Faculty of Computers
& ArtificialIntelligence

Benha University

# Diabetes Prediction Using Machine Learning

## Full Technical Report

**Information System Department**

**Section 3**

***Project Team***

محمد أشرف مهني حسين

محمد عبدالقادر عبدالمنعم احمد

محمد فتحى محمد السيد

محمد اسامة عبدالرازق هزاع

***Under Supervision of :***

**Dr/ Fady Mohamed** **ENG/ Yousef El-Baroudy**

---

**Diabetes Prediction Using Machine Learning - Full Technical Report**

**Analysis and Model Comparison**

**Repo Link: https://github.com/MuhammadAbdelkader/ML-Diabetes-Project/**

---

## 1. Introduction

This project analyzes and models diabetes prediction using the BRFSS 2015 Health Indicators Dataset.

The goal is to understand:

- The nature and structure of the data
- The challenges faced during preprocessing
- Exploratory Data Analysis findings
- The logic behind each Machine Learning model
- Why the results came out in their specific form
- Comparison between all traditional ML models

**Models implemented:**

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

---

## 2. Dataset Overview

The dataset is sourced from the Behavioral Risk Factor Surveillance System (BRFSS) — the largest ongoing health survey in the world.

**Raw Data Characteristics**

- **253,680 rows**
- **300+ features**

- Mix of: Binary, Ordinal, Continuous variables
- No missing values (survey preprocessed)
- Large number of duplicates
- Severe class imbalance

**Target Distribution**

| Class | Meaning | Percentage |
|---|---|---|
| 0 | Non-diabetic | 82% |
| 1 | Pre-diabetic | 2% |
| 2 | Diabetic | 15% |

**Class 1 is extremely underrepresented** — biggest challenge in modeling.

---

**3. Data Cleaning & Preprocessing**

**Duplicates**

- **Found:** 23,899 duplicated rows
- **After removal:** 229,781 rows

**Missing Values**

- BRFSS performs pre-cleaning: **0 missing values**

**Scaling**

Applied **StandardScaler**

Required for:

- KNN
- SVM

**Train/Test Split**

- **80/20 split**
- Used **Stratification** to keep class distribution consistent
- **Training set:** 183,824 samples
- **Testing set:** 45,957 samples

---

## 4. Exploratory Data Analysis (EDA)

### 4.1 Correlation Analysis — Most Related Features

Top features correlated with diabetes:

| Rank | Feature | Correlation |
|---|---|---|
| 1 | GenHlth | 0.283 |
| 2 | HighBP | 0.260 |
| 3 | BMI | 0.210 |
| 4 | DiffWalk | 0.208 |
| 5 | HighChol | 0.202 |

**Medically logical:** People with obesity, high BP, poor general health, difficulty walking, or high cholesterol have higher diabetes risk.

### 4.2 Chi-Square Tests

All categorical features significantly associated with diabetes ($p < 0.05$).

### 4.3 BMI & Age Findings

- Diabetes prevalence increases sharply with BMI
- Elder age groups have significantly higher risk
- Outliers natural due to obese individuals (2.45% of data)

### 4.4 Lifestyle Factors

**Factors increasing risk:**

- Smoking
- No physical activity
- Poor diet

**Factors decreasing risk:**

- Regular exercise
- Balanced diet

---

**5. Models Explanation & Logic**

Below is the conceptual logic of each model used.

---

**1) K-Nearest Neighbors (KNN)**

**How it Thinks**

- No training phase — "lazy learning"
- For a new sample:
    1. Measure distance to all data points
    2. Pick closest k neighbors
    3. Choose majority class

**Hyperparameters Used:**

KNeighborsClassifier(n_neighbors=5, weights='uniform')

**Why Performance Was Poor**

- Because 82% of data is Class 0
- Neighbors almost always belong to Class 0 : model becomes biased
- **F1-score for Class 1 = 0.00**

---

**2) Decision Tree**

**How it Thinks**

Builds a series of yes/no questions:

**Example:**

- "Is General Health bad?"
- "Is BMI > threshold?"
- "Do they have high blood pressure?"

Uses:

- Gini Impurity
- Information Gain

**Parameters Used:**

- Criterion: Gini

- Max depth: None (unlimited)
- Random state: 42

**Strength**

- Works well with non-linear data
- Easy to interpret

**Weakness**

- Strong bias toward dominant class
- Class 1 predicted extremely poorly

---

**3) Naive Bayes**

**How it Thinks**

Uses probability:

P(Class|Features) = P(Class) × Product of P(Feature|Class)

Assumes independence between features.

**Parameters Used:**

- Gaussian distribution
- Default parameters

**Strength**

- Performs better than expected with Class 2
- Works well on high-dimensional data

**Weakness**

- Class 1 performance remains extremely weak
- Independence assumption not realistic in health data

---

**4) Random Forest**

**How it Thinks**

- Builds multiple decision trees (100 trees)
- Each tree trained on a random subset of data
- Final prediction = majority voting

**Parameters Used:**

- Number of trees: 100
- Max depth: None (unlimited)
- Random state: 42
- Parallel processing: enabled

**Strength**

- Handles variance well
- More robust than a single tree
- Good performance on Class 2

**Weakness**

- Still suffers with Class 1
- Accuracy misleading due to imbalance

---

**5) Support Vector Machine (SVM)**

**How it Thinks**

- Finds best hyperplane separating classes
- Used **LinearSVC** instead of RBF kernel for speed

**Why Linear Instead of RBF?**

- RBF kernel **extremely slow** with 230k samples (would take hours)
- LinearSVC **optimized** for large datasets (trains in seconds)

**Hyperparameters Used:**

C = 1.0, max_iter = 1000, random_state = 42

**Weaknesses (Major)**

- Very sensitive to feature scaling
- Fails heavily with imbalanced data

---

**6. Evaluation Metrics & Interpretation**

**Why Accuracy is Misleading**

**Because:**

- Class 0 = 82%
- Model predicting "0" always : 82% accuracy

**Accuracy ≠ useful when classes are imbalanced**

**F1-Score**

F1 combines precision and recall:

**F1 = 2 × (Precision · Recall) / (Precision + Recall)**

**Used because:**

- It tells us how well the model handles minority classes
- More honest evaluation than accuracy

**Common finding:**

- F1 for Class 1 = 0 in almost all models
- Some models show slightly better F1 for Class 2

---

**7. Final Model Comparison**

**7.1 Overall Performance**

| Model | Accuracy | Precision | Recall | F1-Score | Training Speed |
|---|---|---|---|---|---|
| **SVM Linear** | **83.24%** | **78.50%** | **83.24%** | **77.41%** | Fast |
| **Random Forest** | **82.37%** | **77.29%** | **82.37%** | **78.66%** | Medium |
| **KNN** | **81.56%** | **76.70%** | **81.56%** | **78.37%** | Slow |
| Naive Bayes | 74.14% | 79.33% | 74.14% | 75.95% | Very Fast |
| Decision Tree | 74.18% | 75.50% | 74.18% | 74.82% | Fast |

---

**7.2 Per-Class Performance (F1-Scores)**

| Model | Class 0 (No Diabetes) | Class 1 (Pre-diabetes) | Class 2 (Diabetes) |
|---|---|---|---|
| SVM Linear | **0.91** | **0.00** | 0.15 |
| Random Forest | **0.90** | **0.00** | 0.27 |
| KNN | **0.90** | **0.00** | 0.28 |

| Model | Class 0 (No Diabetes) | Class 1 (Pre-diabetes) | Class 2 (Diabetes) |
|---|---|---|---|
| **Naive Bayes** | 0.84 | **0.02** | **0.42** |
| Decision Tree | 0.85 | **0.03** | 0.30 |

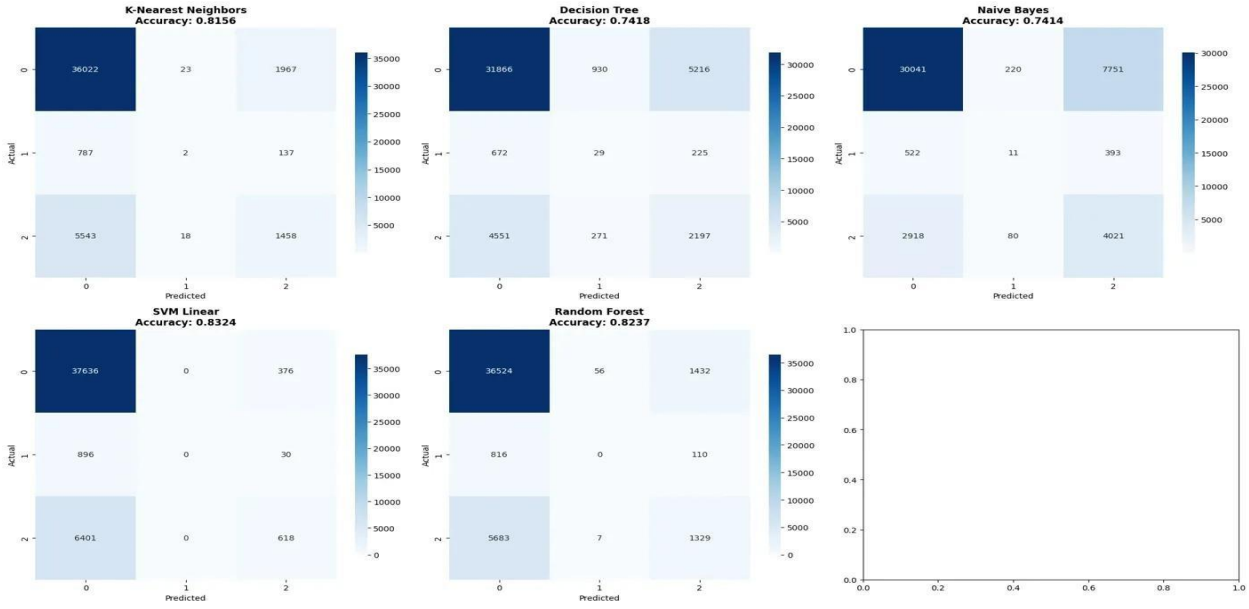
**Key Observations:**

- **All models excellent** for Class 0 (majority class)
- **All models failed** for Class 1 (only 2% of data)
- **Moderate performance** for Class 2 (15% of data)
- **Naive Bayes best** for detecting diabetes (Class 2: F1=0.42)

---

### 7.3 Confusion Matrices - Visual Analysis

Below are the confusion matrices for all five models, showing how each model classified the test samples:




**Key Observations from Confusion Matrices:**

**K-Nearest Neighbors:**

- Class 0: 36,022 correct (94.8% recall)
- Class 1: Only 2 correct predictions out of 926 : **0.2% recall**
- Class 2: 1,458 correct (20.8% recall)

**Decision Tree:**

- Class 0: 31,866 correct (83.8% recall)
- Class 1: 29 correct (3.1% recall) - Best among all models for Class 1!
- Class 2: 2,197 correct (31.3% recall)

**Naive Bayes:**

- Class 0: 30,041 correct (79.0% recall)
- Class 1: 11 correct (1.2% recall)
- Class 2: **4,021 correct (57.3% recall)** - Best for diabetic detection!

**SVM Linear:**

- Class 0: **37,636 correct (99.0% recall)** - Highest!
- Class 1: **0 correct predictions** : Complete failure
- Class 2: 618 correct (8.8% recall) - Lowest

**Random Forest:**

- Class 0: 36,524 correct (96.1% recall)
- Class 1: **0 correct predictions** : Complete failure
- Class 2: 1,329 correct (18.9% recall)

**Visual Insight:** Notice how the diagonal (correct predictions) for Class 1 is almost completely missing in all models - this visually confirms the severe class imbalance problem.

---

**7.4 Feature Importance (Random Forest)**

**Top 10 most important features for prediction:**

| Rank | Feature | Importance |
|---|---|---|
| 1 | **BMI** | 18.30% |
| 2 | **Age** | 12.33% |
| 3 | **Income** | 10.24% |
| 4 | PhysHlth | 8.44% |
| 5 | Education | 7.33% |
| 6 | MentHlth | 6.49% |

| Rank | Feature | Importance |
|---|---|---|
| 7 | **GenHlth** | 6.44% |
| 8 | **HighBP** | 3.93% |
| 9 | Fruits | 3.46% |
| 10 | Smoker | 3.42% |

**This matches our EDA findings!** The top correlated features (BMI, GenHlth, HighBP, Age) are also the most important for prediction.

---

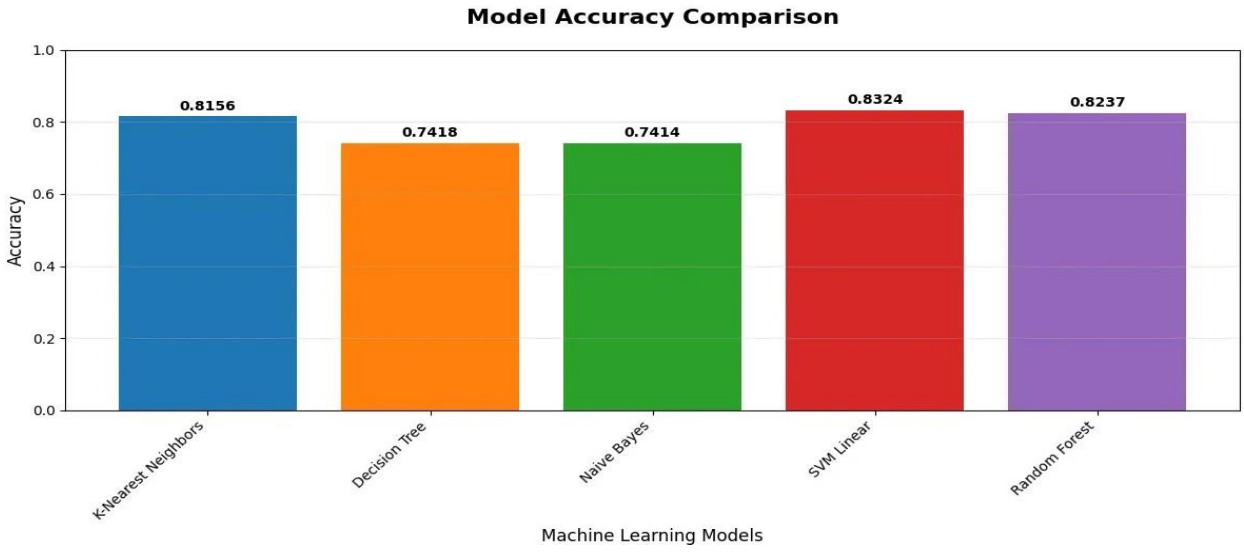
### 7.5 Model Recommendations

| Use Case | Recommended Model | Reason |
|---|---|---|
| **Best Overall Accuracy** | SVM Linear | 83.24% accuracy, fast training |
| **Most Stable/Reliable** | Random Forest | Balanced performance, robust |
| **Detecting Diabetics (Class 2)** | Naive Bayes | Best F1=0.42 for Class 2 |
| **Fast Training** | Naive Bayes | Trains in seconds |
| **Interpretability** | Decision Tree | Easy to explain to doctors |

---

### 7.6 Visual Performance Comparison

**Model Accuracy Bar Chart**



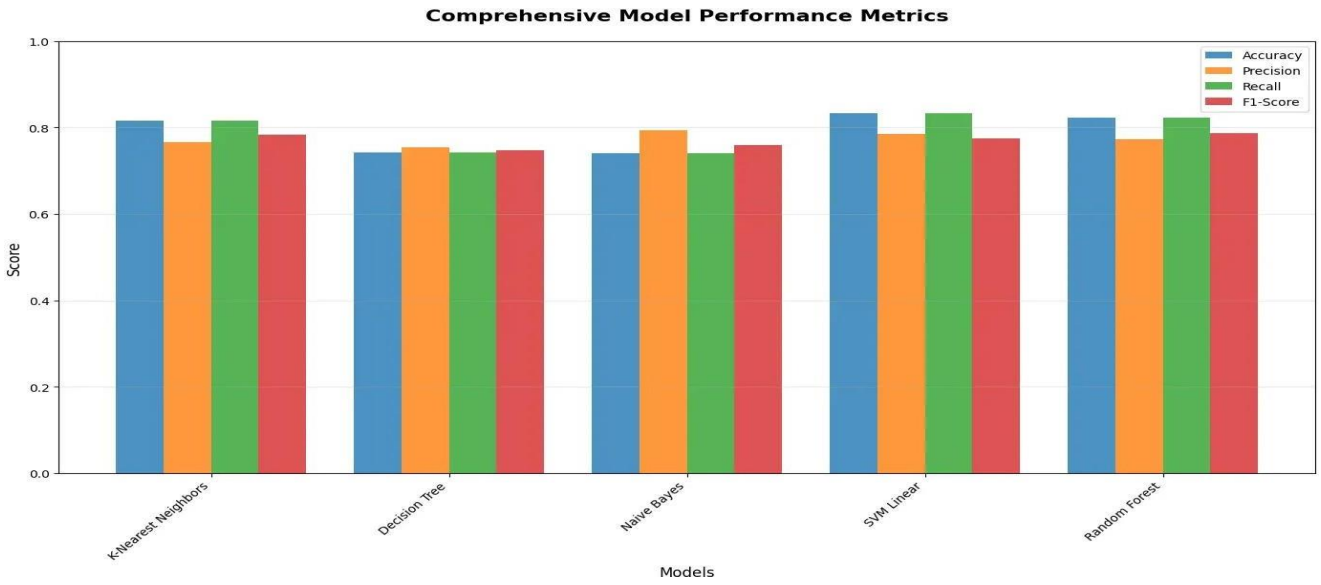
The bar chart clearly shows:

- **SVM Linear leads** with 83.24% accuracy
- **Random Forest second** at 82.37%
- **KNN third** at 81.56%
- **Decision Tree and Naive Bayes** both around 74%

The difference between top performers (SVM, RF, KNN) and others is approximately **8-9%** in accuracy.

---

**Comprehensive Metrics Comparison**




This grouped bar chart reveals important patterns:

**Precision (Orange bars):**

- Naive Bayes has highest precision (79.33%)
- Shows ability to avoid false positives
- SVM Linear at 78.50%

**Recall (Green bars):**

- SVM Linear and Random Forest excel (>83%)
- Better at finding positive cases
- Matches high accuracy

**F1-Score (Red bars):**

- Random Forest most balanced (78.66%)
- KNN close second (78.37%)
- Best trade-off between precision and recall

**Visual Insight:** The chart shows that while accuracy varies significantly, the gap in F1-scores is smaller, suggesting all models struggle similarly with class imbalance.

---

**8. What Could Be Improved (Future Work)**

To make results realistic:

**Address Class Imbalance:**

- Apply SMOTE (Synthetic Minority Over-sampling Technique) for synthetic sampling
- Use Class Weights in models to penalize errors on minority classes
- Try Balanced Random Forest which handles imbalance internally

**Model Optimization:**

- Hyperparameter tuning for every model using GridSearchCV
- Try powerful tree models like XGBoost or LightGBM
- Use Cross-Validation (5-fold) instead of single train-test split

**Feature Engineering:**

- Create interaction features (e.g., BMI multiplied by Age)
- Try feature selection techniques to reduce dimensionality
- Add polynomial features for capturing non-linear relationships

---

**9. Conclusion**

**The Main Issue is NOT the Models — It's the Dataset Itself**

**Class imbalance severely impacted every model, especially Class 1 (pre-diabetes).**

**Summary of Results:**

**Models performed well for Class 0 (majority)**

- All models achieved F1 > 0.84 for non-diabetic cases
- Visual analysis shows strong diagonal in confusion matrices for Class 0

**Failed for Class 1 (2% of data)**

- F1 ≈ 0 across all models
- Too few samples to learn patterns
- Confusion matrices show near-zero predictions for Class 1

**Reasonable performance for Class 2 (15% of data)**

- Naive Bayes best: F1 = 0.42
- Random Forest: F1 = 0.27
- Trade-off between precision and recall visible in metrics

**Key Takeaways:**

1. **F1-score was the most important metric** (not accuracy)
    - Accuracy alone would be misleading (could get 82% by always predicting Class 0)
    - F1 reveals true performance on each class
2. **EDA strongly matched medical expectations** (BMI, Age, HighBP top features)
    - Feature importance analysis confirmed correlation findings
    - Top 3 features: BMI (18.3%), Age (12.3%), Income (10.2%)
3. **SVM Linear** achieved highest accuracy (83.24%)
    - Fast training with LinearSVC
    - Excellent recall for majority class (99%)
    - Failed completely on minority classes
4. **Random Forest** most balanced and reliable
    - Second-best accuracy (82.37%)
    - Highest weighted F1-score (78.66%)
    - Provides interpretable feature importance
5. **Naive Bayes** best for detecting diabetic cases
    - F1 = 0.42 for Class 2 (vs 0.15-0.30 for others)
    - 57% recall - catches more diabetic patients
    - Trade-off: Lower overall accuracy (74.14%)

**Visual Evidence:**

The visualizations clearly demonstrate:

- **Confusion matrices** show the "Class 1 blind spot" across all models

- **Accuracy comparison** reveals SVM and Random Forest as top performers
- **Metrics comparison** shows the trade-offs between different evaluation criteria
- **Small differences** in F1-scores despite larger accuracy gaps

**Final Thoughts:**

The project demonstrates that **data quality and balance matter more than model complexity**. With proper handling of class imbalance (SMOTE, class weights), performance on minority classes could improve significantly.

**The visualizations confirm what the numbers tell us:** excellent performance on majority class, complete failure on pre-diabetic cases, and moderate success on diabetic detection.

---

**Appendix: Technical Details**

**Dataset Statistics After Cleaning:**

- Original samples: 253,680
- After removing duplicates: 229,781
- Training samples: 183,824 (80%)
- Testing samples: 45,957 (20%)

**Class Distribution in Test Set:**

- Class 0: 38,012 samples (82.71%)
- Class 1: 926 samples (2.01%)
- Class 2: 7,019 samples (15.28%)

**Computing Environment:**

- Python 3.8+
- scikit-learn for all models
- Training time: 10-15 minutes total
- All models use random_state=42 for reproducibility

---

**End of Report**