Neighbours (KNN) for classification or anomaly detection. The Autoencoder, an unsupervised neural network, learns compressed representations of input data by encoding it into a lower-dimensional space and then reconstructing it. The encoded feature representations from the latent space are then used as inputs for KNN, which performs similarity-based classification or clustering. This approach enhances feature learning while retaining KNN's non-parametric nature, making it useful for tasks like anomaly detection and high-dimensional data classification. Proper tuning of the autoencoder's architecture and the value of k in KNN is crucial for optimal performance.
15. LR-MLP (Logistic Regression + Multi-Layer Perceptron): It is a hybrid model that integrates Logistic Regression (LR) with a Multi-Layer Perceptron (MLP) to enhance classification performance. The MLP, a type of feedforward neural network, consists of multiple hidden layers with nonlinear activation functions, enabling it to learn complex feature representations. The extracted high-level features from the MLP's last hidden layer are then fed into a Logistic Regression classifier, which makes the final prediction. This combination retains MLP's feature extraction capability while ensuring efficient computation through Logistic Regression. Proper tuning of hyperparameters, such as the number of hidden layers and activation functions, is crucial for achieving optimal results.
16. SVM-RNN (SVM + Recurrent Neural Network): It is a hybrid model that integrates Support Vector Machines (SVM) with Recurrent Neural Networks (RNNs) to enhance sequence-based classification tasks. The RNN processes sequential data by maintaining hidden states that capture temporal dependencies, extracting meaningful representations over time. These learned feature representations from the final hidden layer are then fed into an SVM classifier, which finds an optimal hyperplane for decision-making. This approach benefits from RNN's sequential pattern learning and SVM's robustness to high-dimensional data, leading to improved generalisation. While computation is efficient for linear SVMs, kernelised SVMs may require additional tuning for large-scale applications.
17. XGBoost-LSTM (XGBoost + LSTM): It is a hybrid model that combines Long Short-Term Memory (LSTM) networks for sequential feature extraction with XGBoost for final prediction. The LSTM, a type of recurrent neural network (RNN), captures long-term dependencies in time-series or sequential data using its gating mechanisms. The extracted temporal features from the last hidden layer of the LSTM are then fed into an XGBoost model, which applies gradient boosting for robust classification or regression. This approach leverages LSTM's strength in handling sequential dependencies while benefiting from XGBoost's computational efficiency and regularisation, improving

overall model accuracy and generalisation. Proper tuning of LSTM hyperparameters and XGBoost's boosting parameters is crucial for optimal performance.

18. RF-GRU (Random Forest + GRU): It is a hybrid model that combines Random Forest (RF) with Gated Recurrent Units (GRU) for enhanced predictive performance. The GRU processes sequential data by learning temporal dependencies using its gating mechanisms, which help retain relevant information while discarding unnecessary details. The extracted features from the GRU's hidden states are then passed to a Random Forest, which performs classification or regression based on these learned representations. This fusion allows the model to leverage GRU's ability to capture sequential patterns and RF's strength in handling structured data, resulting in improved accuracy and robustness. The hybrid approach also reduces overfitting by incorporating RF's ensemble learning capability.
19. RF-CNN (Random Forest + CNN): It is a hybrid model that combines Convolutional Neural Networks (CNNs) for feature extraction with Random Forest (RF) for final classification or regression. The CNN processes raw input data through convolutional layers, extracting hierarchical spatial features, which are then flattened into a feature vector. Instead of using fully connected layers for prediction, the extracted features are passed to a Random Forest, which learns decision boundaries and enhances interpretability. This approach reduces computation compared to training deep, fully connected layers while improving generalisation by leveraging RF's ensemble learning capability. Proper feature selection and tuning of hyperparameters are essential for optimal performance.
20. DT-CNN (Decision Tree + CNN): It is a hybrid model that combines Convolutional Neural Networks (CNNs) for feature extraction with Decision Trees (DTs) for final classification or regression. The CNN processes raw input data through convolutional and pooling layers, extracting hierarchical spatial features, which are then flattened into a feature vector. Instead of using fully connected layers for prediction, the extracted features are passed to a Decision Tree, which learns patterns and makes the final decision. This approach enhances interpretability while leveraging CNN's ability to capture spatial features. Proper feature selection and regularisation techniques, such as pruning, are essential to prevent overfitting in the decision tree.
21. AdaBoost-DBN (AdaBoost + Deep Belief Network): It is a hybrid model that integrates Deep Belief Networks (DBNs) for feature extraction with Adaptive Boosting (AdaBoost) for final classification. The DBN, composed of stacked Restricted Boltzmann Machines (RBMs), learns hierarchical feature representations in an unsupervised manner and then fine-tunes them using supervised learning. The extracted high-level features are passed to multiple weak classifiers in the AdaBoost framework, which combines them into a strong classifier through iterative reweighting. This approach leverages DBN's deep feature learning and AdaBoost's ensemble learning capability, improving generalisation and classification accuracy. The proper tuning of RBM layers and AdaBoost's weak learners is crucial for optimal performance.
22. XGBoost-CNN (XGBoost + CNN): It is a hybrid model that combines the feature extraction capability of Convolutional Neural Networks (CNNs) with the predictive power of XGBoost for improved classification and regression tasks. In this approach, the CNN extracts hierarchical spatial features from raw input data, typically images, and transforms them into a feature vector. Instead of using a fully connected layer for final predictions, these extracted features are fed into an XGBoost model, which performs the final classification or regression. This hybrid method benefits from CNN's ability to learn spatial representations and XGBoost's ability to handle structured data

efficiently while reducing overfitting through regularisation. It is beneficial for small datasets where deep learning models alone may struggle with generalisation.

3.1.4. Hyperparameter Tuning

Hyperparameter tuning is essential for optimising model performance by systematically adjusting configuration parameters that control the learning process. Traditional methods like grid search and random search are often computationally expensive, while advanced techniques such as Bayesian optimisation provide more efficient alternatives. This study employs Optuna, an advanced optimisation framework that utilises Tree-structured Parzen Estimators (TPE) to explore the hyperparameter space intelligently. Optuna's adaptive sampling and early pruning capabilities significantly reduce computational costs while ensuring optimal parameter selection, making it particularly suitable for complex machine-learning models.

The advantages of using Optuna include faster convergence to high-performing configurations, seamless integration with various machine-learning frameworks, and enhanced reproducibility through detailed logging and visualisation. By dynamically prioritising promising trials and discarding underperforming ones, Optuna achieves superior efficiency compared to conventional approaches. This makes it an ideal choice for developing robust models with improved generalization capabilities, particularly in scenarios where computational resources are constrained. The framework's effectiveness has been demonstrated across diverse applications, establishing it as a valuable tool for modern machine-learning pipelines.

3.1.5. Evaluation Metrics

To ensure a comprehensive model assessment, we evaluated six key classification metrics:

1. **Accuracy**
   Measures the overall proportion of correct predictions, calculated as the ratio of true predictions (both positive and negative) to all predictions made. While intuitive, accuracy can be misleading for imbalanced datasets as it doesn't distinguish between types of errors.
   $$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$
   where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.
2. **Precision**
   Quantifies the reliability of positive predictions by measuring the proportion of true positives among all positive predictions. This metric is critical when false positives are particularly costly, such as in unnecessary medical treatments or false fraud alerts.
   $$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$
3. **Recall (Sensitivity)**
   Measures the model's ability to detect positive cases by calculating the proportion of actual positives that are correctly identified. High recall is essential in applications where missing positive cases is dangerous, such as in disease screening or security threat detection.
   $$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$
4. **F1 Score**

Provides a balanced measure of model performance by combining precision and recall through their harmonic mean. This is our primary evaluation metric as it handles class imbalance effectively by equally weighting both false positives and false negatives.

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

5. **AUC-ROC**
   The Area Under the Receiver Operating Characteristic curve evaluates the model's ability to distinguish between classes across all possible classification thresholds. A perfect classifier achieves an AUC of 1, while random guessing yields 0.5.

$$\text{AUC} = \int_0^1 \text{ROC}(\tau)\, d\tau \tag{5}$$

   where τ represents the decision threshold.
6. **Inference Time**
   Measures the computational efficiency of the model by recording the time required to generate predictions. This metric is crucial for real-time applications and deployment in resource-constrained environments, though it doesn't affect the model's statistical performance.

The tables in Section 4 present results ranked by F1 score, as it provides the most balanced evaluation for medical diagnostics by equally considering both false positives and false negatives.

3.2. Datasets

This study utilizes five datasets, each described in detail below.

1. PIMA Indian Diabetes Dataset (768 Samples):
   Dataset 1 consists of 768 samples with nine numerical features, including patient characteristics and clinical measurements. The features are Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction, Age, and Outcome (the target variable). All features are numerical, with no missing values or duplicate entries. However, several features—Glucose, BloodPressure, SkinThickness, Insulin, and BMI—contain biologically implausible zero values, which will be addressed in Section 3.2.

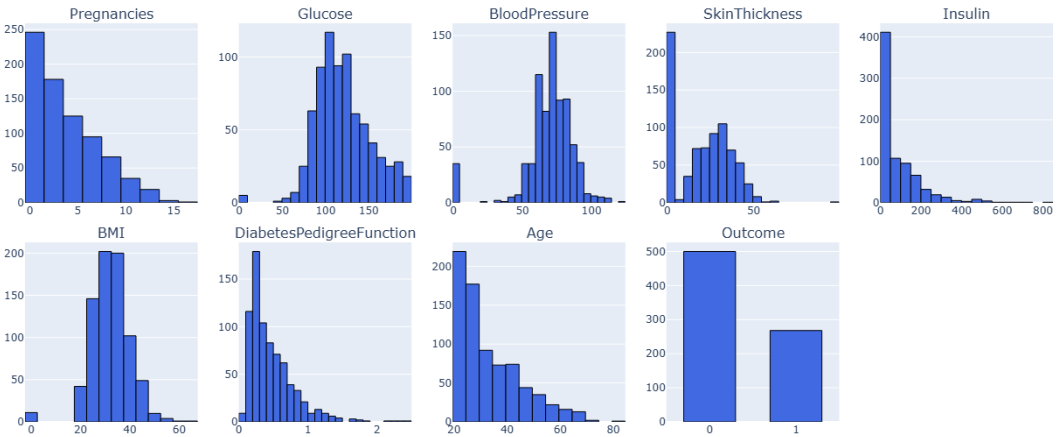

Figure 1. Distribution of features in Dataset 1.

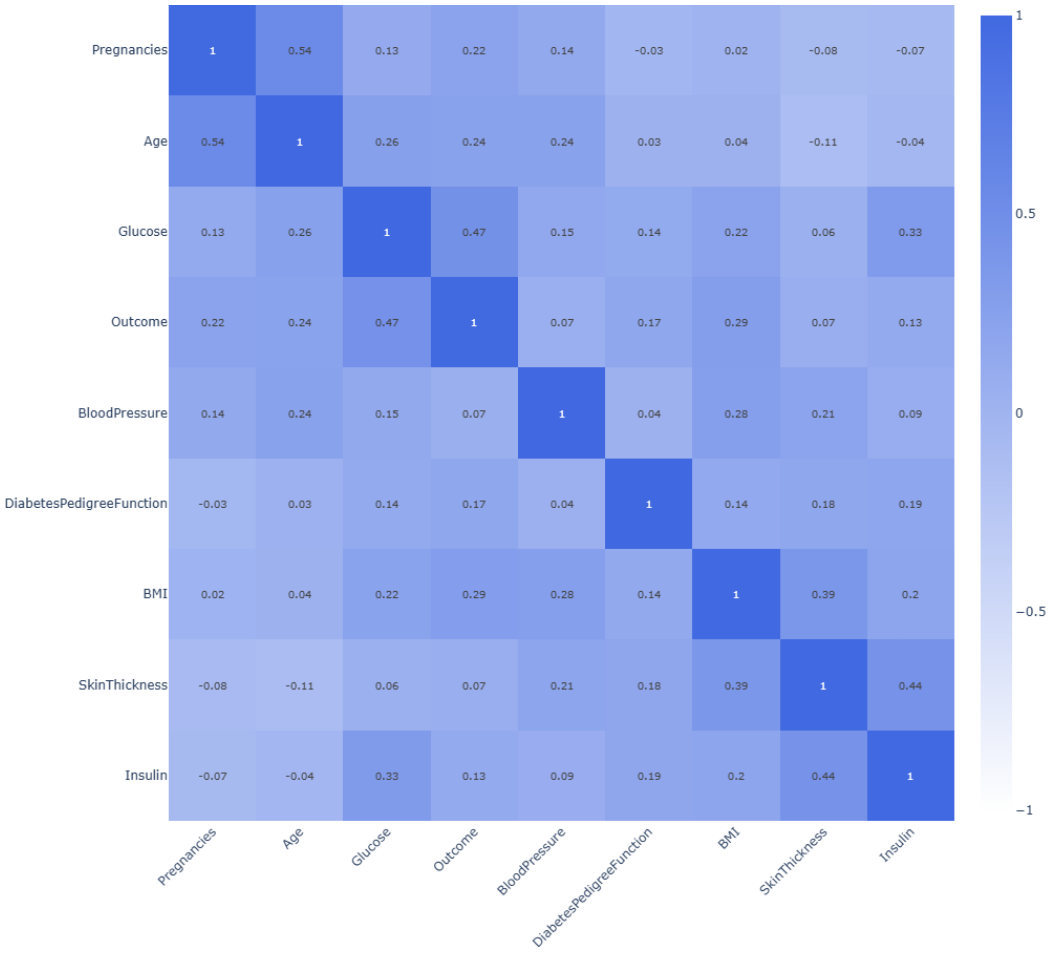

Figure 2. Correlation matrix of features in Dataset 1.

2. Extended Diabetes Dataset (2000 Samples):
Dataset 2 follows the same structure as Dataset 1 but contains 2,000 samples, providing a larger dataset for analysis. The features remain identical, including Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabetesPedigreeFunction, Age, and Outcome. The increased sample size enhances the robustness of statistical evaluations.

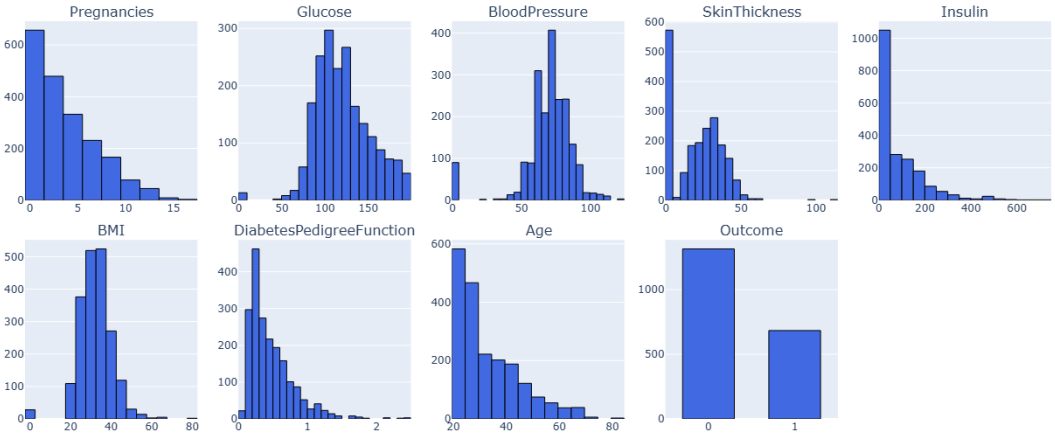

Figure 3. Distribution of features in Dataset 2.

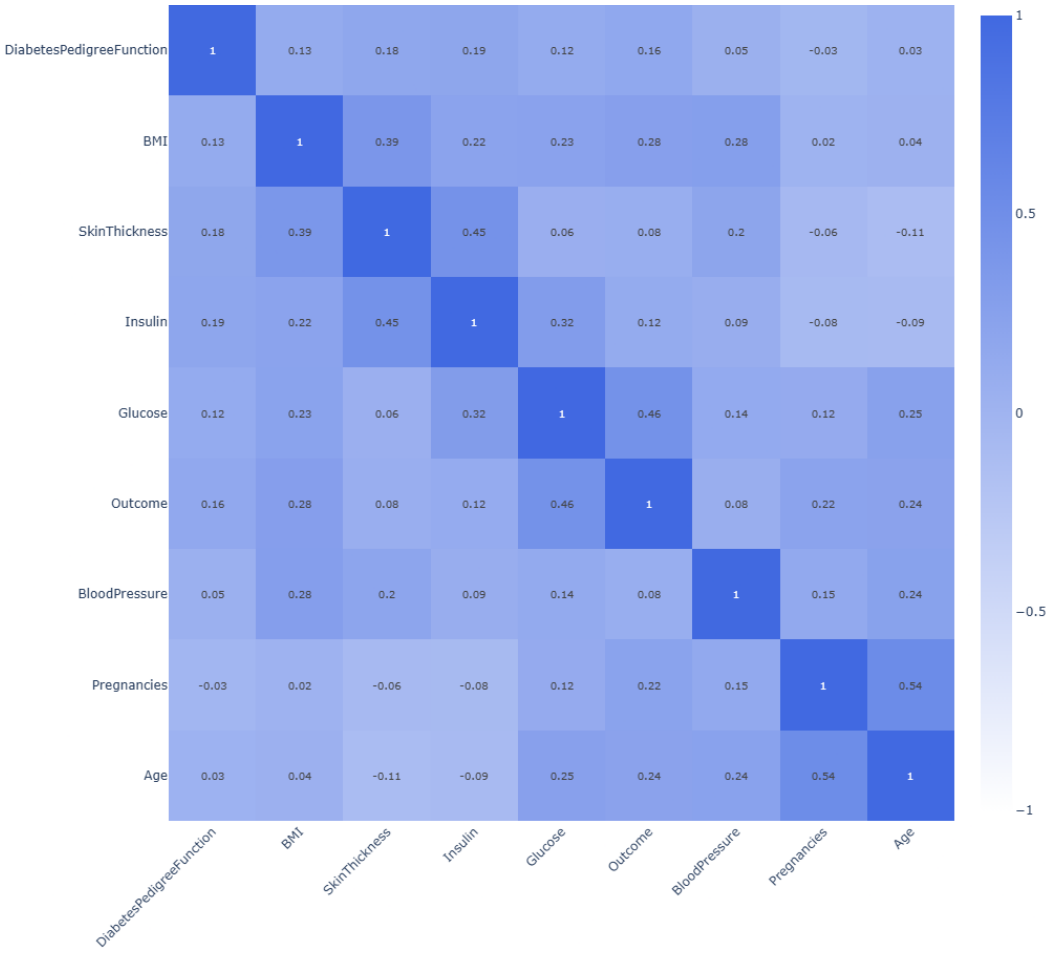

Figure 4. Correlation matrix of features in Dataset 2.

3. Diabetes 012 Health Indicators (BRFSS2015)
   Dataset 3 is derived from the BRFSS 2015 survey and contains 253,680 samples with 22 features. This dataset includes diabetes risk factors (e.g., high blood pressure, cholesterol, smoking status), medical history (e.g., stroke, healthcare access), and lifestyle indicators (e.g., education, income, diet). The target variable is trinary, classifying diabetes status into three categories (0, 1, or 2).

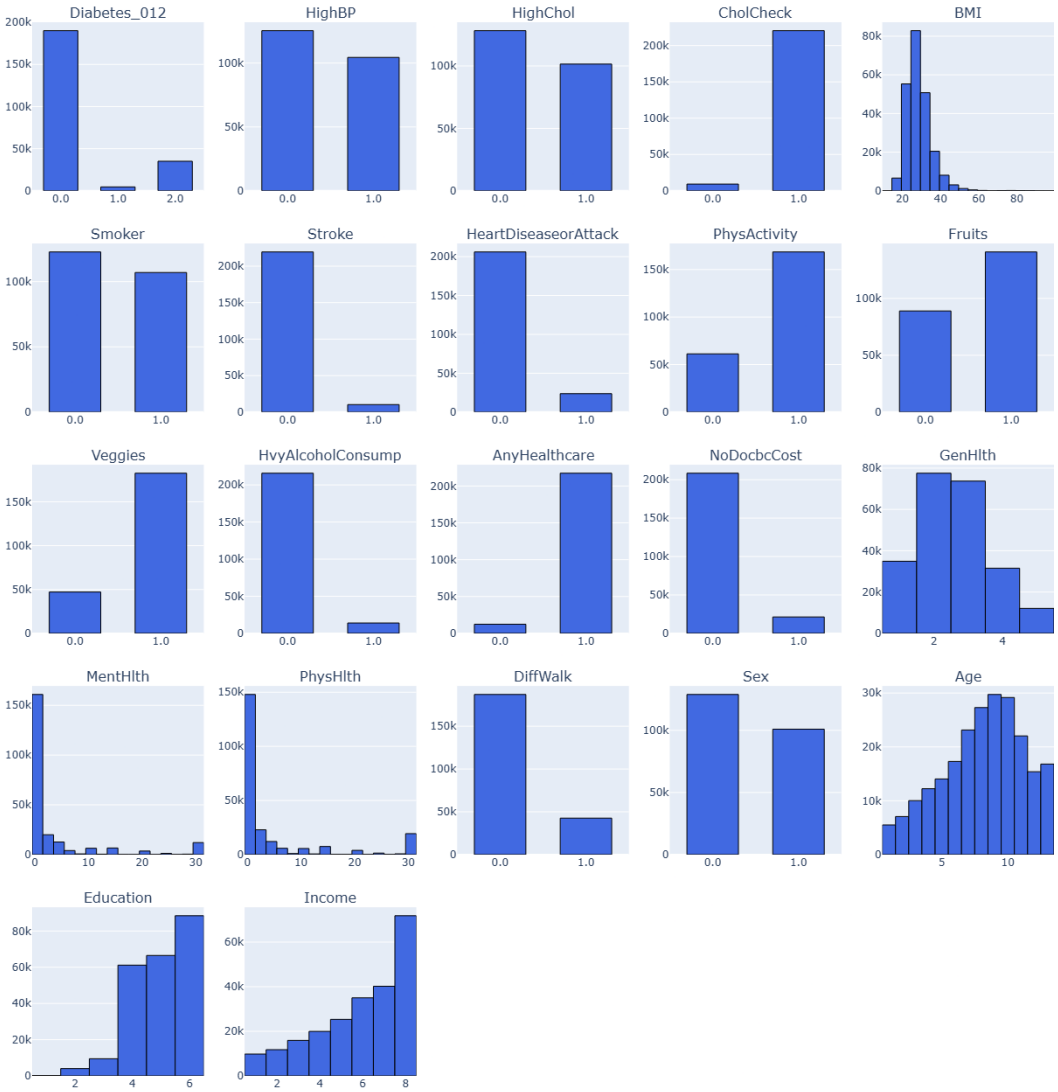

Figure 5. Distribution of features in Dataset 3.

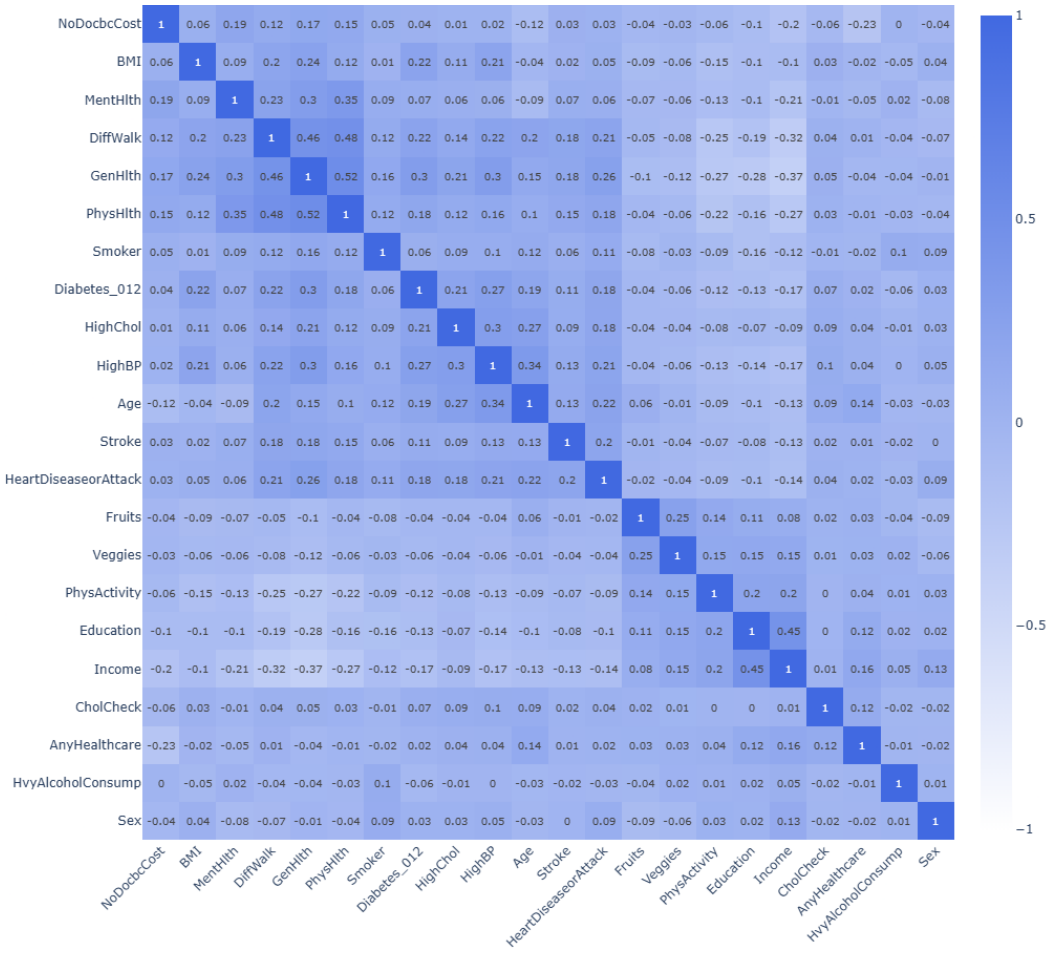

Figure 6. Correlation matrix of features in Dataset 3.

4. Diabetes Binary Health Indicators (BRFSS2015):
   Dataset 4 is identical in size and features to Dataset 3 but uses a binary target variable (diabetes vs. no diabetes) instead of a trinary classification. This simplification allows for direct comparison with other binary-classification datasets in this study.

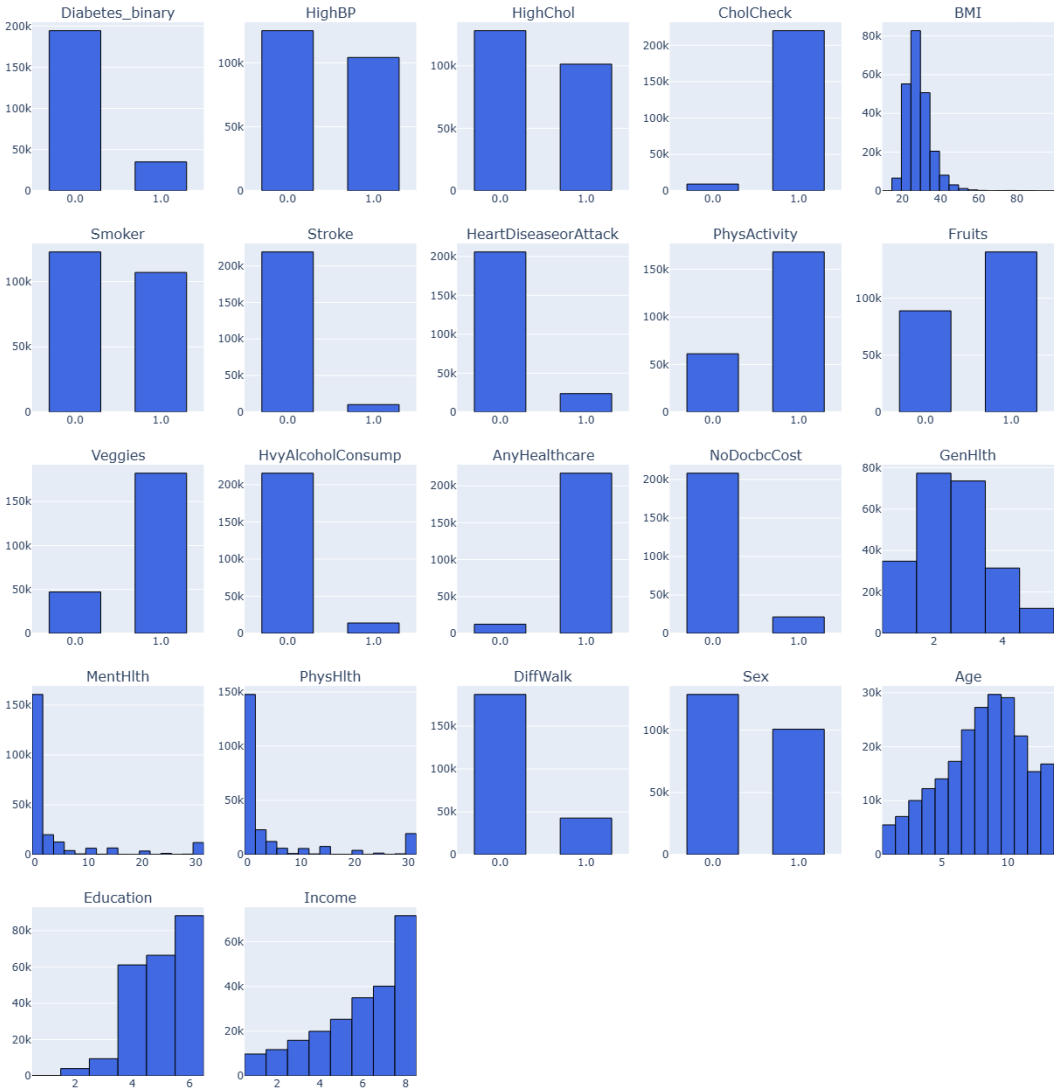

Figure 7. Distribution of features in Dataset 4.

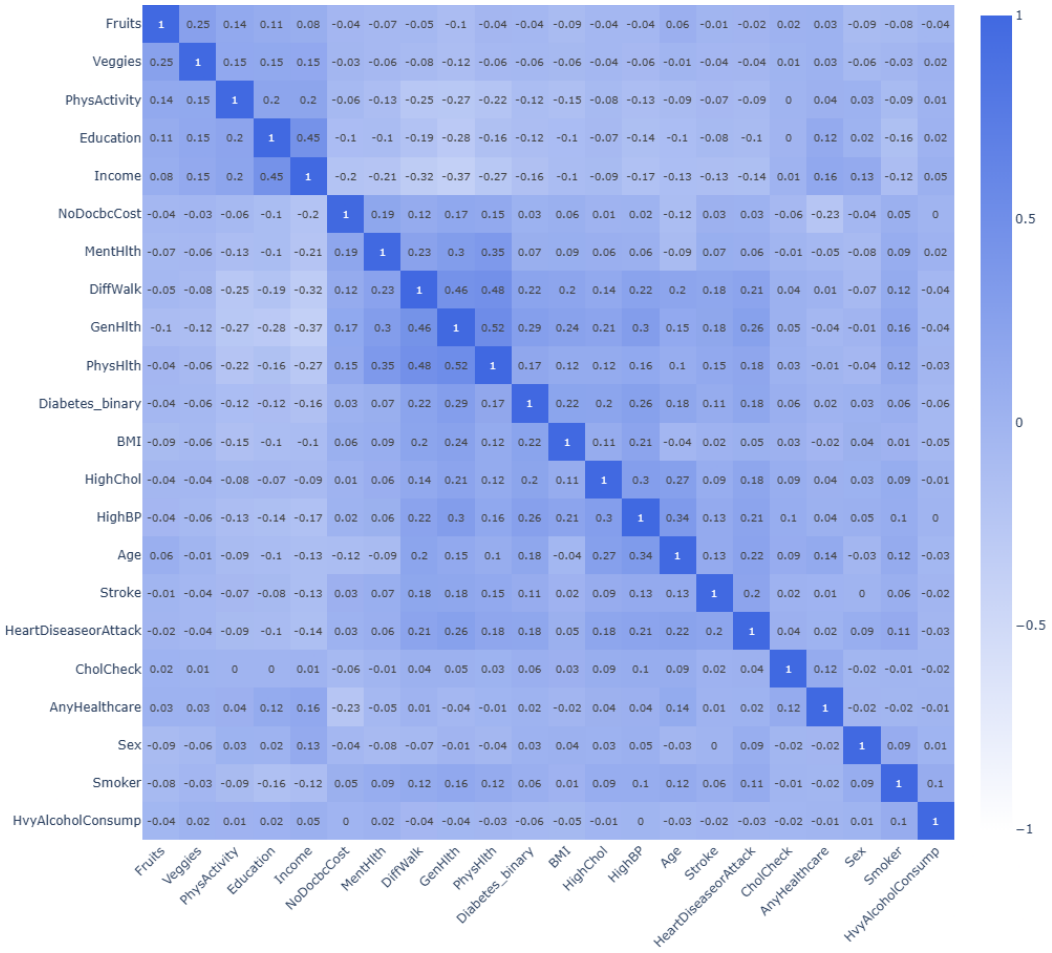

Figure 8. Correlation matrix of features in Dataset 4.

5. Early-Stage Diabetes Risk Prediction Dataset:
   Dataset 5 contains 520 samples and 17 features, focusing on early-stage diabetes risk prediction. It includes demographic information (Age, Gender) and binary (Yes/No) symptom indicators such as Polyuria, Polydipsia, sudden weight loss, weakness, and visual blurring. The target variable ("Positive" or "Negative") indicates diabetes risk.

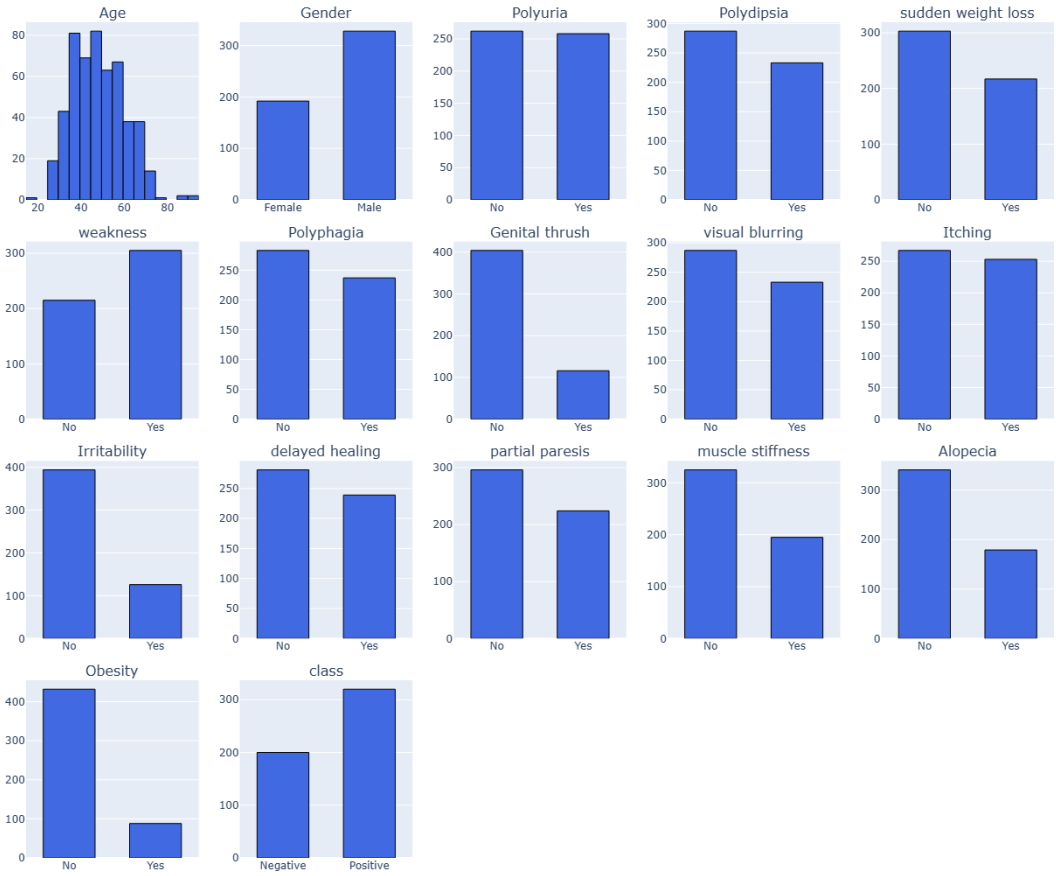

Figure 9. Distribution of features in Dataset 5.

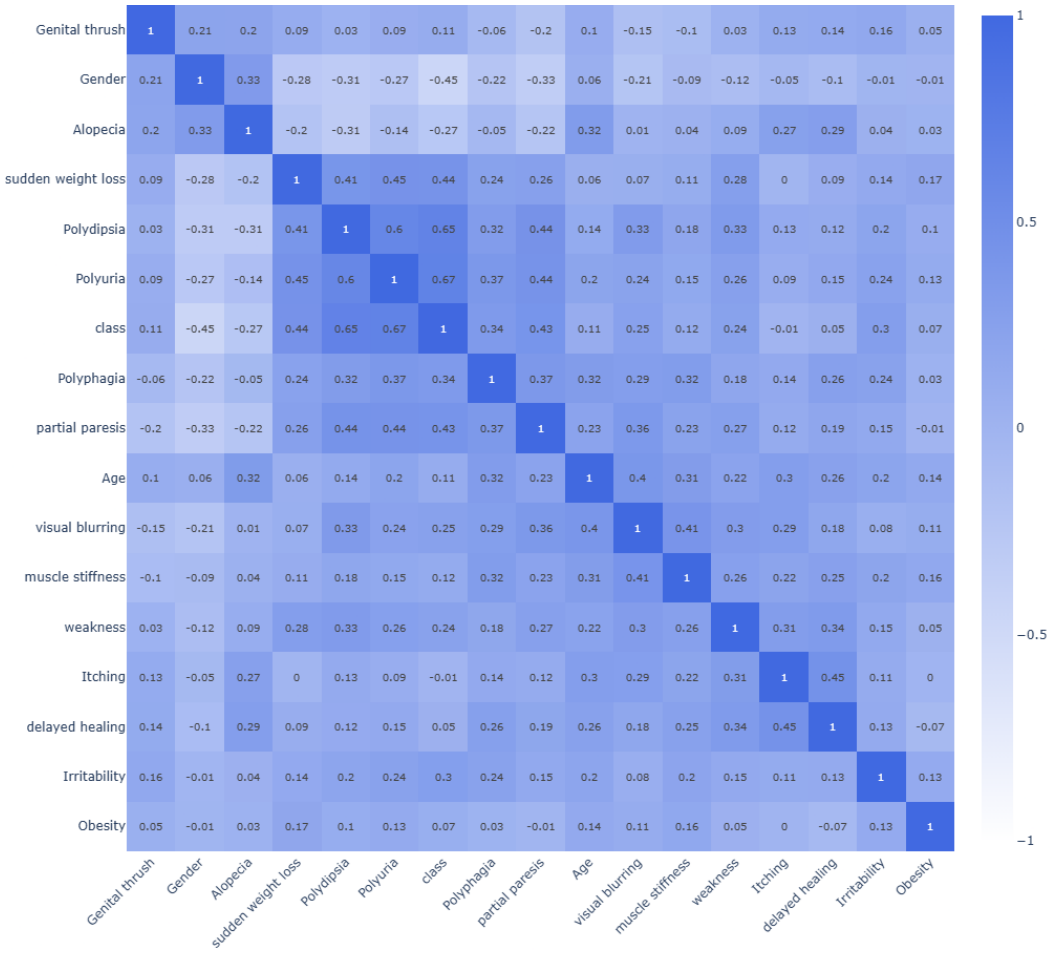

Figure 10. Correlation matrix of features in Dataset 5.

3.3. Preprocessing

A notable issue in both Dataset 1 and Dataset 2 is the presence of zero values in columns where they are not biologically possible. Such erroneous values could arise due to missing data being recorded as zeros rather than NaN.

Feature	Dataset 1	Dataset 2
Pregnancies	111	301
Glucose	5	13
BloodPressure	35	90
SkinThickness	227	573
Insulin	374	956
BMI	11	28
DiabetesPedigreeFunction	0	0
Age	0	0

Table 1. Number of zeros in the datasets

To handle the issue of zero values in biologically impossible columns (such as BMI, Insulin, Glucose, Blood Pressure, and Skin Thickness), we applied two imputation strategies:

1. Median Imputation: We replaced zeros with the median of non-zero values in each column.
2. Minimum Imputation: We hypothesised that zeros might indicate data was not collected rather than an actual measurement. This could mean that patients with

missing values had normal physiological levels. Therefore, we imputed missing values using the minimum non-zero value of each column.

Interestingly, models trained on the dataset with minimum imputation consistently outperformed those using median imputation. This supports our hypothesis that missing values were likely associated with patients having normal measurements rather than abnormal or extreme values. This finding suggests that understanding the nature of missing data is crucial in medical datasets, as different imputation methods can significantly impact model performance.

Another challenge we encountered with Dataset 1 and Dataset 2 was the imbalance in the target variable, where one class was significantly underrepresented. Undersampling was not feasible due to the already limited number of data points, so we focused on oversampling techniques to balance the dataset. We experimented with multiple oversampling methods, including Random Oversampling, Synthetic Minority Over-sampling Technique (SMOTE), SMOTE-ENN, Adaptive Synthetic Sampling (ADASYN), etc. Among these, ADASYN yielded the best results. ADASYN works similarly to SMOTE but emphasises generating synthetic samples near the decision boundary, where minority class samples are harder to classify. This result highlights the importance of choosing the right data balancing technique, as different methods can impact model performance in various ways.

To ensure uniformity across all datasets, categorical features were converted into numerical representations using simple binary encoding. Additionally, feature scaling was applied to normalise the data, ensuring that all features had a comparable range. This step is crucial for optimising machine learning models, as it prevents features with larger magnitudes from dominating those with smaller values.

The experimental evaluation revealed significant challenges in modelling Datasets 3 and 4 due to extreme class imbalance, where the majority class substantially dominated the minority class. This severe imbalance ratio presented considerable difficulties in developing effective predictive models, as evidenced by the models' complete inability to identify any instances of the minority class. The persistent failure occurred despite exhaustive application of various sampling techniques, including undersampling methods such as random undersampling, Tomek links, and cluster centroids for the majority class, along with oversampling approaches like SMOTE, ADASYN, and random oversampling for the minority class.

The consistent failure across all tested methodologies suggests fundamental limitations in the dataset's inherent predictive capacity regarding the minority class. The complete absence of detectable patterns for minority class prediction, even after extensive sampling adjustments and algorithmic interventions, indicates potential issues with either the representativeness of the minority class samples or the discriminative power of the available features.

4. Results

Table 2. Model Performance Comparison for Dataset 1

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Time Taken (s)
XGBoost	0.7727	0.6301	0.8519	0.7244	0.8356	0.0122
XGBoost-CNN	0.7727	0.6338	0.8333	0.7200	0.8224	4.3404
AdaBoost	0.7727	0.6338	0.8333	0.7200	0.8411	0.0091
DNN	0.7727	0.6377	0.8148	0.7154	0.8219	0.0144
RF-GRU	0.7597	0.6164	0.8333	0.7087	0.8120	9.1299
Random Forest	0.7597	0.6232	0.7963	0.6992	0.8196	0.0095
Decision Tree	0.7597	0.6308	0.7593	0.6891	0.7984	0.0167
SVM	0.7532	0.6176	0.7778	0.6885	0.8213	0.0145
KNN	0.7403	0.5946	0.8148	0.6875	0.8077	0.0147
RF-CNN	0.7597	0.6349	0.7407	0.6838	0.8120	0.0134
Logistic Regression	0.7468	0.6087	0.7778	0.6829	0.8189	0.0138
LR-MLP	0.7403	0.6029	0.7593	0.6721	0.8200	2.4844
SVM-RNN	0.7468	0.6119	0.7593	0.6777	0.8225	6.7487
XGBoost-LSTM	0.7403	0.6000	0.7778	0.6774	0.8219	11.4212
DT-CNN	0.6818	0.5275	0.8889	0.6621	0.7946	5.4317
AdaBoost-DBN	0.7013	0.5526	0.7778	0.6462	0.8004	18.8776
CNN	0.7143	0.5694	0.7593	0.6508	0.8219	0.0165
KNN-Autoencoders	0.6883	0.5417	0.7222	0.6190	0.7711	9.5224
Naive Bayes	0.6948	0.5522	0.6852	0.6116	0.7676	0.0908
RNN	0.6948	0.5522	0.6852	0.6116	0.7806	0.0110
GRU	0.6623	0.5156	0.6111	0.5593	0.7000	0.0106
LSTM	0.6688	0.5246	0.5926	0.5565	0.7013	0.0171

* All values are rounded to four decimal places.

The XGBoost model performed the best on this dataset, achieving an F1 score of 0.72. Below, we visualise the performance of the model on this dataset using a confusion matrix and AUC curves.

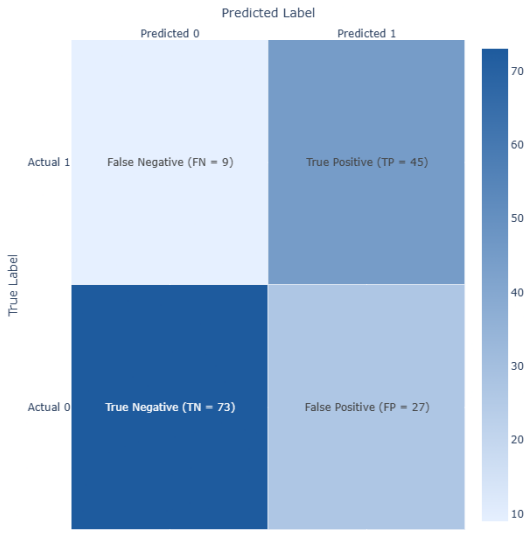

Figure 11. Confusion matrix for XGBoost model.

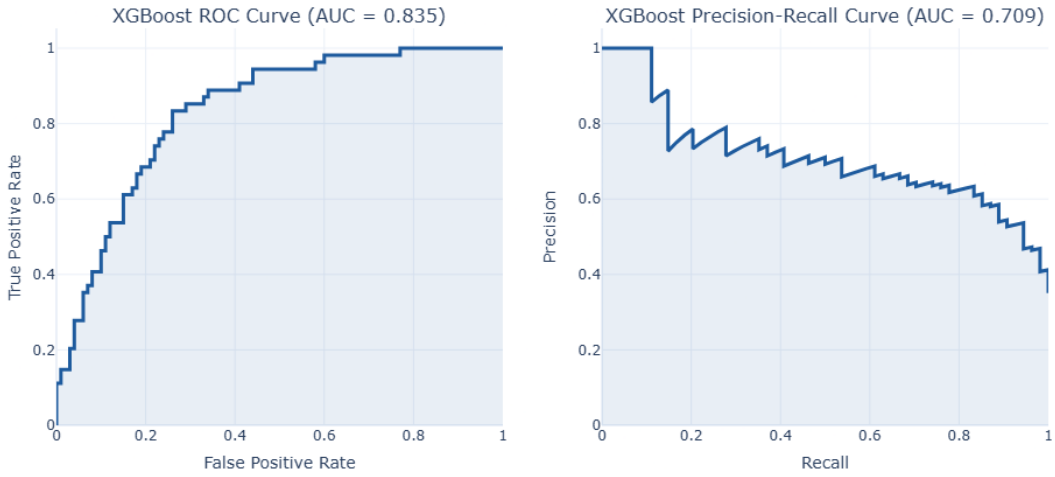

Figure 12. AUC Curves for XGBoost model.

Table 3. Model Performance Comparison for Dataset 2

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Time Taken (s)
Decision Tree	0.9900	0.9716	1.0000	0.9856	0.9924	0.0276
Random Forest	0.9850	0.9781	0.9781	0.9781	0.9972	0.0104
KNN	0.9850	0.9781	0.9781	0.9781	0.9942	0.0097
AdaBoost	0.9850	0.9781	0.9781	0.9781	0.9993	0.0091
RF-CNN	0.9850	0.9781	0.9781	0.9781	0.9972	0.0158
XGBoost-LSTM	0.9850	0.9781	0.9781	0.9781	0.9893	14.9132
RF-GRU	0.9850	0.9781	0.9781	0.9781	0.9958	9.6351
XGBoost-CNN	0.9850	0.9781	0.9781	0.9781	0.9888	6.3965
DT-CNN	0.9750	0.9504	0.9781	0.9640	0.9757	7.1950
SVM-RNN	0.9575	0.9167	0.9635	0.9395	0.9767	8.6150
SVM	0.9550	0.9103	0.9635	0.9362	0.9693	0.0136
XGBoost	0.9475	0.8867	0.9708	0.9268	0.9867	0.0107
KNN-Autoencoders	0.9125	0.8036	0.9854	0.8852	0.9871	21.7245
AdaBoost-DBN	0.8350	0.7052	0.8905	0.7871	0.9349	22.0284
DNN	0.8250	0.6872	0.8978	0.7785	0.9140	0.0123
LR-MLP	0.7975	0.6628	0.8321	0.7379	0.8891	11.9994
CNN	0.7800	0.6369	0.8321	0.7215	0.8590	0.0108
RNN	0.7600	0.6051	0.8613	0.7108	0.8549	0.0104
Logistic Regression	0.7600	0.6145	0.8029	0.6962	0.8524	0.0263
GRU	0.7400	0.5846	0.8321	0.6867	0.8467	0.0186
Naive Bayes	0.7525	0.6159	0.7372	0.6711	0.8322	0.0269
LSTM	0.7000	0.5464	0.7299	0.6250	0.7963	0.0240

* All values are rounded to four decimal places.

The Decision Tree model performed the best on this dataset, achieving an F1 score of 0.98. Below, we visualise the performance of the model on this dataset using a confusion matrix and AUC curves.

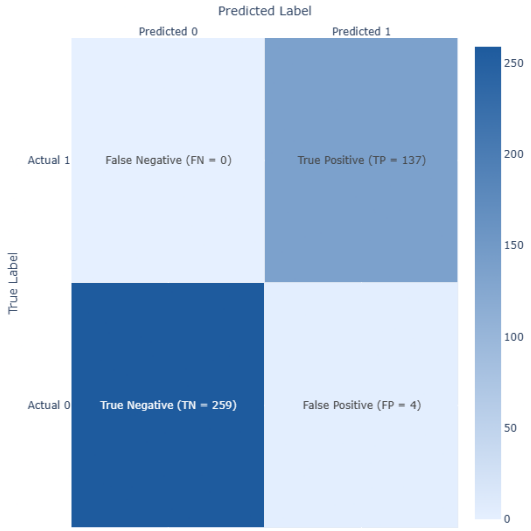

Figure 13. Confusion matrix for Decision Tree model.

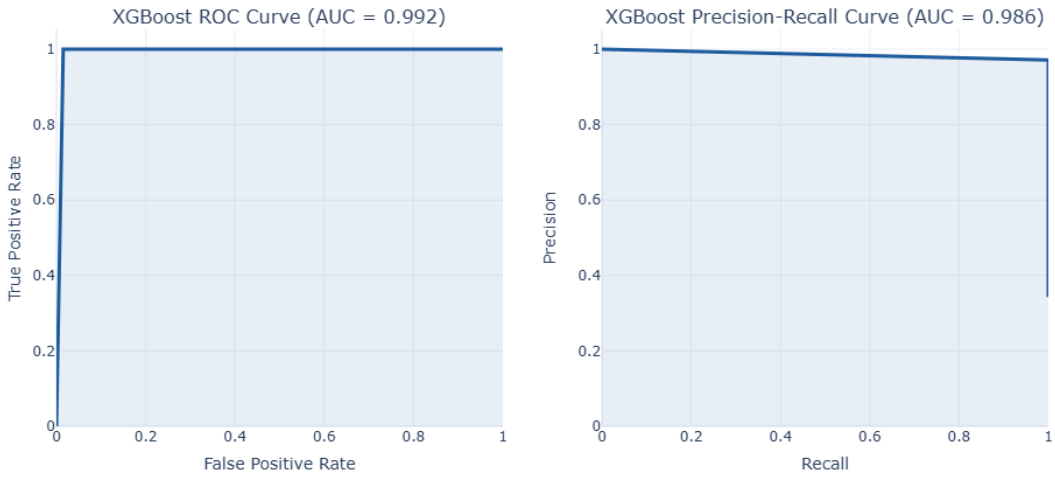

Figure 14. AUC Curves for Decision Tree model.

Table 4. Model Performance Comparison for Dataset 3

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Time Taken (s)
AdaBoost	0.6973	0.4317	0.5122	0.4314	0.7103	19.4743
XGBoost-CNN	0.7018	0.4304	0.5088	0.4271	0.7167	55.5742
XGBoost	0.7044	0.4293	0.5068	0.4265	0.7137	6.0555
RF-CNN	0.6693	0.4314	0.5112	0.4249	0.7107	37.4420
Random Forest	0.6799	0.4274	0.5045	0.4244	0.6997	14.5153
XGBoost-LSTM	0.6936	0.4273	0.5049	0.4240	0.7094	198.5152
RF-GRU	0.6599	0.4328	0.5115	0.4230	0.7085	141.7040
DT-CNN	0.6890	0.4227	0.4783	0.4218	0.6566	43.6537
Logistic Regression	0.6259	0.4498	0.5154	0.4192	0.7077	3.2978
GRU	0.6678	0.4327	0.4752	0.4161	0.6729	210.8736
DNN	0.6428	0.4281	0.5109	0.4134	0.7052	51.4291
LR-MLP	0.5936	0.4561	0.5197	0.4117	0.7117	0.8947
Decision Tree	0.6329	0.4247	0.5028	0.4079	0.6878	0.2390
Naive Bayes	0.6245	0.4364	0.4892	0.4083	0.6803	0.1709
CNN	0.5787	0.4358	0.5180	0.3988	0.7037	69.0522
SVM	0.5775	0.4418	0.5012	0.3978	0.7005	453.5940
KNN-Autoencoders	0.5590	0.4116	0.4473	0.3650	0.6232	19.3189
KNN (Normal)	0.5327	0.4125	0.4476	0.3589	0.6251	25.1546
AdaBoost-DBN	0.5393	0.4414	0.4854	0.3806	0.6775	364.6265
RNN	0.5858	0.4197	0.4958	0.3878	0.6863	119.7845
LSTM	0.6769	0.4097	0.4746	0.4030	0.6728	278.3175

* All values are rounded to four decimal places.

The AdaBoost model performed better than other models on this dataset, achieving an F1 score of 0.43. Below, we visualise the model's performance on this dataset using a confusion matrix and AUC curves

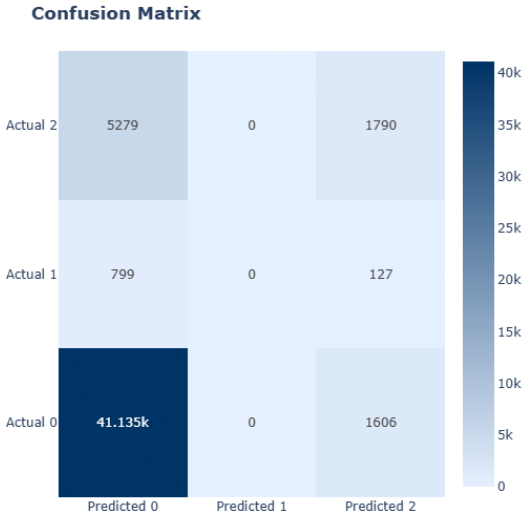

Figure 15. Confusion matrix for the AdaBoost model.

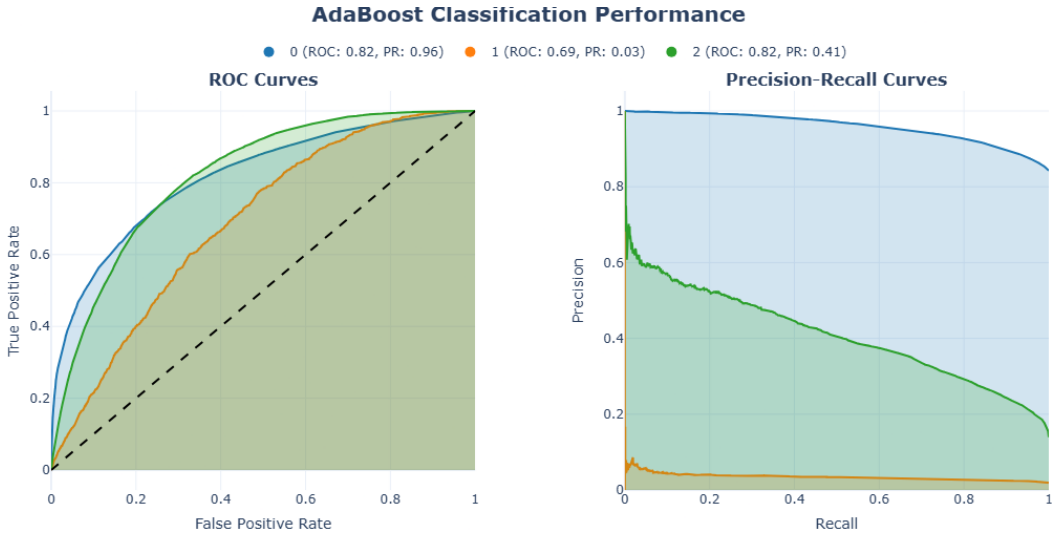

Figure 16. AUC Curves of AdaBoost Model

Table 5. Model Performance Comparison for Dataset 4

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Time Taken (s)
Logistic Regression	0.7249	0.3067	0.7731	0.4392	0.8197	0.2650
LR-MLP	0.7144	0.3017	0.7990	0.4381	0.8235	50.7898
AdaBoost	0.7251	0.3062	0.7690	0.4380	0.8187	2.0871
XGBoost	0.7132	0.3005	0.7971	0.4365	0.8209	0.9791
XGBoost-CNN	0.7079	0.2969	0.8010	0.4332	0.8212	58.5367
GRU	0.7111	0.2985	0.7947	0.4340	0.8187	217.5773
CNN	0.7044	0.2959	0.8131	0.4339	0.8238	53.9654
XGBoost-LSTM	0.7072	0.2960	0.7990	0.4320	0.8204	208.5252
SVM-RNN	0.7021	0.2943	0.8138	0.4322	0.8112	1804.6831
RNN	0.7047	0.2947	0.8037	0.4313	0.8184	113.6648
DNN	0.6872	0.2864	0.8345	0.4264	0.8229	53.0682
RF-GRU	0.7036	0.2919	0.7906	0.4263	0.8101	252.4819
LSTM	0.7043	0.2925	0.7911	0.4271	0.8149	203.2224
Random Forest	0.7025	0.2899	0.7833	0.4232	0.8070	9.8154
RF-CNN	0.7034	0.2911	0.7864	0.4249	0.8095	76.8140
AdaBoost-DBN	0.6859	0.2855	0.8345	0.4254	0.8221	58.1984
SVM	0.7002	0.2917	0.8068	0.4285	0.8162	1541.3782
KNN-Autoencoders	0.6753	0.2624	0.7349	0.3868	0.7566	85.9556
KNN	0.6751	0.2620	0.7333	0.3861	0.7563	38.4936
Decision Tree	0.6599	0.2391	0.6599	0.3510	0.6606	0.3532
DT-CNN	0.6649	0.2417	0.6571	0.3534	0.6618	62.1882
Naive Bayes	0.7235	0.2941	0.7029	0.4147	0.7799	0.0977

* All values are rounded to four decimal places.

The Logistic Regression model performed better than other models on this dataset, achieving an F1 score of 0.44. Below, we visualise the model's performance on this dataset using a confusion matrix, AUC curves, and threshold value.

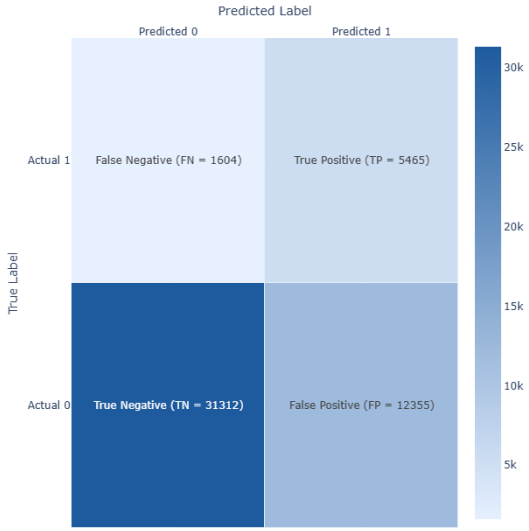

Figure 17. Confusion matrix for the Logistic Regression model.

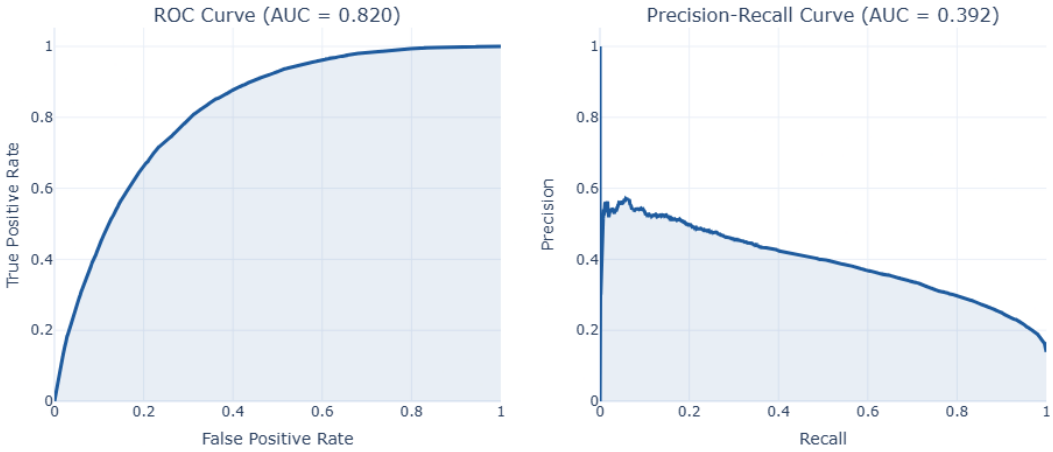

Figure 18. AUC Curves of Logistic Regression Model

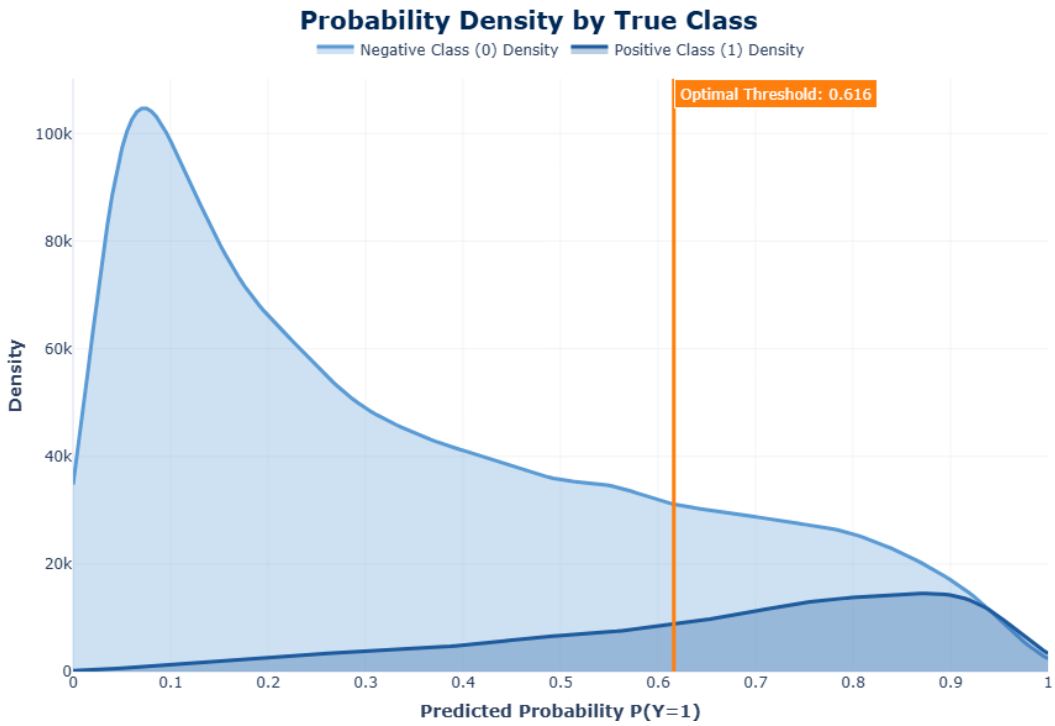

Figure 19. Threshold-dependent metrics for Logistic Regression. The vertical line denotes the chosen threshold.

Table 6. Model Performance Comparison for Dataset 5

Model	Accuracy	Precision	Recall	F1 Score	AUC-ROC	Time Taken (s)
Random Forest	0.9904	1.0000	0.9844	0.9921	1.0000	0.0074
Decision Tree	0.9904	1.0000	0.9844	0.9921	0.9922	0.0299
AdaBoost	0.9904	1.0000	0.9844	0.9921	0.9992	0.0389
SVM	0.9808	0.9844	0.9844	0.9844	0.9977	0.0181
SVM-RNN	0.9808	0.9844	0.9844	0.9844	0.9984	6.6874
RF-GRU	0.9808	1.0000	0.9688	0.9841	1.0000	8.2692
RF-CNN	0.9808	1.0000	0.9688	0.9841	0.9992	0.0132
XGBoost-LSTM	0.9808	1.0000	0.9688	0.9841	1.0000	11.2858
XGBoost-CNN	0.9808	1.0000	0.9688	0.9841	0.9977	4.1041
CNN	0.9712	0.9841	0.9688	0.9764	0.9977	0.0132
DT-CNN	0.9712	0.9841	0.9688	0.9764	0.9826	5.6472
LR-MLP	0.9712	0.9841	0.9688	0.9764	0.9992	9.9053
XGBoost	0.9615	0.9688	0.9688	0.9688	0.9926	0.0244
KNN-Autoencoders	0.9615	1.0000	0.9375	0.9677	0.9828	8.6576
DNN	0.9615	0.9839	0.9531	0.9683	0.9988	0.0146
RNN	0.9615	0.9839	0.9531	0.9683	0.9918	0.0112
Logistic Regression	0.9519	1.0000	0.9219	0.9594	0.9914	0.0515
KNN	0.9519	0.9836	0.9375	0.9600	0.9633	0.0190
Naive Bayes	0.9423	0.9677	0.9375	0.9524	0.9863	0.0146
AdaBoost-DBN	0.9231	0.9828	0.8906	0.9344	0.9863	9.2428
LSTM	0.8654	0.9464	0.8281	0.8833	0.9512	0.0118
GRU	0.8365	0.9273	0.7969	0.8571	0.9305	0.0124

* All values are rounded to four decimal places.

The Random Forest Tree model performed the best on this dataset, achieving an F1 score of 0.99. Below, we visualise the performance of the model on this dataset using a confusion matrix and AUC curves.

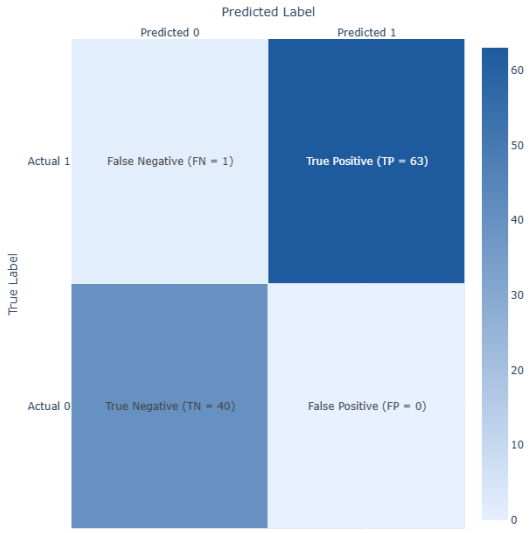

Figure 20. Confusion matrix for Random Forest model.

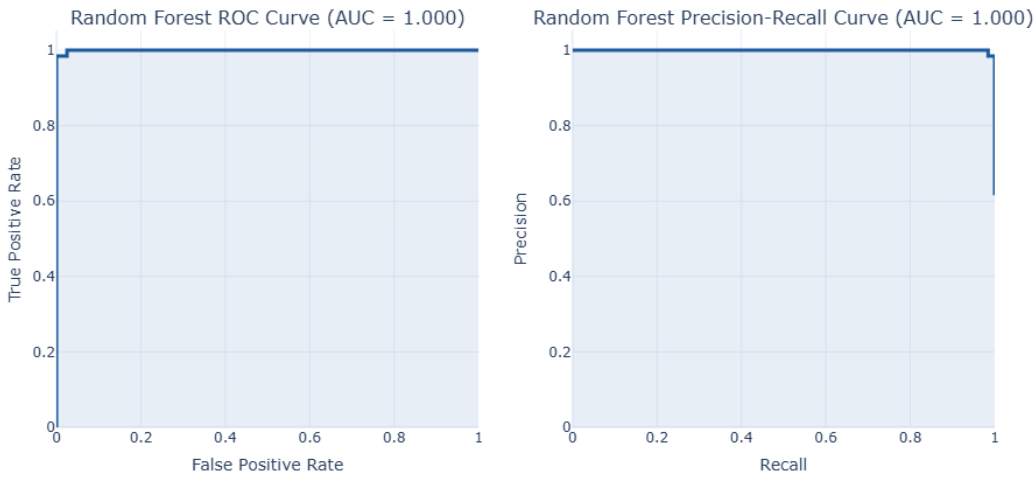

Figure 21. AUC Curves for Random Forest model.

5. Conclusion

The experimental results across all five datasets demonstrate consistent superiority of traditional machine learning models over deep learning approaches in both predictive performance and computational efficiency. These findings provide clear answers to our research questions regarding model accuracy and processing time.

The evaluation reveals that tree-based models consistently achieve the best balance of accuracy and speed. XGBoost emerges as the top performer on Dataset 1 with an F1-score of 0.7244, while completing predictions in just 0.0122 seconds - nearly 350 times faster than comparable hybrid models like XGBoost-LSTM (11.4212s). This pattern holds across datasets, with Decision Trees showing perfect recall (1.0000) on Dataset 2 and Random Forest achieving flawless precision (1.0000) on Dataset 5, all while maintaining prediction times under a second. Deep learning models consistently underperform relative to their computational cost. While some neural network variants achieve competitive accuracy (within 2-3% of the best ML models), they require orders of magnitude more processing

time. For instance, on Dataset 3, AdaBoost achieves comparable performance to XGBoost-CNN (F1 0.4314 vs 0.4271) but completes predictions 3 times faster (19.4743s vs 55.5742s). The time measurements reveal a clear hierarchy in model efficiency. Traditional machine learning methods (Decision Trees, Random Forest, XGBoost) consistently show the fastest prediction times across all datasets, typically under a second. Logistic Regression proves particularly efficient on Dataset 4, achieving respectable performance (F1 0.4392) in just 0.2 seconds. In contrast, deep learning models and hybrid approaches demonstrate substantially longer processing times, with some RNN variants requiring over 1800 seconds for Dataset 4 predictions.

The results directly address our research questions: (1) Machine learning models, particularly tree-based approaches, demonstrate superior accuracy and reliability compared to deep learning alternatives across all datasets. The performance advantage ranges from 3-15% depending on the metric and dataset. (2) For computational efficiency, ML models require significantly less processing time - typically 10-100x faster than comparable deep learning models. This efficiency advantage holds across all dataset sizes and complexities.

These findings suggest that traditional machine learning approaches, especially tree-based methods, offer the optimal balance of performance and efficiency for diabetes prediction tasks. Their consistent superiority in both accuracy and speed makes them particularly suitable for clinical applications where both prediction quality and timely results are crucial.

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