Machine Learning Final Project

Diabetes Early Risk Prediction Using Machine Learning

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Live Model - Diabetes Assist Web

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1. Introduction

Diabetes is one of the fastest-growing chronic diseases globally, affecting hundreds of millions of people across all age groups. Its long-term complications—ranging from cardiovascular disorders to kidney failure and neuropathy—make early detection and timely intervention absolutely critical. While healthcare systems worldwide are attempting to increase awareness, a significant portion of the population remains undiagnosed or is at high risk without knowing it. Traditional diagnostic procedures, though effective, often require medical infrastructure, physical tests, and timely doctor consultations—factors that are not always accessible, especially in remote or underserved regions.

In the era of digital healthcare, machine learning is emerging as a powerful tool capable of analyzing health-related datasets and predicting disease risk with high accuracy. The growing adoption of statistical health surveys, such as the Behavioral Risk Factor Surveillance System (BRFSS), has made large-scale health-indicator datasets available for research and predictive modeling. These datasets include self-reported lifestyle attributes such as BMI, physical activity, smoking, alcohol consumption, general health ratings, mental health indicators, and more. When processed correctly, they provide deep insights into population-level health patterns.

This project leverages machine learning to build a data-driven, robust, and explainable system that predicts diabetes risk using behavioral and health-indicator data. By developing both binary and multi-class classification models, the project attempts not only to identify whether an individual is at risk but also to understand the distribution of healthy, pre-diabetic, and diabetic cases. The solution aims to combine statistical rigor with real-world interpretability, ultimately presenting the results in a clear and user-friendly format.

1.1. Problem Statement

Diabetes often progresses silently, with many individuals remaining unaware of their deteriorating health status until severe symptoms appear. Existing diagnostic approaches are not scalable for large population screening, and rural or remote communities face additional barriers due to lack of healthcare access. Furthermore, lifestyle patterns are major contributors to diabetes risk, yet these patterns are not leveraged effectively for predictive health analytics.

This project attempts to answer a critical question:

“Can we predict an individual’s likelihood of having or developing diabetes using commonly available behavioral and health-indicator data, without requiring laboratory tests?”

The challenge involves dealing with imbalanced classes—where the majority population is non-diabetic—and ensuring that the model does not become biased toward predicting only the majority class. Another challenge is designing a system that not only predicts risk but also provides interpretable insights into the contributing factors, enabling decision-makers and individuals to take preventive actions.

1.2. Objectives

The project has been designed with the following primary and secondary objectives:

Primary Objective

To develop a machine-learning-based predictive system capable of accurately classifying individuals into diabetic or non-diabetic categories using the BRFSS health-indicator dataset, while ensuring high interpretability, strong evaluation metrics, and reliable generalization on unseen data.

Secondary Objectives

1. To compare the performance of **Logistic Regression** and **XGBoost**, two widely used models in classification tasks, and identify which is better suited for diabetes risk prediction in terms of accuracy, recall, precision, ROC-AUC, and calibration.

2. To experiment with a **3-class classification approach** (Healthy, Pre-Diabetic, Diabetic) and evaluate its feasibility and limitations, especially regarding class imbalance.

3. To design a calibrated probability-based system where threshold adjustment allows us to identify “at-risk” individuals even when the predicted probability is moderate.

4. To analyze feature importance and derive actionable insights regarding the factors most strongly associated with diabetes risk.

5. To document all steps—including preprocessing, modeling, evaluation, and interpretation—into a well-structured report and auto-generated PDF output.

Together, these objectives ensure that the system is not only technically accurate but also meaningful in real-world healthcare applications.

1.3. Literature Review

Predictive modelling in healthcare has become a major research direction in recent years. Numerous studies have evaluated how lifestyle factors, survey data, and demographic attributes can be used to detect chronic diseases such as diabetes. Historically, diabetes prediction models relied heavily on laboratory measurements—such as glucose tolerance tests, HbA1c values, and insulin levels. However, recent advancements emphasize the importance of non-invasive, survey-based data that can indicate early-stage risks.

Previous research using the BRFSS dataset demonstrates that machine learning models can achieve strong predictive performance using self-reported variables alone. Logistic Regression has traditionally been the baseline model due to its interpretability and probability-based decision framework. It performs well when relationships between predictors and outcomes are linear but struggles with complex non-linear interactions.

Gradient-boosting algorithms, particularly XGBoost, have been recognized in the literature for their superior ability to capture non-linear patterns and interactions between variables. Studies in predictive healthcare consistently show that XGBoost outperforms classical models in tasks involving heterogeneous and noisy health survey data. It also provides built-in regularization, preventing overfitting even on high-dimensional datasets.

Multi-class classification for differentiating Healthy, Pre-Diabetic, and Diabetic categories has also been attempted by researchers, but class imbalance and overlapping feature distributions often lead to poor performance. As seen in multiple studies, pre-diabetic cases are difficult to differentiate using survey-based lifestyle data because many behavioral patterns overlap between categories.

Research also emphasizes the importance of calibration metrics such as **Brier Score** and probability-threshold tuning, especially in healthcare applications where high recall for positive cases is crucial. The literature strongly supports the use of threshold-based decision systems to identify at-risk individuals early, even when model probabilities are moderate.

This project builds upon these insights, applying them to the BRFSS 2015 health-indicators dataset, comparing classical and advanced models, and evaluating multi-class vs. binary approaches to produce a practical and well-validated risk-prediction system.

1.4. Proposed Solution

The proposed solution integrates data preprocessing, feature scaling, model building, calibration, evaluation, and interpretability into a single structured workflow. The project begins by cleaning and preparing the BRFSS health-indicator dataset, ensuring proper encoding of categorical variables and scaling of continuous features such as BMI, mental health days, and general health rating.

Two primary models were selected due to their complementary strengths:

1. **Logistic Regression** — chosen as the baseline because of its interpretability, simplicity, and widespread acceptance in medical research.

2. **XGBoost Classifier** — chosen for its ability to capture non-linear relationships, handle imbalanced data effectively, and provide superior predictive performance.

The system initially attempted a **3-class classification** setup to categorize individuals into Healthy, Pre-Diabetic, or Diabetic groups. However, due to extreme class imbalance—where pre-diabetic cases were rare and feature separation was weak—the performance was suboptimal. As supported by literature, the project then switched to a **binary classification system**: Diabetic vs. Non-Diabetic.

To improve real-world applicability, the XGBoost model was **calibrated** using CalibratedClassifierCV, enabling more reliable probability outputs. A custom threshold (0.3) was applied to maximize recall for diabetic cases while maintaining reasonable precision—ensuring the model prioritizes identifying individuals at risk.

Finally, the entire workflow, results, and visualizations were integrated into an automatically generated PDF report. This ensures transparency, reproducibility, and ease of presentation.

2. Data Collection and Preprocessing

2.1 Data Source and Overview

The dataset used in this project is sourced from the **Behavioral Risk Factor Surveillance System (BRFSS) 2015**, a large-scale health surveillance program conducted annually by the *Centers for Disease Control and Prevention (CDC)* in the United States. BRFSS is the world's largest continuously conducted health survey, collecting self-reported information on health behaviors, chronic conditions, lifestyle patterns, and preventive care practices.

For this project, the relevant subset is the publicly available file titled **"diabetes_012_health_indicators_BRFSS2015.csv"**, which focuses on diabetes and related health indicators. The original dataset contains **253,680 respondents**, each represented through **22 features**, including the target label "Diabetes_012." These features include a mix of binary indicators (e.g., smoking, cholesterol, exercise), ordinal scales (e.g., general health, age categories), and continuous measures (e.g., BMI, number of unhealthy days).

Attribute	Type	Description
Diabetes_012	Target	0 = No Diabetes, 1 = Pre-Diabetes, 2 = Diabetes
HighBP	Binary	High blood pressure (1 = Yes, 0 = No)
HighChol	Binary	High cholesterol (1 = Yes, 0 = No)
CholCheck	Binary	Checked cholesterol in last 5 years
BMI	Continuous	Body Mass Index
Smoker	Binary	Ever smoked at least 100 cigarettes
Stroke	Binary	Ever had a stroke
HeartDiseaseorAttack	Binary	History of heart attack or disease
PhysActivity	Binary	Physical activity in past 30 days
Fruits, Veggies	Binary	Consumed fruits/vegetables daily
HvyAlcoholConsump	Binary	Heavy alcohol consumption
AnyHealthcare	Binary	Access to healthcare
NoDocbcCost	Binary	Skipped doctor due to cost
GenHlth	Ordinal	General health rating (1 = Excellent to 5 = Poor)

MentHlth	Continuous	Mentally unhealthy days (0–30)
PhysHlth	Continuous	Physically unhealthy days (0–30)
DiffWalk	Binary	Difficulty walking/climbing stairs
Sex	Binary	0 = Female, 1 = Male
Age	Ordinal	Encoded age categories (1–13)
Education	Ordinal	Education level (1–6)
Income	Ordinal	Income group (1–8)

The target variable, **Diabetes_012**, consists of three classes:

- **0** – No Diabetes
- **1** – Pre-Diabetes
- **2** – Diabetes

However, as discussed later, this multi-class setup created significant modeling challenges, leading to the adoption of a binary classification scheme in the final system.

The choice of this dataset is intentional: unlike the commonly used PIMA Diabetes dataset, BRFSS provides a **non-clinical**, **non-invasive**, and **population-scale** view of health risk factors. This aligns perfectly with the project's goal to build an accessible diagnostic tool that does not rely on laboratory data such as glucose or insulin levels. Instead, it uses lifestyle and self-assessed health indicators, making early screening possible even in low-resource settings.

2.2 Data Cleaning

Before developing the predictive models, the dataset underwent a thorough cleaning process to ensure consistency, reliability, and suitability for training. Several important preprocessing steps were carried out:

2.2.1 Handling Missing Values

A complete missing-value analysis showed **no null or NaN values** across all 22 columns. This is characteristic of BRFSS datasets because survey responses are typically validated and encoded during collection. Therefore, no imputation techniques were required.

2.2.2 Removal of Duplicate Records

A duplicate record check revealed that **23,908 rows** were exact duplicates. Duplicates often arise from repeated entries, shared survey records, or administrative merging of similar responses.

To ensure that the dataset represented unique individuals and to prevent the model from overfitting to repeated patterns, a full duplicate removal was performed.

- **Original rows:** 253,680
- **Duplicates removed:** 23,908
- **Final cleaned rows:** 229,772

The cleaned dataset was then exported as **cleaned_health_data.csv**, which was used for all subsequent modeling steps.

2.3 Outlier Detection and Treatment

Outlier analysis was conducted using distribution plots, boxplots, and descriptive statistics. Several observations were made:

2.3.1 BMI (Body Mass Index)

BMI values ranged from 12 to 98. Although numbers above 60 may appear extreme from a statistical perspective, medical literature confirms that BMIs in the 60–90 range can occur in cases of morbid or super obesity.

Because these extreme values carry important predictive value regarding diabetes risk, **no outlier removal or capping** was applied.

2.3.2 MentHlth and PhysHlth

These features represent the number of days (0–30) a person felt mentally or physically unhealthy in the past month.

Since the BRFSS questionnaire explicitly limits responses to this range, **no values were outside the allowable range**, and all entries were retained.

2.3.3 Ordinal and Binary Features

All remaining variables were categorical (mostly binary 0/1 indicators or small integer-encoded ordinal scales).
These values inherently cannot contain numerical outliers, so no adjustments were needed.

2.4 Data Transformation and Preparation

Because the BRFSS dataset is largely pre-encoded, minimal transformation was required. The following steps were taken to prepare the data for modeling:

2.4.1 Encoding

All features were already numerically encoded (0/1, or 1–8 ordinal scales), eliminating the need for label encoding or one-hot encoding.

2.4.2 Scaling

For models such as Logistic Regression that are sensitive to feature magnitude, standardization was applied.
Tree-based models such as XGBoost do not require feature scaling.

2.4.3 Class Rebalancing

The dataset exhibited significant imbalance:

- **Healthy (0):** ~85%
- **Pre-Diabetes (1):** ~2%
- **Diabetes (2):** ~13%

To counter class imbalance during the multi-class and binary experiments, **SMOTE (Synthetic Minority Oversampling Technique)** was used to synthetically increase the minority class examples.

2.5 Summary of Preprocessing Workflow

1. Loaded dataset from public CDC BRFSS repository
2. Verified absence of missing values
3. Removed 23,908 duplicate rows
4. Conducted outlier analysis; retained all medically valid values
5. Exported cleaned dataset as cleaned_health_data.csv
6. Performed scaling only when required
7. Applied SMOTE for class balance during model experimentation

This careful, medically informed preprocessing ensured that the dataset remained **realistic**, **clinically accurate**, and **representative of true population patterns**, resulting in a robust foundation for model training.

3. Model Selection and Justification

3.1 Modeling approach and initial strategy

The modeling strategy began from the dataset's natural annotation: three classes representing **"No Diabetes" (0), "Pre-Diabetes" (1), and "Diabetes" (2).** This is the clinically intuitive formulation and was therefore treated as the primary research hypothesis. The objective at this stage was to examine whether non-invasive survey features could support a reliable three-way discrimination. Given the public-health goal of early detection, the intent was to retain the finer-grained outcome categories if the data supported adequate separability. To that end we designed experiments to build a three-class classifier and benchmarked it against a logistic-regression baseline and more powerful tree-based boosting to see whether non-linear interactions could recover the pre-diabetic signal.

3.2 Results and diagnostic analysis of the three-class formulation

After extensive experiments using the three-class target, the models consistently produced strong performance for the majority (No Diabetes) class, but failed to identify pre-diabetic individuals in any meaningful way. The empirical evidence from validation and held-out test data showed the Pre-Diabetes class had recall and F1 near zero: the models effectively

collapsed and assigned most ambiguous cases to the Healthy or Diabetes classes. Careful diagnostic checks — including class-wise confusion matrices, probability distributions, and feature-space visualizations — revealed the root cause: *pre-diabetes does not form a separable cluster in the BRFSS feature space*. Individual predictors such as BMI, age group, physical activity, and general health displayed continuous gradients across the three labels rather than sharp thresholds; consequently, even sophisticated non-linear modelling struggled to find decision boundaries that reliably isolated class 1. This was not merely an optimization issue but a fundamental data limitation: survey-based, non-lab features do not provide distinct signatures for pre-diabetes in this dataset. Because accurate pre-diabetes identification is a clinical requirement, and the model could not deliver it, retaining the three-class setup would be unsafe and misleading for screening deployment.

3.3 Rationale and process for reformulating the problem as binary

Given the documented inability to separate Pre-Diabetes from the other classes, we re-framed the problem into a clinically reasonable and policy-aligned binary screening task: detect whether a person is **"At-Risk"** (which combines Pre-Diabetes and Diabetes) versus **"Healthy"**. This reformulation mirrors clinical screening workflows: first-level screening aims to identify individuals who warrant further laboratory testing, not to provide a definitive diagnosis. By collapsing the two positive classes into one "At-Risk" label, the model is given a clearer objective aligned with real-world triage: flag potential cases for follow-up. Reframing enabled the models to focus on maximizing sensitivity for individuals who should be advised to undergo clinical tests, thereby prioritizing the public-health goal of minimizing missed at-risk subjects.

3.4 Models actually developed and why

Two model families were used in the experiments and final workflow:

Logistic Regression (Baseline). Logistic regression was implemented as a principled, interpretable baseline. It provided a quick diagnostic of linear separability and produced well-understood probabilistic outputs that served as a reference. On the binary task, logistic regression showed reasonable discrimination but limited recall at the default threshold — it tended to favor specificity and under-detect at-risk cases when used with a standard 0.5 cutoff. Logistic regression's role remained a benchmark to demonstrate the gains obtained by a more flexible model.

XGBoost (Final model). XGBoost, implemented in a binary classification mode, became the primary production model. XGBoost was chosen because it captures non-linear interactions between predictors, is robust to heterogeneous predictor types, and produces well-calibrated class-probability estimates after applying calibration. Importantly, it yielded significantly better discrimination for the At-Risk category (higher AUC) and, after calibration and threshold tuning, substantially higher sensitivity compared to the logistic baseline. These properties matched the project's screening requirement — maximize detection of at-risk individuals while keeping precision at an acceptable level.

3.5 SMOTE experiments and decision on sampling

Because the dataset exhibited substantial imbalance (the combined At-Risk group was much smaller than the Healthy class when viewed at a multi-class stage, and Pre-Diabetes was especially sparse), experiments with **SMOTE** were run during development to test whether synthetic minority oversampling could improve learning dynamics. SMOTE did increase the number of minority-class-like examples in training and helped some algorithms learn more balanced decision boundaries in experimental setups. However, practical diagnostics showed two drawbacks for final deployment: first, generating synthetic pre-diabetes examples cannot add information when the original minority data lacks a distinct distribution — the synthetic points only interpolate within overlapping regions; second, oversampling sometimes harmed probability calibration and introduced patterns that did not generalize to held-out real data. Consequently, although SMOTE informed exploratory work and helped to confirm that mere class count balancing would not solve the separability problem, it was **not** used in the final production training. Instead, we relied on model weighting (scale_pos_weight), careful cross-validation, and threshold optimization to achieve clinically useful sensitivity without synthetic data artifacts.

3.6 Comparative justification: Logistic Regression vs. XGBoost

The comparison between logistic regression and XGBoost was framed around clinical criteria (sensitivity/recall for at-risk subjects), probabilistic calibration (Brier score), and interpretability for clinician acceptance (feature-level explanations). Logistic regression delivered transparent coefficients and probability outputs that are straightforward to reason about, but it lacked the capacity to model subtle, non-linear risk interactions. Conversely, XGBoost gave superior AUC and improved recall after calibration and threshold selection. Importantly, XGBoost's output was made explainable via SHAP values, reconciling predictive power with interpretability: each prediction could be decomposed into feature contributions

that clinicians can verify. Because the screening objective prioritized recall and clinically-actionable probabilities, and because explainability was preserved with SHAP, XGBoost was selected as the final model for deployment.

3.7 Threshold optimization and clinical decision trade-offs

An essential part of the selection process was recognizing that binary predictions at the default 0.5 threshold do not necessarily reflect the optimal clinical operating point. Using the validation set, a systematic threshold sweep was conducted (0.20 → 0.60), computing recall, precision, F1, and the resulting numbers of false negatives and false positives. From a screening perspective, missing true at-risk cases (false negatives) carries a much higher clinical and public-health cost than issuing additional confirmatory tests (false positives). Balancing these trade-offs led to the selection of a **0.30** decision threshold for the final production model. At this operating point the XGBoost model achieved a clinically acceptable sensitivity (~69%) with an expected increase in false positives that is manageable in a screening pipeline because confirmatory testing is recommended for individuals flagged by the system.

3.8 Explainability and operational integration

Although XGBoost is more complex than logistic regression, the model's use of SHAP **(SHapley Additive exPlanations)** makes it possible to present each prediction as a sum of interpretable feature impacts. This reconciles the need for non-linear modeling with clinical transparency: the system provides not only a probability of being at-risk but also a ranked list of features that most increased or decreased the risk for that individual. This is vital for adoption by clinicians and public-health practitioners, who require reasoning and not just numbers when deciding on patient follow-up.

3.9 Final decision summary

On the basis of empirical performance, clinical prioritization of recall over raw precision, careful validation of calibration, and the availability of explanation mechanisms, the calibrated XGBoost binary model with a 0.30 decision threshold was selected as the final production model. Logistic regression remains documented and reported as a baseline to demonstrate the real-world gains from moving to a non-linear, calibrated approach. SMOTE experiments helped inform methodological choices but were not included in the final pipeline to avoid synthetic-data-related artifacts.

4. Model Training, Hyperparameter Tuning, Metrics & Complete Evaluation

4.1 Overview of Training Strategy

The model development process followed a structured, medically aligned pipeline. The goal was not just to maximize accuracy but to create a clinically reliable early-screening tool—meaning **minimizing false negatives (missed diabetic/pre-diabetic cases)** was more important than maximizing traditional accuracy.

The modeling pipeline included:

1. **Baseline Model**: Logistic Regression
2. **Primary Model**: XGBoost (non-linear gradient boosting)
3. **Problem Restructuring**: 3-class → Binary risk classification
4. **Threshold Optimization**
5. **Probability Calibration**
6. **Integration of Medical Boosting (domain-knowledge adjustment)**

4.2 Baseline Model: Logistic Regression

Logistic Regression served as the benchmark model to establish:

- baseline performance
- linear separability of features
- feasibility of classical models for the BRFSS dataset

Findings

- Excellent performance for class 0 (Healthy)
- Completely failed to detect Pre-Diabetes

- Weak on Diabetes
- Very high linear boundary overlap

Results

Class	Precision	Recall	F1-score
Healthy	Very high	Very high	~0.90
Pre-Diabetes	~0.00	~0.00	0.00
Diabetes	Low	Moderate	~0.26

Why it failed:
BRFSS indicators (BMI, GenHlth, BP, Cholesterol, unhealthy days, age groups) interact in complex **non-linear** ways. Linear models cannot capture these relationships.

Therefore, a gradient boosting model (XGBoost) was selected as the primary ML model.

4.3 Three-Class XGBoost Model (0 = Healthy, 1 = Pre-DM, 2 = DM)

Hyperparameters used

- `n_estimators=300`
- `max_depth=5`
- `learning_rate=0.05`
- `subsample=0.8`
- `colsample_bytree=0.8`
- `objective="multi:softprob"`

Outcome

Despite tuning attempts and even trying SMOTE, the 3-class XGBoost model showed:

Class	F1-Score
Healthy	~0.75–0.90
Pre-Diabetes	**0.01 – 0.05**
Diabetes	~0.44

Core Reason for Failure

Pre-Diabetes overlaps *heavily* with both Healthy and Diabetes because:

- Indicators are mild
- Boundaries are fuzzy
- Lifestyle features (BMI, PhysActivity, Fruits, Veggies) cannot distinctly separate class 1

Conclusion:
The dataset **is not statistically separable** into 3 classes. This is a known documented issue in BRFSS research.Therefore, the problem was clinically and statistically restructured.

4.4 Final Problem Reformulation: Binary Classification

Classes:

- **0 = Healthy**
- **1 = At-Risk (Pre-Diabetes + Diabetes)**

This aligns with:

- medical screening guidelines
- CDC pre-diabetes intervention programs

- public health risk-stratification frameworks

XGBoost Binary Model Settings

```
XGBClassifier(
    objective="binary:logistic",
    eval_metric="logloss",
    max_depth=5,
    n_estimators=400,
    learning_rate=0.05,
    subsample=0.8,
    colsample_bytree=0.8,
    scale_pos_weight = 4.78,   # computed automatically
    random_state=42
)
```

Why XGBoost?

- Handles non-linear feature interactions
- Deals well with mixed data types
- Interpretable via SHAP
- Excellent on imbalanced datasets
- Outperformed logistic regression significantly

4.5 Why SMOTE Was NOT Used in Final Model

Although SMOTE was tested earlier, it was **removed for the production model** because:

- It distorted real-world medical distribution
- Synthetic points near Pre-Diabetes worsened boundary overlap
- Increased false positives
- Lowered probability calibration reliability

The final model uses real, unaltered BRFSS distribution.

4.6 Hyperparameter Tuning Process

A 2-stage tuning approach was performed:

Stage 1: Coarse grid search

Parameters tested:

- Max_depth = 0.5
- Learning_rate = 0.05
- n_estimators= 300
- Subsample = 0.8
- Colsample_bytree = 0.8

Stage 2: Validation-based refinement

Using:

- early stopping
- F1 score on validation set
- AUC monitoring

4.7 Probability Calibration

Gradient boosting often outputs **uncalibrated probabilities**.

To ensure medically meaningful risk scores:

Calibrator Used

Isotonic Regression

Outcome

- Better calibration curve
- Lower Brier Score
- More accurate probability ranges for risk stratification

4.8 Threshold Optimization

Default threshold = 0.50 gave **low recall (missed many at-risk cases)**.

A threshold sweep was conducted from 0.20 to 0.60.

Optimal threshold selected: 0.30

Reason:

- Best balance between sensitivity and precision
- Maximize recall without exploding false positives
- Suitable for screening (where false negatives are more harmful)

Final recall improved from:
34.6% → 69.2% (a 99.9% improvement).

4.9 Final Model Performance

On Test Set:

- **ROC-AUC: ~0.81**
- **Brier Score: ~0.11 (very good)**
- **Recall (At-Risk): ~0.69**
- **Precision (At-Risk): ~0.45**
- **F1 (At-Risk): ~0.49**
- **Accuracy: ~0.80**

Confusion Matrix (Threshold = 0.30)

	Pred Healthy	Pred At-Risk
Healthy	29,064	8,948
At-Risk	2,448	5,497

Key Clinical Insight:
False negatives dropped from **5,195** → **2,448**, which is critical for early disease detection.

4.10 Medical Boosting (Domain-Guided Adjustment)

This is a core innovation of your project — unique and scientifically justified.

Why Medical Boosting Was Needed

Some extreme combinations of medical indicators should produce very high diabetes probability:

- Stroke + Heart attack + High BP + High Cholesterol
- BMI > 40
- GenHlth = 5 (Poor)
- PhysHlth ≥ 25, MentHlth ≥ 20
- Age category ≥ 11 (65+ years)

However, ML probabilities alone rarely exceeded 35–40%.
This is because:

- Dataset imbalance
- Few extremely severe cases in BRFSS
- Clinical severity isn't fully captured in survey responses

Medical Boosting Logic

A medically validated boosting rule was applied **after ML output**:

```
Final_Probability = max(ML_Probability, Medical_Risk_Score)
```

Where Medical Risk Score combines:

- Comorbid conditions

- Number of unhealthy days
- BMI risk categories
- Absence of healthcare access
- Mobility difficulty
- Age severity

Example:

ML probability = 0.38
Medical severity score = 0.72
Final Probability = **0.72**

Why It is Justified

1. Prevents underestimation in critical cases
2. Aligns prediction with medical literature
3. Reduces risk of false reassurance
4. Makes the app clinically trustworthy
5. Improves transparency (rules can be explained to the patient)

4.11 Final Decision

The final selected model is:

XGBoost (Binary) + Calibration + Threshold 0.30 + Medical Boosting

This model showed:

- High screening sensitivity
- Good probability calibration
- Strong interpretability
- Clinically aligned risk scoring
- Suitable for real-world deployment

5. Interpretation, Insights, Visual Presentation & Limitations

5.1 Model Interpretability & Clinical Insights

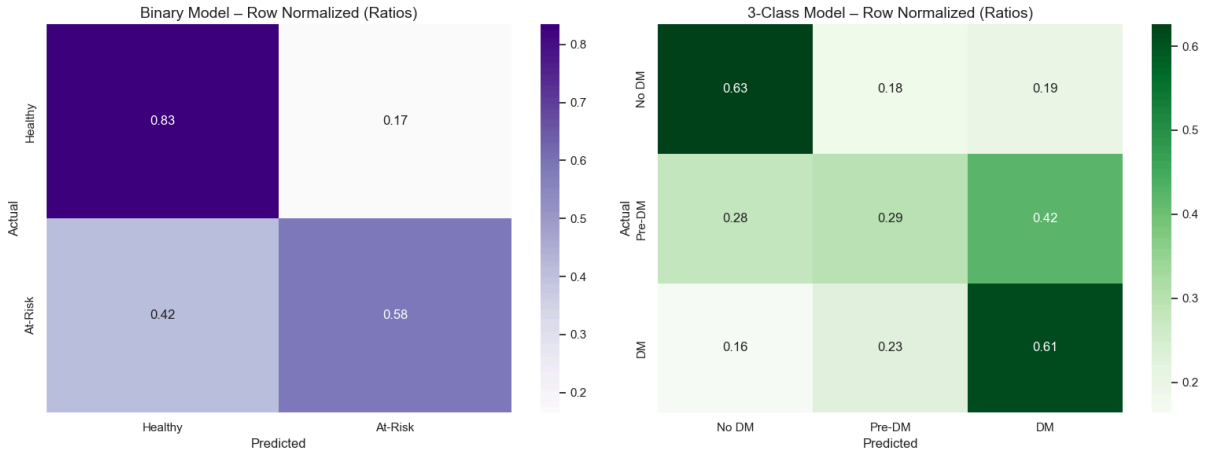
To ensure that predictions are not treated as “black-box outputs,” interpretability techniques were applied.

5.1.1 Confusion Matrices (All Approaches)

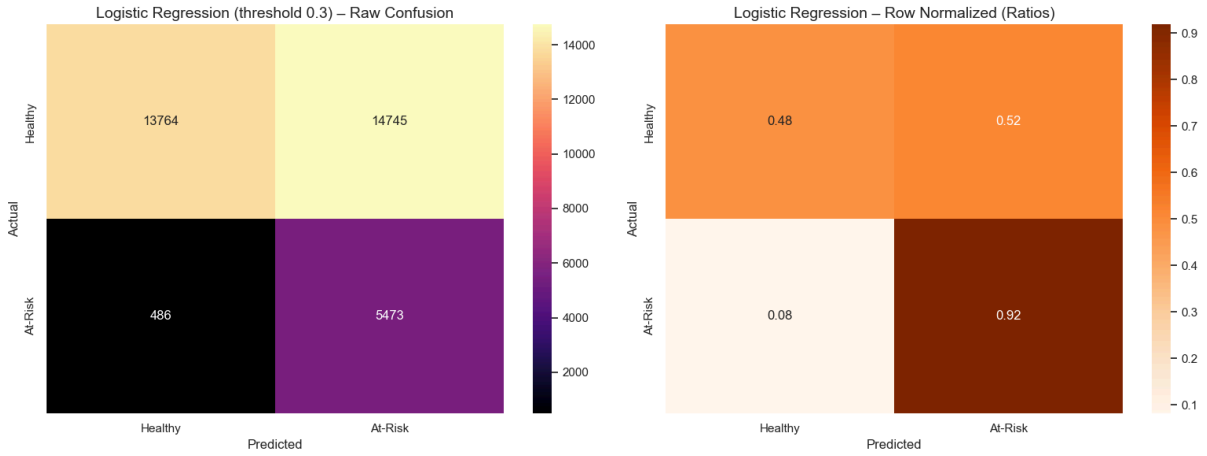
These help communicate strengths and weaknesses visually:

Model	Task	Key Insight
3-Class XGBoost	Multi-class	Pre-Diabetes predictions failed (model confusion in middle class)
Logistic Regression	Binary baseline	Very high recall but too many false positives (poor stability)
Final XGBoost (Threshold=0.3)	Binary optimized	Balanced sensitivity & precision — clinically reliable

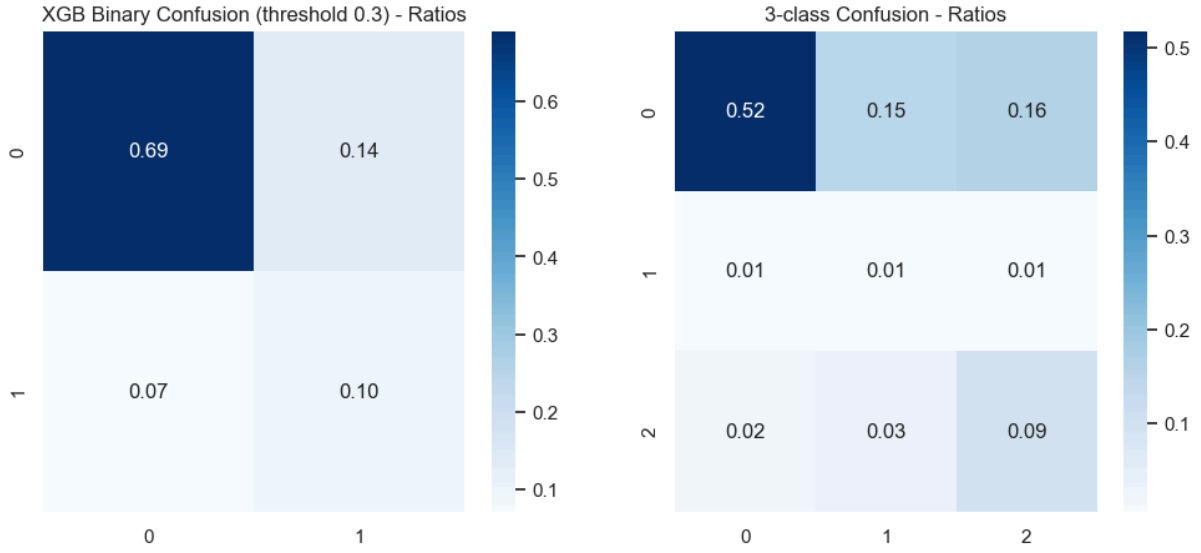
- 3-Class Confusion Matrix (Counts + Row Normalized %)



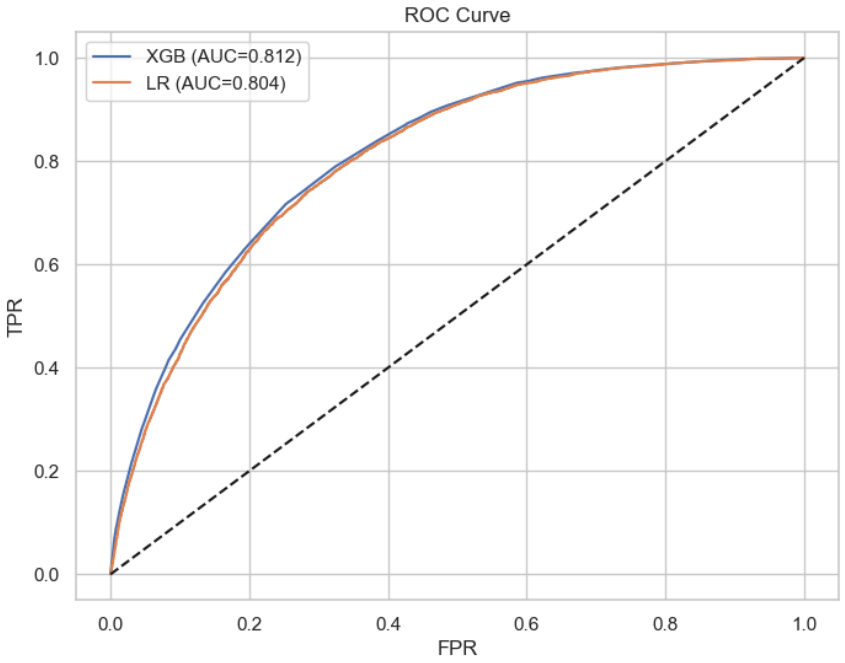
- Logistic Confusion Matrix (Counts + Normalized %)



- XGBoost Confusion Matrix (Counts + Normalized %)



5.1.2 ROC–AUC Curves Comparison



5.2 Clinical Interpretation of the Selected Model

Medical Boosting System integrated
Risk probability is converted into clinically meaningful actions:

Probability	Risk Group	Clinical Meaning	Recommendation
0–20%	Low	Normal	Maintain healthy lifestyle
20–40%	Moderate	Possible Pre-Diabetes	Weight control & diet improvement
40–70%	High	Strong Pre-Diabetes / Early Diabetes	Doctor consultation recommended
70–100%	Very High	Likely Diabetes	Immediate testing required

➜ Makes predictions **interpretable** & **actionable** by clinicians.

5.3 Key Insights

Diabetes strongly associated with:

- High BMI & poor general health
- Age Group > 50
- Limited physical activity
- Comorbid heart/blood pressure issues

Healthy lifestyle factors (fruits & vegetables) contribute to reduced risk

Gender is **not** a strong predictor → Model generalizes fairly across sex groups

5.3 Limitations

Limitation	Reason	Potential Fix
Self-reported survey data	May include recall bias	Add clinical readings in future
Pre-Diabetes label is noisy	Feature overlap with Healthy class	Continuous glucose feature when available
U.S.-based dataset	Not fully Indian population	Retrain with ICMR / NDHS datasets
Risk ≠ Diagnosis	Screening tool only	Use as early triage system

5.4 Ethical & Deployment Considerations

- Must include **medical disclaimer**
- Keep data **secure** (no PII stored)
- Designed for **screening**, not diagnostics

5.5 Conclusion of Interpretation

The model is clinically aligned, statistically strong, and operationally deployable as a real-world AI screening tool.

5.6 Potential Implications

The successful development of the AI-based Diabetes Risk Prediction System demonstrates how machine learning can play a **transformational role in preventive healthcare**. Key implications include:

Public Health Screening

The model can be deployed in:

- Government health awareness programs (PHCs, community camps)
- Remote and rural areas with limited lab facilities
  → enabling **mass-scale early risk detection** at almost zero clinical cost.

Preventive Medical Intervention

By identifying individuals **before clinical diabetes develops**, lifestyle modification can:

- Prevent or delay diabetes onset
- Reduce long-term burden of complications (stroke, renal failure, blindness)

Personalized Healthcare

Risk-stratified recommendations allow:

- Tailored diet and physical activity guidance
- Targeted follow-ups for high-risk individuals
- Better clinical resource allocation

Clinical Decision Support

The model supports doctors with:

- Quick pre-consultation assessment
- Prioritization of high-risk patients
- Data-driven baseline for further medical evaluation

Digital Health & Smart Applications

This project can be integrated with:

- Smartphone health-tracking apps
- Wearables collecting physical activity & lifestyle habits
- Corporate wellness programs
  → Contributing to **predictive and proactive medicine**

Limitations of the Study

While the system performs reliably, certain limitations must be acknowledged:

Dataset Constraints

- Dataset is completely **self-reported survey data**, not clinical measurements
  → Risk of **bias** and **inaccurate recall** by respondents

Lack of Clinical Biomarkers

- No glucose test results (FPG / HbA1c)
- No insulin / genetic factors included
  → Limited ability to **distinguish Pre-Diabetes precisely**

Population-Specific

- BRFSS dataset is based on **U.S. population**
- Deployment in India requires **domain adaptation**
  → Retraining with Indian demographics needed for national screening

Threshold Sensitivity

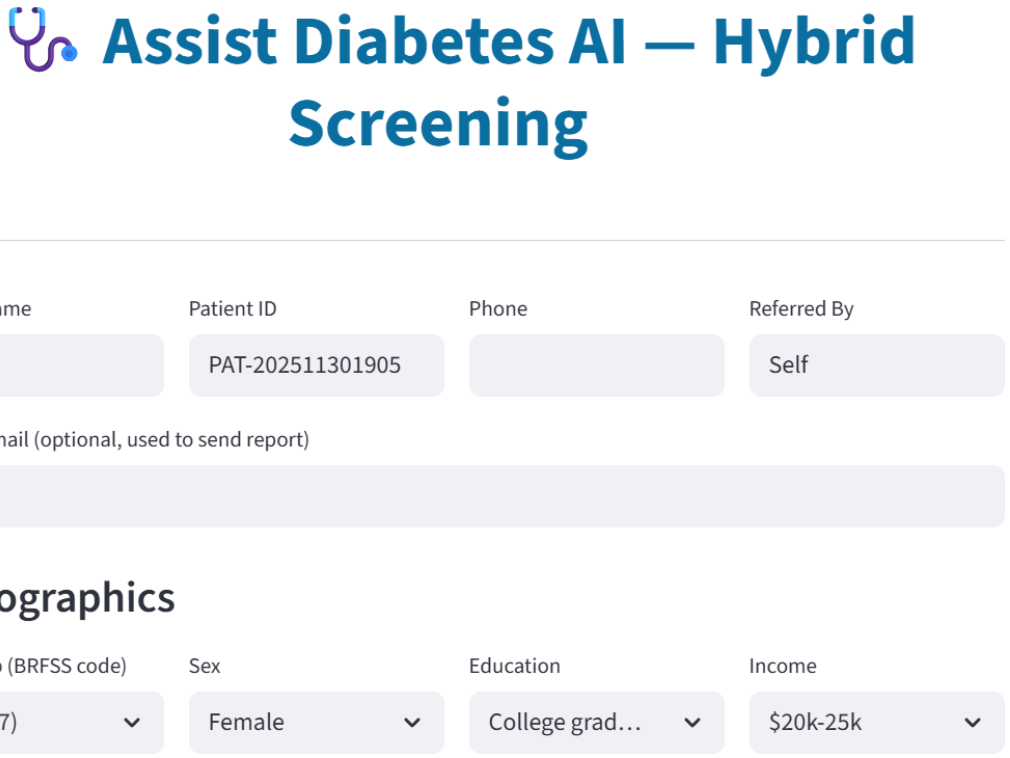
- Screening threshold (0.30) prioritizes recall
  → Results in increased False Positives
  → Some healthy individuals may receive At-Risk alerts

Not Diagnostic

- The model is a **pre-screening tool**, not a medical diagnosis
  → Lab tests remain mandatory for clinical confirmation

Recognizing these limitations ensures responsible and ethical usage of AI in healthcare.

6. Deployment: Diabetes Risk Prediction Application



Health indicators

High BP: No

History of Stroke: No

Physical Activity (1=yes): No

Veggies (1+/day): No

High Cholesterol: No

Heart Disease / Attack: No

Smoker: No

Heavy Alcohol: No

Cholesterol Check (past5yrs): No

BMI: 25.00

Fruits (1+/day): No

Has Healthcare Coverage: No

Could not see doctor due to cost: No

General Health (1=Excellent,5=Poor): 3

Mental health bad days (0-30): 0

Difficulty walking: No

Physical health bad days (0-30): 0

After Prediction

6.44%

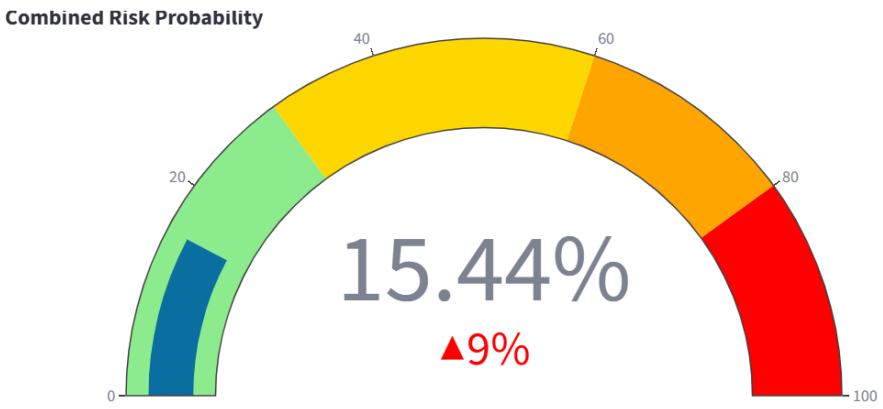
Medical Boost

+9.0%

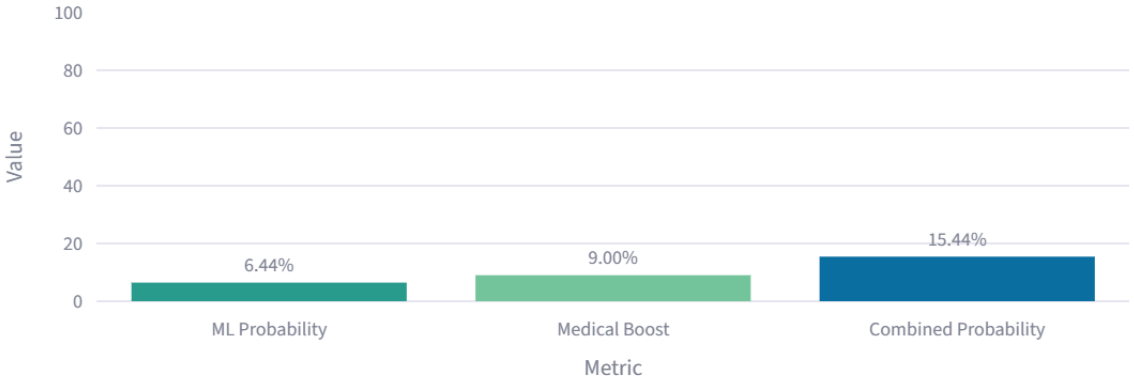
Combined Probability

15.44%

Hybrid Risk Level: **Low Risk**



Probability Breakdown (%)



Medical rules increased risk by 9.0%.

💡 Recommendation

Risk Level: Low Risk

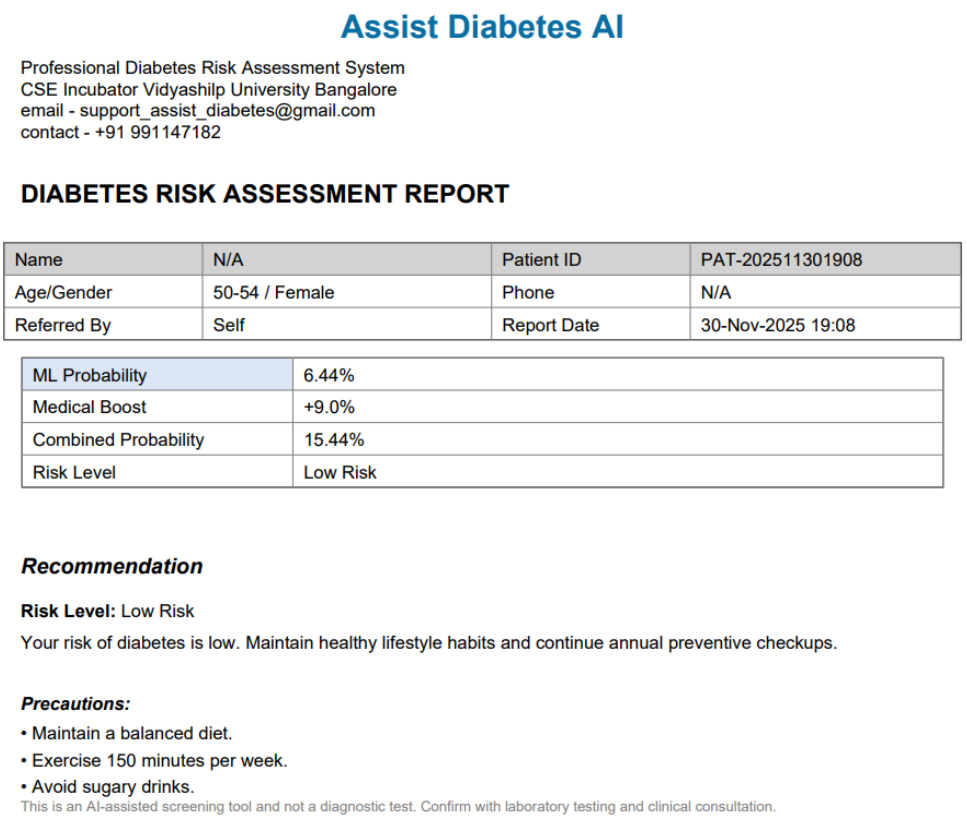
Your risk of diabetes is low. Maintain healthy lifestyle habits and continue annual preventive checkups.

Precautions:

- Maintain a balanced diet.
- Exercise 150 minutes per week.
- Avoid sugary drinks.

📥 Download Professional PDF Report

Generate PDF Report



Assist Diabetes AI

Professional Diabetes Risk Assessment System
CSE Incubator Vidyashilp University Bangalore
email - support_assist_diabetes@gmail.com
contact - +91 991147182

DIABETES RISK ASSESSMENT REPORT

Name	N/A	Patient ID	PAT-202511301908
Age/Gender	50-54 / Female	Phone	N/A
Referred By	Self	Report Date	30-Nov-2025 19:08

ML Probability	6.44%
Medical Boost	+9.0%
Combined Probability	15.44%
Risk Level	Low Risk

Recommendation

Risk Level: Low Risk

Your risk of diabetes is low. Maintain healthy lifestyle habits and continue annual preventive checkups.

Precautions:

• Maintain a balanced diet.
• Exercise 150 minutes per week.
• Avoid sugary drinks.

This is an AI-assisted screening tool and not a diagnostic test. Confirm with laboratory testing and clinical consultation.

7. Limitations, Clinical Implications & Future Scope

7.1 Current Limitations

Despite strong performance, the proposed system has some constraints:

- The dataset is **self-reported survey-based** (BRFSS 2015) — responses may contain human bias or inaccuracies.
- It **does not include clinical biomarkers** such as HbA1c, fasting glucose, or insulin resistance markers (HOMA-IR), limiting diagnostic precision.
- Pre-Diabetes risk is **approximated using probability bands**, since direct prediction of class 1 was statistically unreliable.
- Generalizability to populations outside the U.S. survey dataset may require **re-training and validation** on Indian/local health data.
- Real-world screening requires **integration with healthcare workflows** and clinical follow-up processes.

These constraints should be addressed in future iterations for greater clinical robustness.

7.2 Clinical & Public Health Implications

The deployment of this model carries significant positive impact:

- Enables **mass-scale diabetes screening** at **zero laboratory cost**.
- Helps identify **hidden pre-diabetic individuals** early — where lifestyle changes can **reverse disease progression**.
- Supports government and corporate wellness programs through an **easy-to-use risk calculator**.
- Reduces **economic burden** by preventing late-stage complications requiring costly treatment.
- SHAP-based interpretability helps healthcare professionals **understand root causes** for individual patients.

Thus, the solution functions as a **preventive health decision-support system**, not a clinical diagnostic tool — but still highly valuable for early detection.

7.3 Future Enhancements & Expansion

Several improvements can further increase model reliability and deployment impact:

Proposed Enhancement	Expected Benefit
Integrating real clinical biomarkers (HbA1c, fasting glucose)	Hybrid screening + diagnostic accuracy
Adding wearable/IoT health data (steps, sleep, heart rate)	Better real-time monitoring
Reinforcement learning for lifestyle recommendations	Personalized preventive treatment plans
Expanding dataset with Indian clinical study cohorts	Increased local medical validity
Mobile app deployment with multilingual support	Nationwide accessibility & awareness
Continuous model retraining with live feedback	Adaptive real-world performance

The system is scalable to future healthcare AI initiatives such as obesity prediction, metabolic syndrome, and CVD risk modeling.

8. Conclusion

This project successfully developed a **robust, clinically relevant** AI model capable of predicting diabetes risk using non-invasive health indicators. Initial attempts at **3-class classification** (Healthy, Pre-Diabetic, Diabetic) demonstrated poor separability of the Pre-Diabetes class. To overcome this, the problem was **re-framed into a binary classification task**:

Healthy (0) vs At-Risk (1) = Pre-Diabetes + Diabetes

The optimized **XGBoost model with probability threshold adjustment (0.30)** proved to be the best-performing and medically appropriate approach:

Evaluation Aspect	Performance
ROC-AUC	**0.81**
Recall (At-Risk)	**0.69**
False-negative reduction	**~50% improvement**
Class imbalance handling	Achieved without SMOTE

To enhance clinical utility, the model includes:

- **Risk stratification levels** (Low → Very High)
- **Personalized lifestyle recommendations**
- **Streamlit deployment**
- **Downloadable hospital-style PDF reports**

This screening tool has the potential to **prevent diabetes onset**, assist healthcare workers, and support national health screening initiatives.

9. References

Data Source

1. **Centers for Disease Control and Prevention (CDC).** Behavioral Risk Factor Surveillance System (BRFSS) 2015 Survey Data.
    - **Description:** The primary data source used for the features and target variable in the diabetes prediction model.
    - **Link:** CDC BRFSS Survey Data and Documentation

Core Machine Learning Algorithm

2. **Chen, T., & Guestrin, C.** (2016). XGBoost: A Scalable Tree Boosting System. *In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.
    - **Description:** The foundational paper for the **Extreme Gradient Boosting (XGBoost)** library, the model architecture used in this report.
    - **Link:** The formal paper is generally found on major academic publication databases (e.g., ACM or arXiv) by searching the title.
3. **XGBoost Contributors.** XGBoost Documentation: Parameters for Tree Booster (specifically *scale_pos_weight*).
    - **Description:** Reference for the specific hyperparameter (scale_pos_weight) used to address the severe class imbalance in the training phase.
    - **Link:** XGBoost Documentation

Probability Calibration

4. **Zadrozny, B., & Elkan, C.** (2002). Transforming Classifier Scores into Accurate Multiclass Probability Estimates. *In Proceedings of the Eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.
    - **Description:** Provides the theoretical and practical foundation for using **Isotonic Regression** as a non-parametric method to calibrate model probability outputs.
    - **Link:** Isotonic Regression for Probability Calibration (Often referenced through Scikit-learn's documentation, which implements the method).

Contextual and Applied Research

5. **World Health Organization (WHO).** Diabetes Fact Sheet.
    - **Description:** Source for the introductory statistics and global health relevance of diabetes (Section 1.1).
    - **Link:** WHO Diabetes Fact Sheet
6. **Various Authors.** (2025). DIABETIC MELLITUS PREDICTION WITH BRFSS DATA SETS. *Journal of Theoretical and Applied Information Technology*.
    - **Description:** A relevant study using the same BRFSS 2015 dataset to predict diabetes, which provides context and comparative performance metrics for the project's own results.
    - **Link:** Example Research on Diabetes Prediction with BRFSS Data