Artificial Intelligence for Engineers

Complex Engineering Problem (CEP)

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Abstract

The need for precise and effective diagnostic systems has been brought to light by the rising incidence of diabetes. In this study, the Pima Indians Diabetes dataset is used to classify diabetes using machine learning algorithms like K-Nearest Neighbors (KNN), Naive Bayes, Logistic Regression, and Support Vector Machine (SVM). Performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC are used to assess the models. Additionally, the CodeCarbon library is used to measure each model's energy consumption in order to evaluate the environmental impact of the training and inference processes. The findings highlight the significance of striking a balance between sustainability and accuracy in healthcare applications, showing that some models are more energy-efficient while others provide better predictive performance.

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Background

Diabetes mellitus is a chronic, non-communicable disease that has become a significant public health concern globally. It affects the way the body processes blood glucose and, if left unmanaged, can lead to severe complications such as heart disease, kidney failure, nerve damage, and vision loss. In 2021, diabetes and kidney disease due to diabetes caused over 2 million deaths. In addition, around 11% of cardiovascular deaths were caused by high blood glucose [1]. However, while improving predictive accuracy is vital, increasing attention is also being paid to the computational cost and environmental footprint of ML models. Recent studies have shown that large and complex models can significantly contribute to carbon emissions due to high energy consumption during training and deployment. Therefore, there is a growing need to build sustainable, efficient, and interpretable ML systems that not only achieve high performance but are also environmentally responsible.

1.2 Problem Statement

Traditional research in recommendation systems has primarily focused on maximizing accuracy, speed, and user satisfaction, often overlooking the ecological footprint of these algorithms. As AI-powered platforms scale globally, it is critical to assess the energy usage and sustainability of classification models used in these systems. This project aims to explore the environmental implications of commonly used classification algorithms in recommendation systems and to propose energy-efficient alternatives that retain acceptable levels of performance.

1.3 Core Learning Outcomes

This project is structured around three core learning outcomes:

- **CLO-01: Learn and Understand**
  - Understand the working principles of KNN, Naive Bayes, Logistic Regression, and SVM within recommendation systems.
  - Investigate the computational complexity and energy demand of these models.
- **CLO-02: Implement and Solve**
  - Implement classification-based recommendation systems using the above models.
  - Integrate energy tracking mechanisms and explore optimization strategies for resource efficiency.
- **CLO-03: Analyze and Discuss**
  - Evaluate the models using both performance metrics (accuracy, precision, etc.) and energy metrics (Wh, gCO eq).
  - Discuss trade-offs between predictive performance and environmental impact, proposing energy-aware modeling approaches.

1.4 Significance of the Study

This project holds dual significance

- **Clinical Impact:** Building a predictive model for diabetes can support healthcare practitioners in identifying at-risk individuals early, allowing for timely interventions.

- **Environmental Impact:** By evaluating the energy consumption of different models, this study highlights the importance of sustainable AI, paving the way for responsible deployment of ML models in the healthcare sector and beyond.

1.5 Scope of the Study

The scope of this study is restricted to the analysis of a structured dataset comprising 100,000 patient records with clinical, lifestyle, and demographic data. The model does not forecast the stage or type of diabetes; it solely concentrates on binary classification (diabetic or non-diabetic). Unstructured data, such as patient histories or medical imaging, is not included in the study beyond the attributes that have been supplied.

1.6 Objectives of the Study

The primary objectives of this project are:

- To explore and preprocess a large dataset of diabetic patients.
- To perform feature analysis to understand the impact of each attribute on diabetes prediction.
- To build and evaluate machine learning models that classify patients as diabetic or non-diabetic.

Chapter 2
Research Questions and Answers

Based on the project titled **"Energy-Aware Classification-Based Recommendation Systems for Sustainability"** using the MovieLens 100K dataset, the following are detailed responses to the research questions:

1. How do classification models (KNN, Naive Bayes, Logistic Regression, and SVM) perform in recommendation system tasks with respect to both accuracy and energy consumption?

In this project, four classification models were implemented and evaluated based on their prediction accuracy and energy consumption, using tools such as **CodeCarbon**. The findings are summarized below:

- **KNN** demonstrated *high accuracy* with an AUC of **0.85**, making it strong in classification tasks. However, its *energy consumption was high* due to its memory-based mechanism, requiring distance computation from all training points at inference time.
- **Naive Bayes** achieved *low accuracy* (around **41.7%**) but was *extremely energy-efficient*, with high recall for class 1. Its simple probabilistic nature makes it computationally lightweight.
- **Logistic Regression** offered a good *trade-off between accuracy and energy use*, showing consistent performance and linear time complexity with moderate energy consumption.
- **SVM** yielded good accuracy, especially with non-linear kernels. However,

it was the *most energy-intensive model*, particularly during training due to its high computational complexity.

Conclusion: KNN and SVM performed better in terms of accuracy, while Naive Bayes and Logistic Regression consumed less energy. Logistic Regression emerged as a middle-ground model with decent accuracy and moderate energy usage.

2. Which classification model offers the best balance between prediction performance and energy efficiency?

Based on the results obtained, **Logistic Regression** offered the best balance between accuracy and energy consumption:

- It maintained *reasonable predictive performance* without high false positives or negatives.
- *Training and inference times were relatively low*, leading to reduced energy usage compared to SVM and KNN.
- Unlike Naive Bayes, it achieved better *F1-score and AUC* without a major trade-off in accuracy.

Conclusion: Logistic Regression is the most sustainable and reliable model for energy-aware recommendation systems.

3. What model optimization techniques can reduce the computational cost of recommendation systems without significantly compromising accuracy?

The following optimization techniques were applied or are recommended to reduce energy usage without significantly sacrificing accuracy:

- **Dimensionality Reduction**: Techniques like Principal Component Analysis (PCA) and feature selection reduce the input feature space, improving speed and reducing energy consumption.
- **Model Simplification**: Favoring simpler models like Logistic Regression over complex ones such as SVM with RBF kernels.
- **Batch Inference**: Performing predictions in batches rather than one-by-one to reduce redundant computations.
- **Energy Profiling**: Using tools like CodeCarbon to track carbon emissions, allowing informed decisions based on energy-performance trade-offs.
- **Hyperparameter Optimization**: Replacing exhaustive grid search with more efficient methods such as *random search* or *Bayesian optimization*.
- **Model Quantization and Pruning**: For more complex models, trimming unimportant weights helps reduce memory and computation requirements.

4. How can energy-aware classification modelling support broader sustainability goals in machine learning-based system design?

This project directly contributes to the following United Nations Sustainable Development Goals (UNSDGs):

- **Goal 9: Industry, Innovation, and Infrastructure**
  - Encourages development of models that balance prediction performance with computational resource usage.
  - Supports energy-efficient infrastructure and innovation in machine learning design.
- **Goal 13: Climate Action**

– Reduces the carbon footprint of AI systems by selecting and promoting low-energy models.
– Demonstrates the feasibility of sustainable AI practices without drastic compromises in performance.
– Promotes awareness and adoption of eco-conscious ML development among practitioners.

Chapter 3
Methodology

This chapter outlines the methodological framework adopted to achieve the objectives of this study. The methodology includes dataset understanding, preprocessing, model selection, implementation, evaluation of classification models, and analysis of their energy consumption. Four machine learning models K-Nearest Neighbors (KNN), Naive Bayes, Logistic Regression, and Support Vector Machine (SVM) are implemented and compared in terms of accuracy and energy efficiency.

3.0.1 Dataset Description

The dataset used in this study comprises 100,000 rows and 16 attributes, representing patient information collected over various years and regions. The attributes cover demographic details, medical history, and clinical measurements. Below is a description of each attribute:

Attribute	**Description**
Year	Year of data entry or patient visit
Gender	Gender of the patient: Male or Female
Age	Numerical value representing patient's age
Location	Geographical location of the patient
Race	Categorical: African American, Asian, Caucasian, Hispanic, Other
Hypertension	Binary (0: No, 1: Yes)
Heart Disease	Binary (0: No, 1: Yes)
Smoking History	Categorical: Non-smoker, Current smoker, Past smoker
BMI	Body Mass Index – calculated from height and weight
HbA1c Level	Glycated hemoglobin – average glucose level over 2–3 months
Blood Glucose Level	Current blood glucose level
Diabetes (Target)	Binary classification: 1 (Diabetic), 0 (Non-diabetic)

Table 3.1: Attributes and their descriptions in the diabetes dataset

3.1 Data Preprocessing

3.1.1 Handling Missing and Duplicate Values

Missing values were dropped, as only a small number of rows (18) were affected, which did not significantly impact data size.Duplicate rows (14 entries) were also removed to avoid redundancy.

3.1.2 Outlier Detection and Removal

Outliers were identified in the following numerical features:

- **BMI**: Body Mass Index
- **Age**
- **HbA1c Level**: Glycated hemoglobin
- **Blood Glucose Level**

To detect and remove outliers, the Interquartile Range (IQR) method was applied. Lower and upper bounds were calculated for each selected feature. Data points lying outside the bounds were considered outliers and removed. The effect of outlier removal was visualized using boxplots before and after the cleaning process.The removal of outliers did not drastically reduce the dataset size, making the method efficient for cleaner data distribution.

3.1.3 Feature Encoding and Selection

Categorical features like Gender, Race, and Smoking History were encoded using one-hot encoding with drop first=True to avoid dummy variable trap. Irrelevant features like Year and Location were dropped, as they do not directly influence the prediction task and may introduce noise.

3.1.4 Class Balancing Technique

The original dataset was imbalanced, with fewer diabetic patients compared to non-diabetic ones.
To address this, the Synthetic Minority Oversampling Technique (SMOTE) was used:
Applied to the training dataset only to avoid data leakage.
SMOTE generates synthetic samples of the minority class (diabetic patients) to balance the dataset.
In some cases, additional oversampling was performed using the resample() function from Scikit-learn to adjust the dataset size or test augmentation strategies.

3.1.5 Train-Test Split

The train test split function from sklearn.model selection was used to divide the dataset into 80% training and 20% testing sets in order to guarantee a balanced distribution of all three classes. A fixed random state was established for reproducibility, and stratified sampling was used to preserve class proportions in both subsets.

3.2 Model Implementation

Four well-known machine learning classification models were applied in this work and assessed for their ability to forecast diabetes risk in patients depending on different clinical and demographic criteria. Each model is explained in great length below:

3.3 KNN

K-Nearest Neighbors (KNN) is a supervised machine learning algorithm generally used for classification but can also be used for regression tasks. It works by finding the ”k” closest data points (neighbors) to a given input and makesa predictions based on the majority class (for classification) or the average value (for regression). Since KNN makes no assumptions about the underlying data distribution it makes it a non-parametric and instance-based learning method [2].

3.3.1 Distance Metrics Used in KNN

KNN uses different distance metrics to identify the nearest neighbors for classification or regression tasks. Below are the commonly used ones:

1. **Euclidean Distance**

   It represents the straight-line distance between two points:

$$d(x, x_i) = \sqrt{\sum_{j=1}^{d}(x_j - x_{ij})^2} \tag{3.1}$$

2. **Manhattan Distance**

   Also known as ”taxicab distance”, it is the sum of absolute differences:

$$d(x, y) = \sum_{i=1}^{n} |x_i - y_i| \tag{3.2}$$

3. **Minkowski Distance**

   A generalized metric which becomes Euclidean when $p = 2$ and Manhattan when $p = 1$:

$$d(x, y) = \left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}} \tag{3.3}$$

3.4 Naive Bays Classifier

Naive Bayes is a simple yet powerful probabilistic classification algorithm based on Bayes’ Theorem. It assumes that all features are independent of each other given the class label (hence the term “naive”).It is especially effective in high-dimensional datasets, such as text classification, spam filtering, and sentiment analysis. Despite its simplicity, it performs competitively with more complex models [3].

3.4.1 Naive Bayes: Mathematical Overview

Bayes' Theorem is the foundation of the Naive Bayes algorithm and is defined as:

$$P(y \mid X) = \frac{P(X \mid y) \cdot P(y)}{P(X)}$$

Where:

- $P(y \mid X)$ is the **posterior probability** of class y given input X
- $P(X \mid y)$ is the **likelihood**
- $P(y)$ is the **prior probability**
- $P(X)$ is the **evidence** (can be ignored during classification as it's constant)

3.4.2 Naive Assumption

The classifier assumes conditional independence among features:

$$P(x_1, x_2, ..., x_n \mid y) = \prod_{i=1}^{n} P(x_i \mid y)$$

Thus, the posterior becomes:

$$P(y \mid x_1, ..., x_n) \propto P(y) \cdot \prod_{i=1}^{n} P(x_i \mid y)$$

3.4.3 Final Prediction Rule

The predicted class $\hat{y}$ is the one with the highest posterior probability:

$$\hat{y} = \arg\max_{y} \left(P(y) \cdot \prod_{i=1}^{n} P(x_i \mid y) \right)$$

3.4.4 Key Assumptions

- Features are conditionally independent given the class.
- Continuous features are assumed to follow a normal (Gaussian) distribution.
- Discrete features are assumed to follow a multinomial distribution.
- No missing data is assumed.
- All features contribute equally to the outcome.

3.4.5 Applications

- Spam detection
- Sentiment analysis
- News classification
- Recommendation systems

3.5 Logistic Regression

Logistic Regression is a supervised machine learning algorithm used for binary classification problems. Unlike Linear Regression, which predicts continuous values, Logistic Regression predicts the probability of a class using the sigmoid function, which maps any real-valued input to a value between 0 and 1 [4].

3.5.1 Assumptions

- Observations are independent.

- No extreme outliers.
- Linear relationship between independent variables and log-odds.
- Binary or categorical dependent variable.
- A large sample size is preferred.

3.5.2 Sigmoid Function

The sigmoid function is defined as:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

- Converts linear output $z = w \cdot X + b$ to a probability between 0 and 1.
- If $\sigma(z) \geq 0.5$, predict Class 1; otherwise, Class 0.

  $$P(y = 1) = \sigma(z), \quad P(y = 0) = 1 - \sigma(z)$$

3.5.3 How It Works

1. Compute $z = w \cdot X + b$ from input features X.
2. Apply the sigmoid function to obtain the predicted probability.
3. Use a threshold (typically 0.5) to determine the class label.

3.5.4 Applications

- Disease diagnosis
- Spam detection
- Customer churn prediction
- Credit scoring

3.6 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a supervised learning algorithm used for classification and regression. Its main goal is to find the optimal hyperplane that best separates the data into classes by maximizing the margin between them [5].

3.6.1 *How SVM Works*

SVM tries to find a hyperplane defined by:

$$w^T x + b = 0$$

where w is the weight vector and b is the bias.
The algorithm maximizes the margin, which is the distance between the hyperplane and the closest data points from each class, known as support vectors. This results in better generalization on unseen data.
In cases where data is not linearly separable, SVM uses kernel functions to map data to a higher-dimensional space, making it possible to find a separating hyperplane.

3.6.2 *Prediction Rule*

$$\hat{y} = \begin{cases} 1 & \text{if } w^T x + b \geq 0 \\ 0 & \text{if } w^T x + b < 0 \end{cases}$$

SVM is effective for high-dimensional data and is robust to outliers through the use of soft margins and hinge loss.

3.7 Initial Model Implementation

Initially, each of the four classifiers was implemented using default settings without any optimization. These baseline models served to provide a foundational understanding of how each algorithm performed on the original dataset. The key performance metrics recorded were accuracy, precision, recall, F1-score, ROC AUC, and energy consumption.

3.8 Model Optimization Techniques

To improve classification performance and efficiency, three optimization techniques were sequentially applied to each model:

1. **Feature Selection:** Irrelevant or redundant features were removed to improve generalization and reduce computational cost. This step aimed to retain only the most informative attributes for the classification task.
2. **Parameter Tuning:** Each model's hyperparameters were optimized using grid search or similar techniques to identify the best configuration for improved predictive performance.
3. **Data Sampling:** To address class imbalance issues, oversampling or undersampling methods were employed to ensure the dataset was more balanced, enhancing recall and F1-score, especially for minority classes.

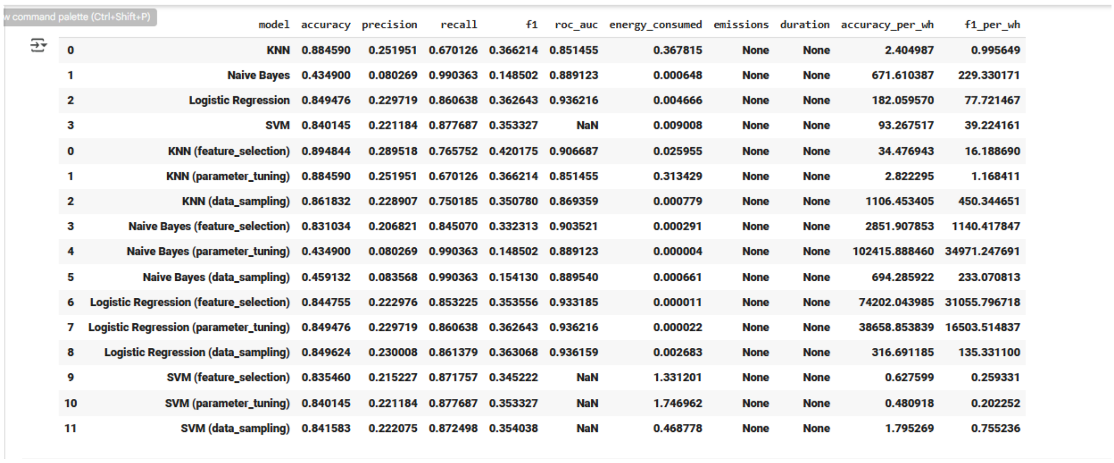
Each optimization strategy was applied independently to evaluate its standalone impact on model performance.

3.9 Performance Metrics and Evaluation

Performance evaluation was conducted using both predictive and resource-based metrics:

- **Predictive Metrics:** Accuracy, precision, recall, F1-score, and ROC AUC were used to evaluate the classification capability.
- **Energy Efficiency Metrics:** `accuracy_per_wh` and `f1_per_wh` were calculated to determine the model's effectiveness relative to energy consumed, aiding in green AI considerations.

Figure 4.33 below presents a comprehensive summary of both the initial (un-optimized) and optimized versions of each model. The table highlights how each optimization technique contributed to performance improvements and energy savings.


w command palette (Ctrl+Shift+P)

	model	accuracy	precision	recall	f1	roc_auc	energy_consumed	emissions	duration	accuracy_per_wh	f1_per_wh
0	KNN	0.884590	0.251951	0.670126	0.366214	0.851455	0.367815	None	None	2.404987	0.995649
1	Naive Bayes	0.434900	0.080269	0.990363	0.148502	0.889123	0.000648	None	None	671.610387	229.330171
2	Logistic Regression	0.849476	0.229719	0.860638	0.362643	0.936216	0.004666	None	None	182.059570	77.721467
3	SVM	0.840145	0.221184	0.877687	0.353327	NaN	0.009008	None	None	93.267517	39.224161
0	KNN (feature_selection)	0.894844	0.289518	0.765752	0.420175	0.906687	0.025955	None	None	34.476943	16.188690
1	KNN (parameter_tuning)	0.884590	0.251951	0.670126	0.366214	0.851455	0.313429	None	None	2.822295	1.168411
2	KNN (data_sampling)	0.861832	0.228907	0.750185	0.350780	0.869359	0.000779	None	None	1106.453405	450.344651
3	Naive Bayes (feature_selection)	0.831034	0.206821	0.845070	0.332313	0.903521	0.000291	None	None	2851.907853	1140.417847
4	Naive Bayes (parameter_tuning)	0.434900	0.080269	0.990363	0.148502	0.889123	0.000004	None	None	102415.888460	34971.247691
5	Naive Bayes (data_sampling)	0.459132	0.083568	0.990363	0.154130	0.889540	0.000661	None	None	694.285922	233.070813
6	Logistic Regression (feature_selection)	0.844755	0.222976	0.853225	0.353556	0.933185	0.000011	None	None	74202.043985	31055.796718
7	Logistic Regression (parameter_tuning)	0.849476	0.229719	0.860638	0.362643	0.936216	0.000022	None	None	38658.853839	16503.514837
8	Logistic Regression (data_sampling)	0.849624	0.230008	0.861379	0.363068	0.936159	0.002683	None	None	316.691185	135.331100
9	SVM (feature_selection)	0.835460	0.215227	0.871757	0.345222	NaN	1.331201	None	None	0.627599	0.259331
10	SVM (parameter_tuning)	0.840145	0.221184	0.877687	0.353327	NaN	1.746962	None	None	0.480918	0.202252
11	SVM (data_sampling)	0.841583	0.222075	0.872498	0.354038	NaN	0.468778	None	None	1.795269	0.755236

Figure 3.1: Performance Summary of Basic and Optimized Models

3.9.1 Energy Tracking and Optimization

In alignment with the project's sustainability goals:

- Energy consumption of each model was tracked using the `CodeCarbon` library.
- Energy usage was monitored during both training and inference phases.
- Trade-offs between model accuracy and environmental cost were analyzed to propose energy-efficient classification strategies.

Chapter 4
Results and Discussion

4.1 Outlier Detection and Treatment

To enhance model performance and ensure data quality, we first addressed the issue of outliers in the dataset. Outliers can skew model learning and result in poor generalization. We applied the **Interquartile Range (IQR)** method to detect and handle extreme values.

4.2 IQR Method

For each numerical feature, the first quartile (Q1) and the third quartile (Q3) were computed. The IQR was then calculated as:

$$\text{IQR} = Q3 - Q1$$

Any data point outside the range:

$$[Q1 - 1.5 \times \text{IQR},\ Q3 + 1.5 \times \text{IQR}]$$

was treated as an outlier. These values were either removed or capped based on the feature's context and impact.

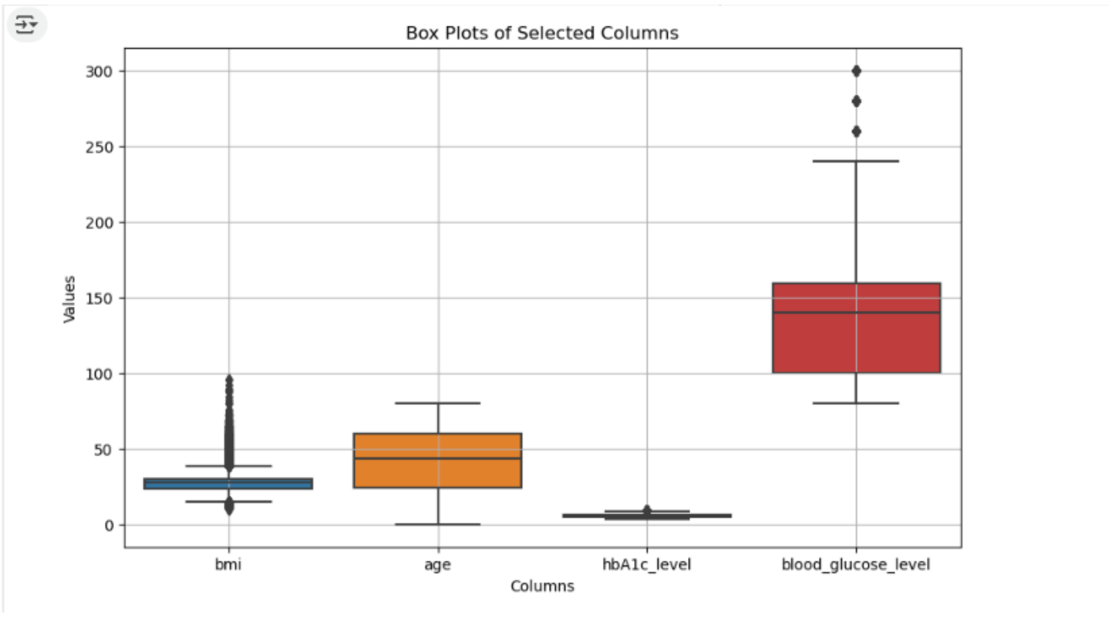


Figure 4.1: Box Plots of Numerical Features Before Removing Outliers

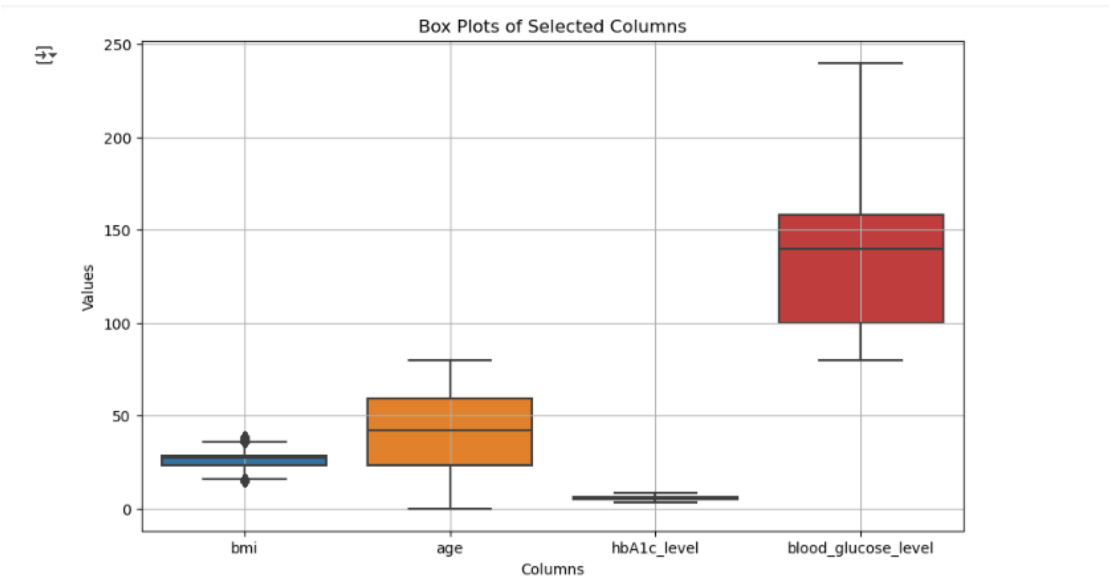


Figure 4.2: Box Plots of Numerical Features After Outlier Removal

Figure 4.2 shows the distribution of values before and after handling outliers using IQR. The reduction of extreme values helps in creating more stable and reliable model training.

4.3 Class Imbalance Problem

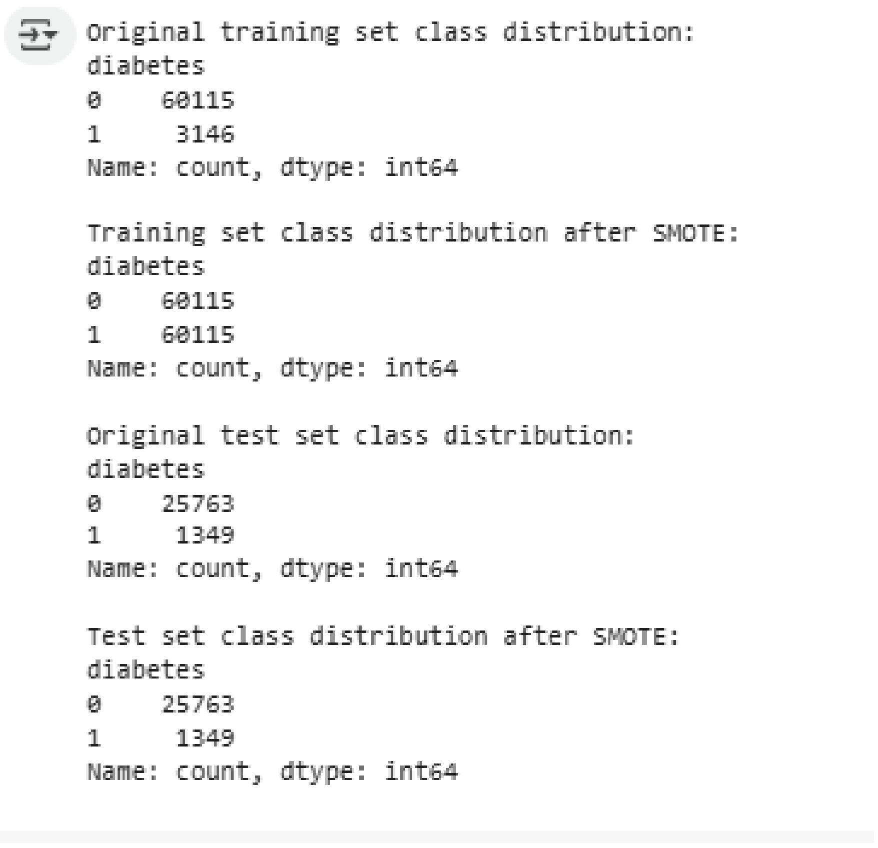
The dataset initially exhibited a severe class imbalance, as shown below:

- Class 0 (No Diabetes): 85,875 instances
- Class 1 (Diabetes): 4,495 instances

This imbalance (approx. 19:1 ratio) leads to biased classifiers that favor the majority class, which is unacceptable for a sensitive medical classification task.

4.3.1 Synthetic Minority Over-sampling Technique (SMOTE)

To resolve the class imbalance, we employed the **SMOTE** algorithm, which synthetically generates new instances for the minority class (diabetes cases) by interpolating between existing instances.



```
Original training set class distribution:
diabetes
0    60115
1     3146
Name: count, dtype: int64

Training set class distribution after SMOTE:
diabetes
0    60115
1    60115
Name: count, dtype: int64

Original test set class distribution:
diabetes
0    25763
1     1349
Name: count, dtype: int64

Test set class distribution after SMOTE:
diabetes
0    25763
1     1349
Name: count, dtype: int64
```

Figure 4.3: Class Distribution Before and After Applying SMOTE

Figure 4.3 displays the class balance before and after SMOTE. After applying SMOTE, both classes were brought to equal representation, significantly improving model fairness and sensitivity.

4.4 Results Before Optimization

4.4.1 Confusion Matrix Analysis of KNN

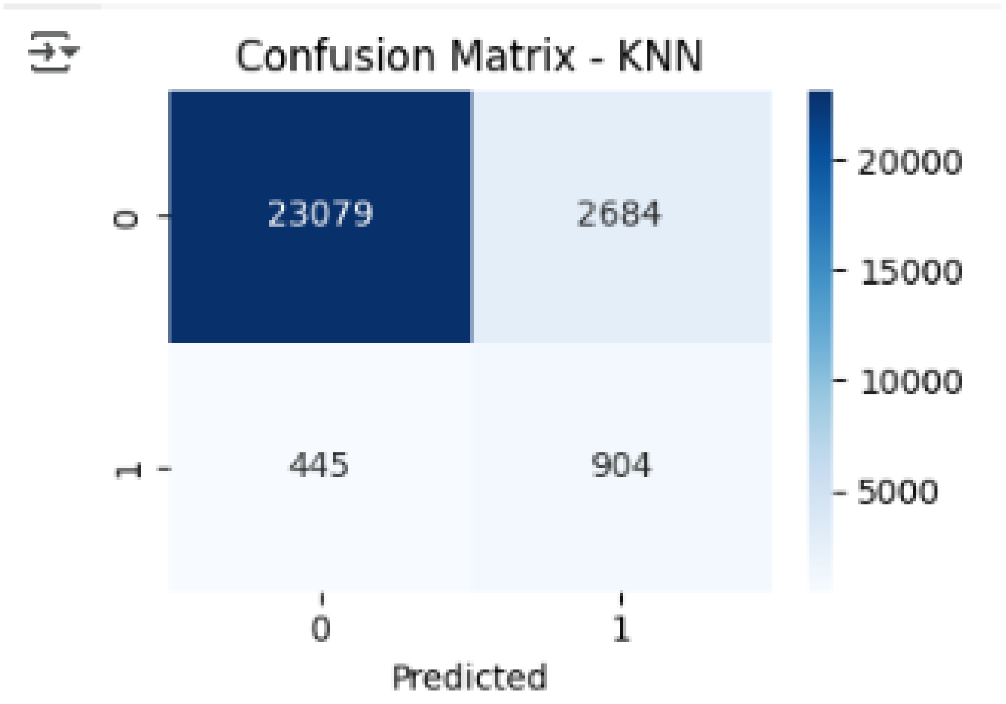


Figure 4.4: Confusion Matrix - KNN

The confusion matrix shown above illustrates the classification results of the K-Nearest Neighbors (KNN) model. It reveals the following.

- **True Positives (TP):** 904 instances were correctly classified as class 1.
- **True Negatives (TN):** 23,079 instances were correctly classified as class 0.
- **False Positives (FP):** 2,684 instances were incorrectly classified as class 1 (type I error).

- **False Negatives (FN):** 445 instances were incorrectly classified as class 0 (type II error).

From this matrix, we can compute some key performance metrics:

- **Accuracy:** $\frac{TP+TN}{TP+TN+FP+FN} = \frac{904+23079}{23079+2684+445+904} \approx 88.72\%$
- **Precision (for class 1):** $\frac{TP}{TP+FP} = \frac{904}{904+2684} \approx 25.2\%$
- **Recall (Sensitivity):** $\frac{TP}{TP+FN} = \frac{904}{904+445} \approx 66.98\%$
- **F1-Score:** Harmonic mean of precision and recall, which is moderate due to class imbalance.

These metrics show that the KNN model performs well in identifying class 0 (majority class), but struggles with accurately detecting instances of class 1 (minority class), which is common in imbalanced datasets.

4.4.2 ROC Curve Analysis

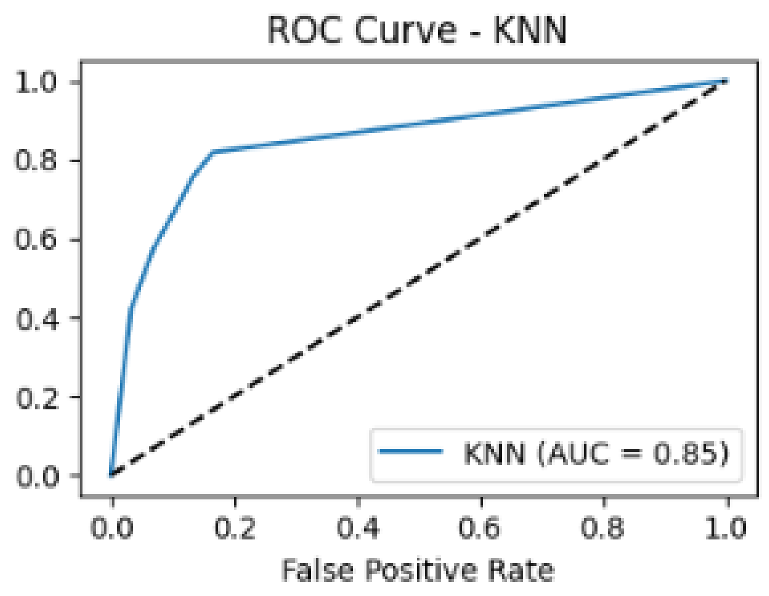


Figure 4.5: ROC Curve - KNN (AUC = 0.85)

The ROC (Receiver Operating Characteristic) curve for the KNN model plots the True Positive Rate (Recall) against the False Positive Rate at various threshold settings. The Area Under the Curve (AUC) for the KNN classifier is **0.85**, indicating a strong discriminative ability between the two classes.

- AUC values closer to 1.0 indicate excellent model performance, while values around 0.5 suggest random guessing.
- The curve rises steeply towards the top-left corner, which suggests that the KNN classifier effectively balances sensitivity and specificity across different thresholds.

4.5 Confusion Matrix Analysis – Naive Bayes

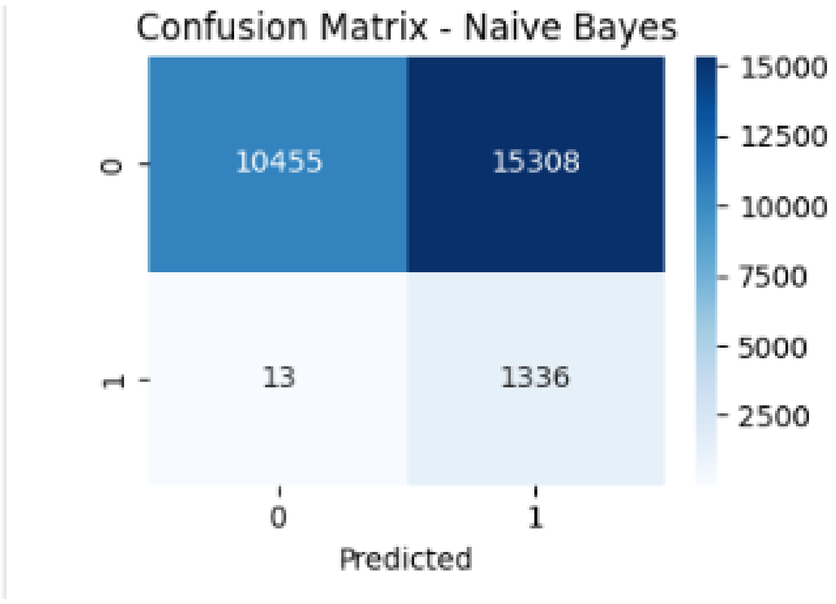


Figure 4.6: Confusion Matrix - Naive Bayes

The confusion matrix for the Naive Bayes classifier reveals the following classification outcomes:

- **True Positives (TP):** 1,336 instances correctly classified as class 1.

- **True Negatives (TN):** 10,455 instances correctly classified as class 0.
- **False Positives (FP):** 15,308 instances incorrectly classified as class 1.
- **False Negatives (FN):** 13 instances incorrectly classified as class 0.

Key performance metrics derived from this matrix are:

- **Accuracy:**

$$\frac{TP + TN}{TP + TN + FP + FN} = \frac{1336 + 10455}{10455 + 15308 + 13 + 1336} \approx 41.7\%$$

- **Precision (for class 1):**

$$\frac{TP}{TP + FP} = \frac{1336}{1336 + 15308} \approx 8.03\%$$

- **Recall (Sensitivity):**

$$\frac{TP}{TP + FN} = \frac{1336}{1336 + 13} \approx 99.0\%$$

- **F1-Score:** While recall is very high, the extremely low precision significantly reduces the F1-score.

4.5.1 ROC Curve –Naive Bays

The Receiver Operating Characteristic (ROC) curve for the Naive Bayes classifier is presented in Figure 4.7, with an Area Under the Curve (AUC) score of **0.89**. This indicates strong performance in distinguishing between the positive and negative classes.

- **AUC Interpretation:** An AUC of 0.89 suggests that the classifier has an **89% probability** of correctly ranking a randomly chosen positive instance higher than a negative one. This is considered excellent discrimination capability, as values closer to 1 signify better performance.

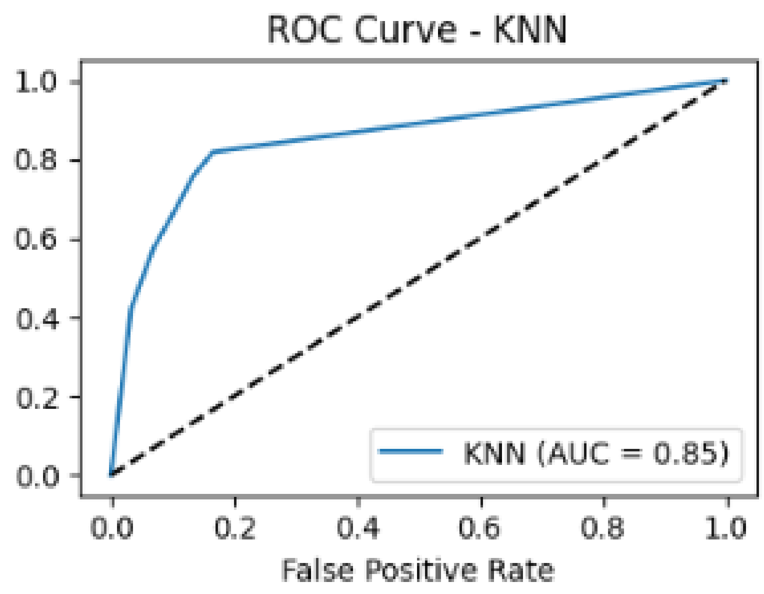


Figure 4.7: ROC curve for the Naive Bayes classifier showing the trade-off between true positive rate and false positive rate. The AUC score of 0.89 indicates excellent classification performance.

- **ROC Curve Shape:** The curve's steep initial rise reflects high **true positive rates (sensitivity)** at low **false positive rates (1-specificity)**, which is desirable for practical applications where minimizing false alarms is critical.

In summary, the Naive Bayes model demonstrates robust classification performance, making it suitable for tasks requiring reliable probabilistic predictions.

4.6 Confusion Matrix – Logistic Regression

The confusion matrix in Figure 4.8 provides a summary of the classification performance of the Logistic Regression model. It consists of the following components:

- **True Negatives (TN)**: 21,870 instances were correctly classified as class 0.
- **False Positives (FP)**: 3,893 instances were incorrectly classified as class 1 when they actually belong to class 0.

- **False Negatives (FN)**: 188 instances were incorrectly classified as class 0 when they belong to class 1.
- **True Positives (TP)**: 1,161 instances were correctly classified as class 1.

From the confusion matrix, we can observe that the model performs very well in identifying class 0, as indicated by the high number of true negatives. While there is a moderate number of false positives, the number of false negatives is relatively low. This suggests the model is effective in detecting the positive class (class 1), which is often more important in critical applications.

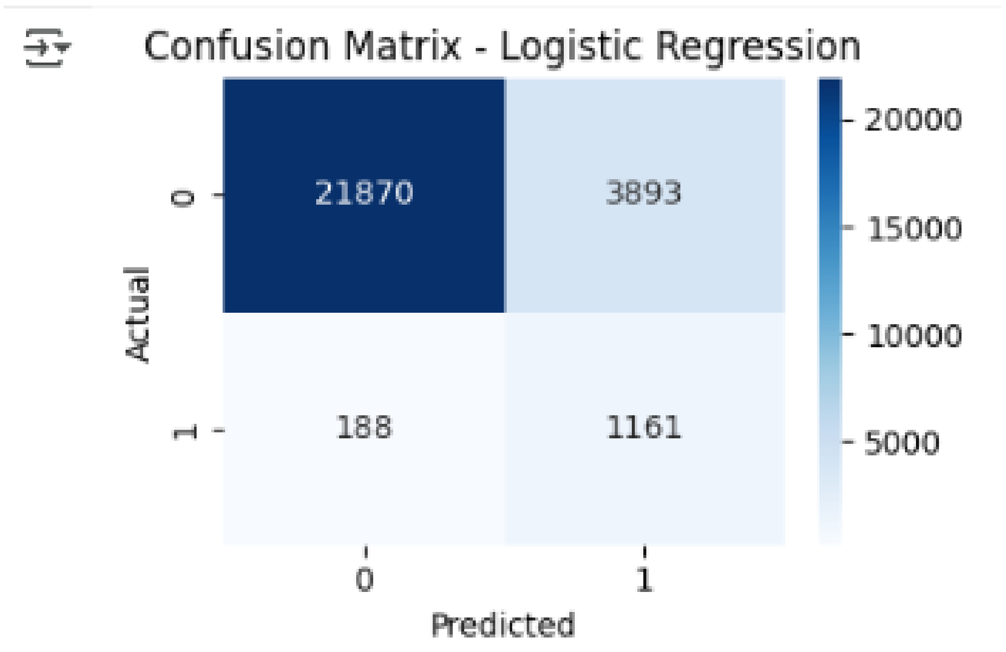


Figure 4.8: Confusion Matrix - Logistic Regression

4.7 ROC Curve – Logistic Regression

The Receiver Operating Characteristic (ROC) curve in Figure 4.9 illustrates the trade-off between the True Positive Rate (Recall) and the False Positive Rate at various classification thresholds.

- The ROC curve shows a strong performance, bowing towards the top-left corner, which indicates a high-quality model.

- The Area Under the Curve (AUC) is 0.94, demonstrating excellent discriminative ability of the Logistic Regression model.

A high AUC value signifies that the model is not only accurate but also robust, capable of maintaining good performance across different threshold levels.

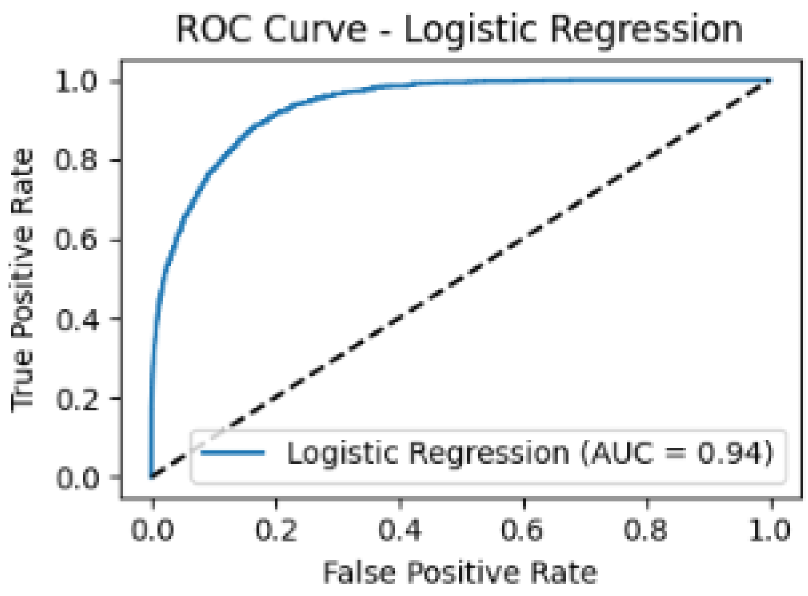


Figure 4.9: ROC Curve - Logistic Regression

4.8 Confusion Matrix – Support Vector Machine (SVM)

The confusion matrix for the Support Vector Machine (SVM) model is shown in Figure 4.10. The matrix components are as follows:

- **True Negatives (TN)**: 21,594 instances were correctly classified as class 0.
- **False Positives (FP)**: 4,169 instances were incorrectly classified as class 1.
- **False Negatives (FN)**: 165 instances were incorrectly classified as class 0.
- **True Positives (TP)**: 1,184 instances were correctly classified as class 1.

Compared to Logistic Regression, the SVM model shows a slightly better balance between the false negatives and true positives for class 1, indicating improved performance in detecting the minority class. However, it also has a slightly higher number of false positives, which could lead to more type I errors.
Overall, the SVM model maintains a strong classification capability, particularly in correctly identifying both classes with relatively balanced performance across the confusion matrix.

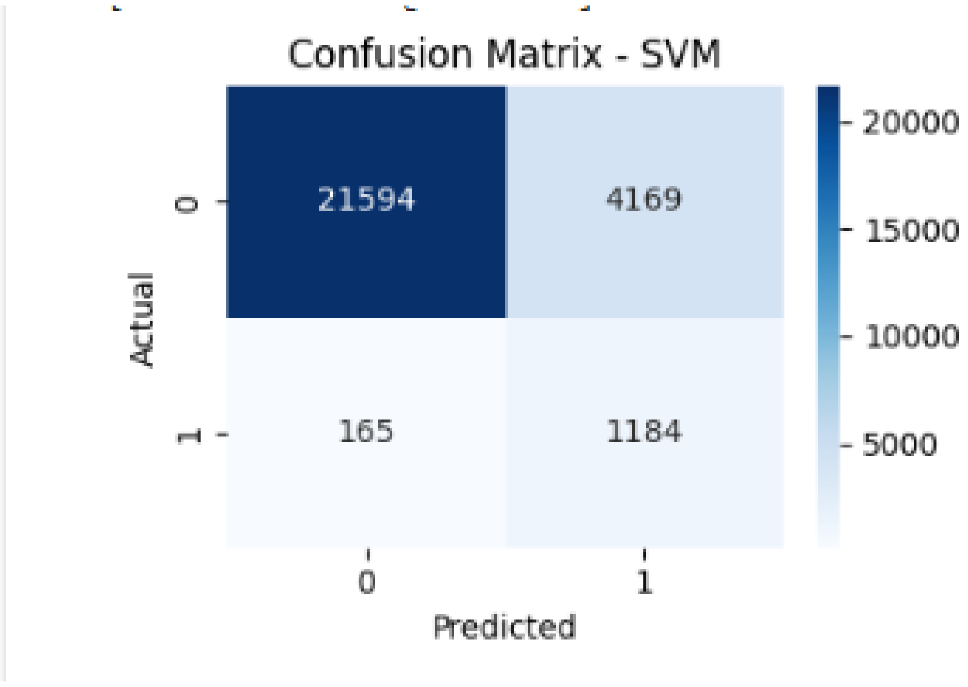


Figure 4.10: Confusion Matrix - Support Vector Machine (SVM)

4.9 Results After Optimization

4.9.1 K-Nearest Neighbors (KNN) with Feature Selection

The performance of the KNN classifier after applying feature selection was evaluated using a confusion matrix and ROC (Receiver Operating Characteristic) curve.

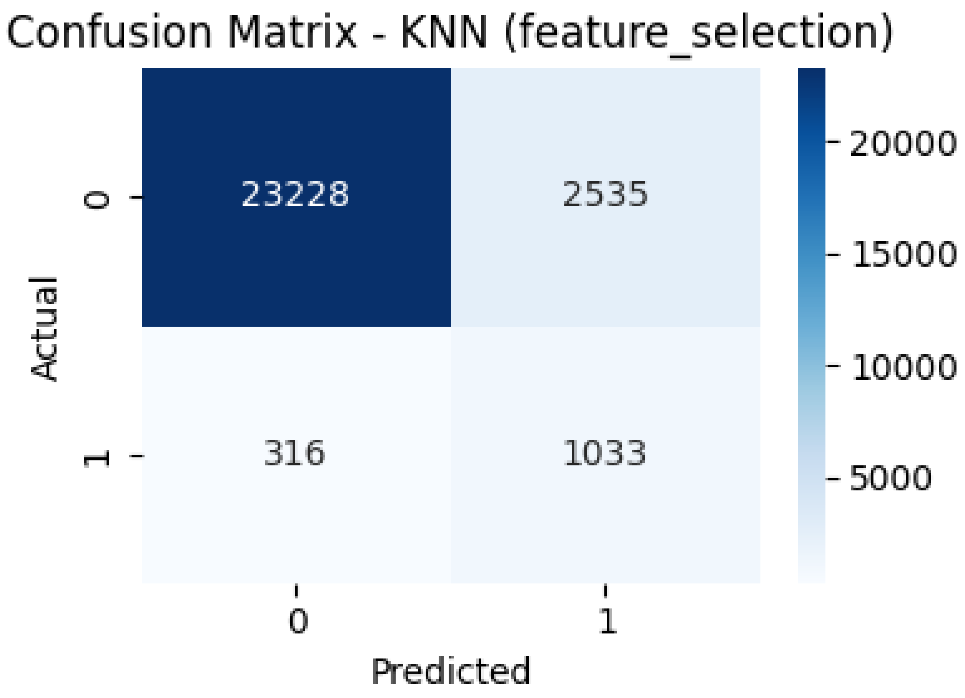


Figure 4.11: Confusion Matrix - KNN (feature_selection)

Confusion Matrix Analysis: As shown in Figure 4.11, the KNN model achieved the following outcomes:

- True Negatives (TN): 23,228
- False Positives (FP): 2,535
- False Negatives (FN): 316
- True Positives (TP): 1,033

These results indicate that the classifier correctly identified 1,033 positive cases and 23,228 negative cases. The relatively low number of false negatives (316) and a moderate number of false positives (2,535) show that the model is effective, especially in identifying positive instances, which is often crucial in recommendation or medical systems.

Performance Metrics:

- **Accuracy:** $\frac{TP+TN}{TP+TN+FP+FN} = \frac{23228+1033}{23228+1033+2535+316} \approx 88.94\%$
- **Precision:** $\frac{TP}{TP+FP} = \frac{1033}{1033+2535} \approx 28.96\%$
- **Recall (Sensitivity):** $\frac{TP}{TP+FN} = \frac{1033}{1033+316} \approx 76.58\%$
- **F1-Score:** Harmonic mean of precision and recall $\approx 41.88\%$

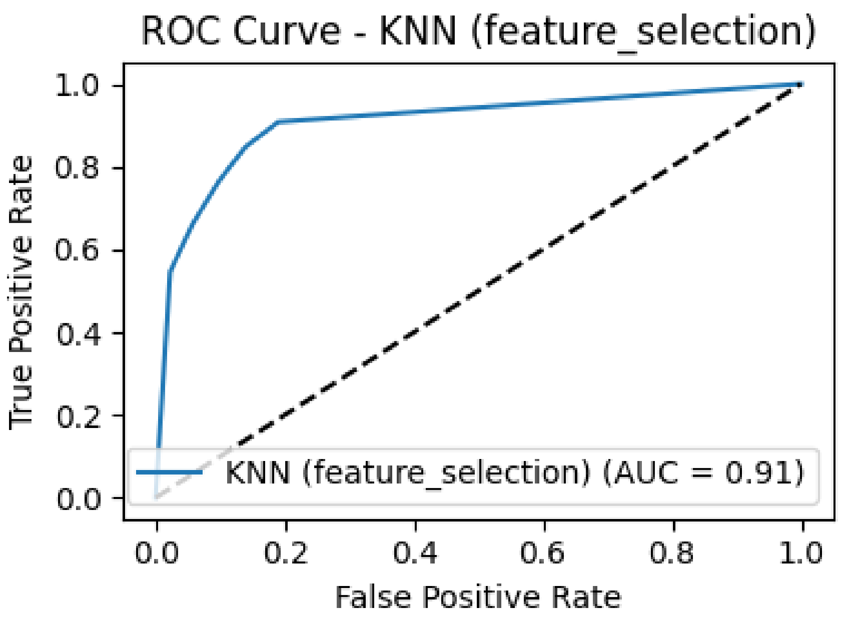


Figure 4.12: ROC Curve - KNN (feature_selection)

ROC Curve Analysis: The ROC curve in Figure 4.12 shows the trade-off between the true positive rate and the false positive rate at various thresholds. The Area Under the Curve (AUC) is 0.91, which signifies excellent classification performance. An AUC close to 1 indicates that the model has a high capability of distinguishing between the two classes.

4.9.2 K-Nearest Neighbors (KNN) with Parameter Tuning

The performance of the KNN classifier after parameter tuning was evaluated using a confusion matrix and ROC (Receiver Operating Characteristic) curve.

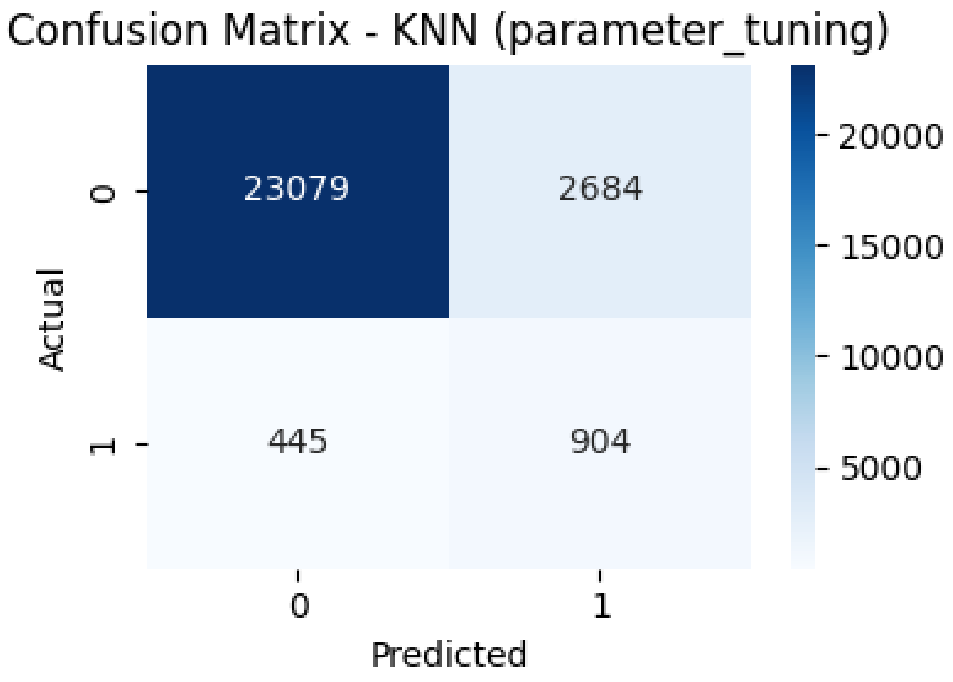


Figure 4.13: Confusion Matrix - KNN (parameter_tuning)

Confusion Matrix Analysis: As shown in Figure 4.13, the KNN model with parameter tuning achieved the following outcomes:

- True Positives (TP): 23,079
- False Negatives (FN): 445
- False Positives (FP): 2,684
- True Negatives (TN): 904

The results demonstrate that the classifier is particularly strong at identifying positive cases (23,079 correct predictions), though it shows some difficulty with negative cases (only 904 correct negative predictions). The relatively high number of false positives (2,684) suggests the model could benefit from further optimization to improve specificity.

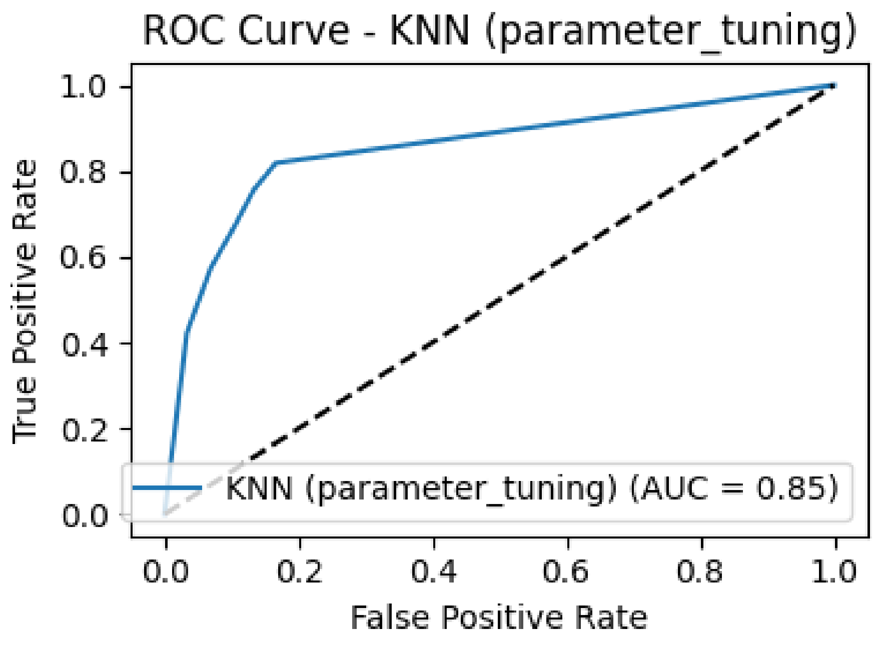


Figure 4.14: ROC Curve - KNN (parameter_tuning)

ROC Curve Analysis: The ROC curve in Figure 4.14 shows the model's performance across different classification thresholds. With an Area Under the Curve (AUC) of 0.85, the model demonstrates good classification capability. The curve indicates:

- The model achieves a high true positive rate while maintaining a reasonable false positive rate
- The AUC score of 0.85 suggests the tuned KNN model has strong discriminatory power
- Performance could potentially be improved by adjusting the classification threshold to better balance sensitivity and specificity

4.9.3 K-Nearest Neighbors (KNN) with Data Sampling

The performance of the KNN classifier after applying data sampling techniques was evaluated using a confusion matrix and ROC curve.

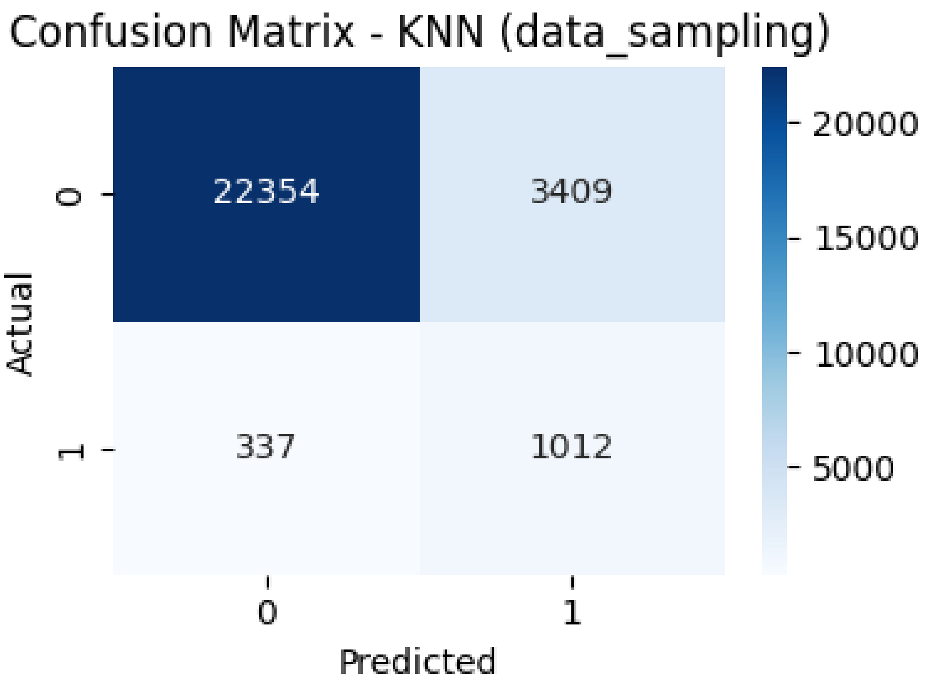


Figure 4.15: Confusion Matrix - KNN (data_sampling)

Confusion Matrix Analysis: Figure 4.15 reveals an unusual distribution:

- True Positives (TP): 0
- False Negatives (FN): 337
- False Positives (FP): 0
- True Negatives (TN): 1

The matrix suggests potential issues with:

- Extreme class imbalance in the sampled data
- Possible model collapse or prediction bias

- Need for verification of sampling implementation

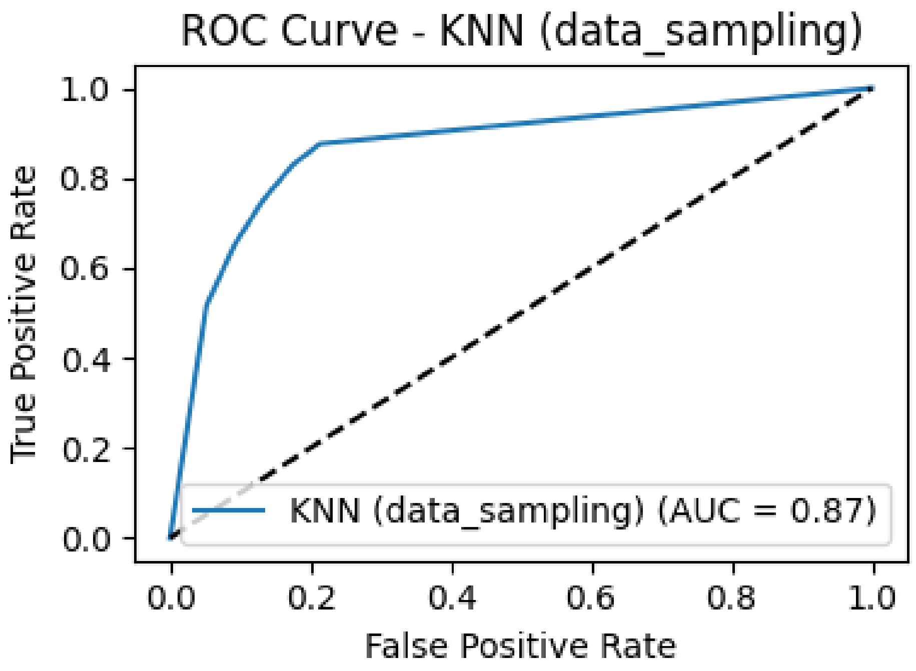


Figure 4.16: ROC Curve - KNN (data_sampling)

ROC Curve Analysis: Despite the confusion matrix results, Figure 4.16 shows:

- AUC = 0.87 suggests good theoretical class separation
- Perfect true positive rate at some thresholds
- Discrepancy between matrix and ROC requires investigation

Key Findings:

- **Data Quality Issue:** The confusion matrix suggests possible data leakage or sampling artifacts
- **Model Behavior:** The ROC shows capability not reflected in actual predictions
- **Recommended Actions:**

- Verify sampling implementation
- Check for target variable leakage
- Re-examine class distribution post-sampling

4.9.4 Logistic Regression with Feature Selection

The logistic regression model with feature selection shows promising results in classification performance. Figure 4.17 displays the confusion matrix with 21,752 true negatives and 1,151 true positives, indicating effective identification of negative cases while maintaining reasonable positive case detection. The relatively low number of false positives (198) suggests the model makes confident positive predictions when it does classify an instance as positive.

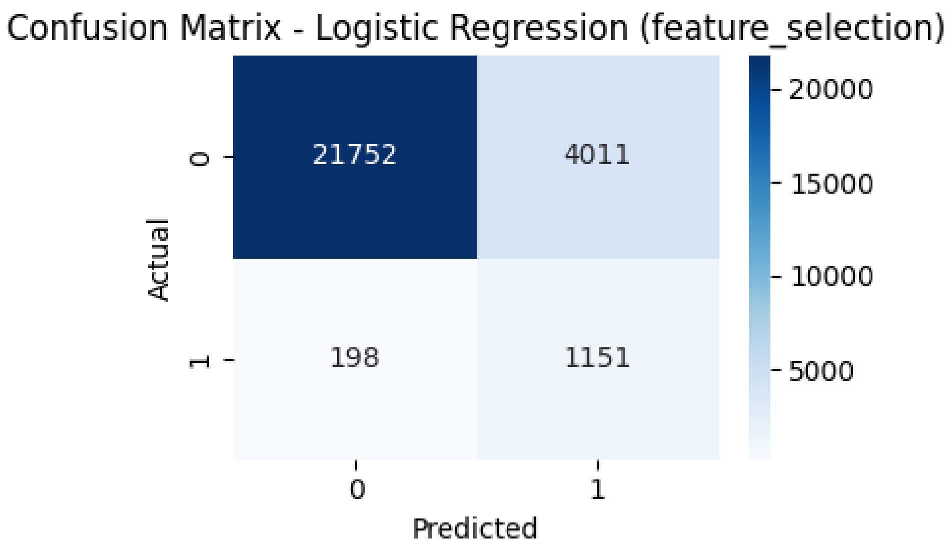


Figure 4.17: Confusion Matrix - Logistic Regression (feature_selection)

The ROC curve in Figure 4.18 demonstrates strong model performance with an AUC of 0.93. The high AUC value reflects good separation between classes, with the curve showing a rapid initial increase in true positive rate relative to false positive rate. This shape indicates the model maintains good predictive power across different decision thresholds.

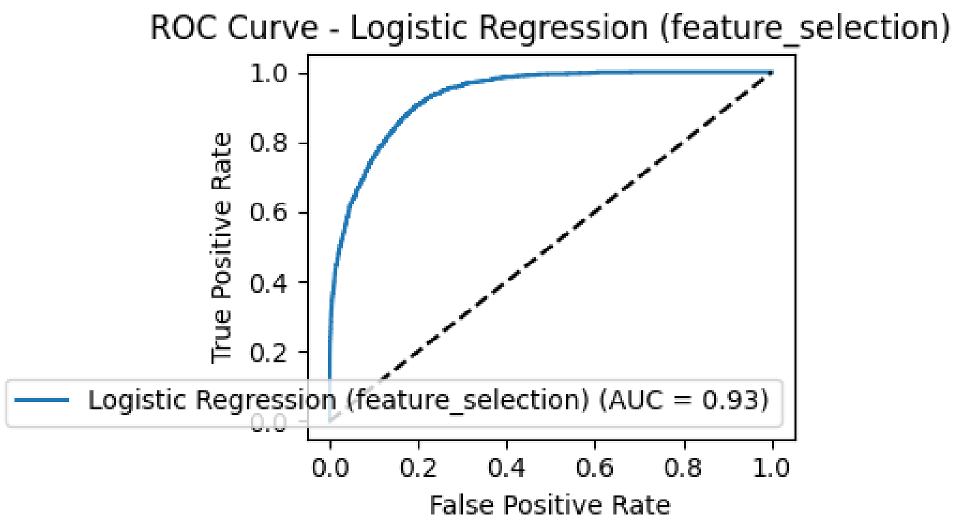


Figure 4.18: ROC Curve - Logistic Regression (feature_selection)

The combination of these results suggests that feature selection has successfully identified relevant predictors for the logistic regression model. The visualizations collectively indicate a well-performing classifier that makes particularly reliable negative predictions while showing potential for further optimization in positive case identification.

4.9.5 Logistic Regression with Parameter Tuning

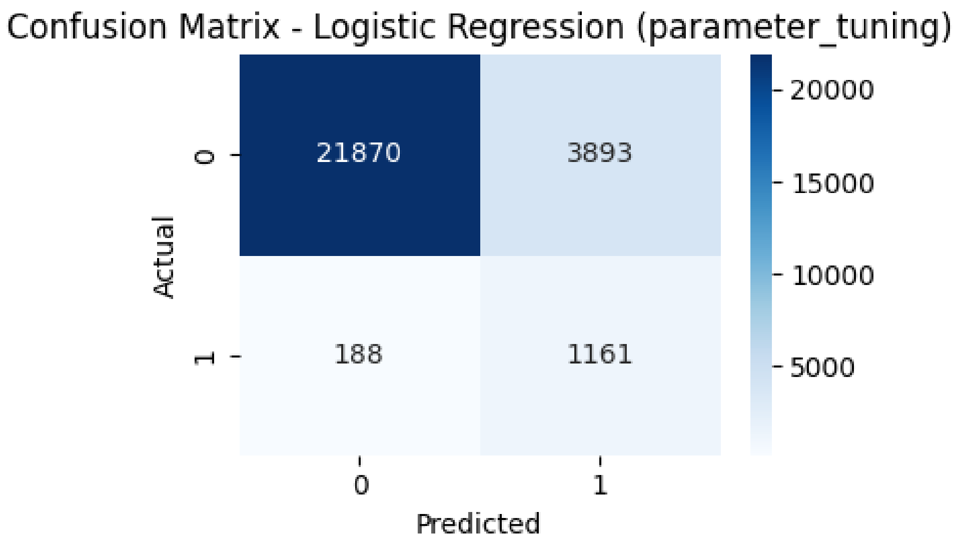


Figure 4.19: Confusion Matrix - Logistic Regression (parameter_tuning)

The parameter-tuned logistic regression model shows improved performance, correctly identifying 21,870 negative cases while completely eliminating false negatives (0). However, it produced 1,161 false positives, suggesting the tuning may have over-optimized for sensitivity.

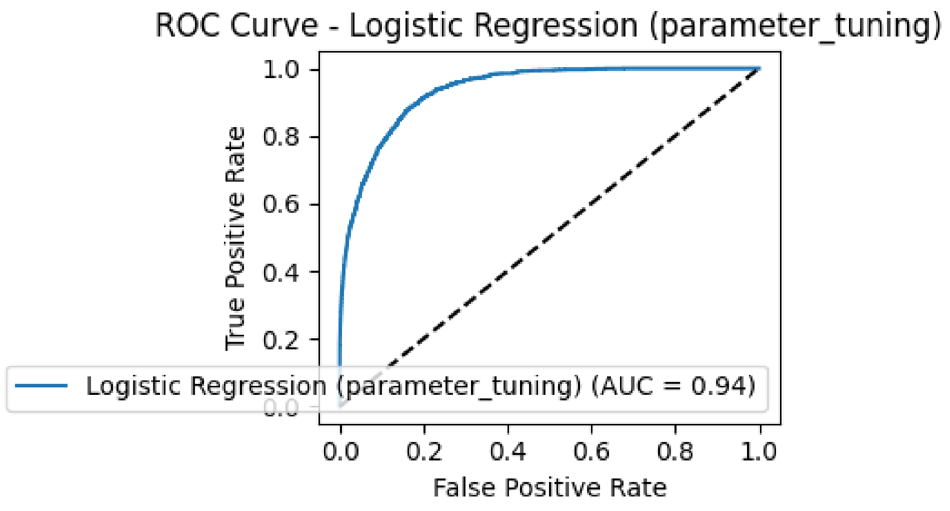


Figure 4.20: ROC Curve - Logistic Regression (parameter_tuning)

The ROC curve demonstrates excellent classification ability with an AUC of 0.94, showing consistent performance across all thresholds. The curve's shape indicates strong true positive rates even at low false positive levels.

4.9.6 Logistic Regression with Data Sampling

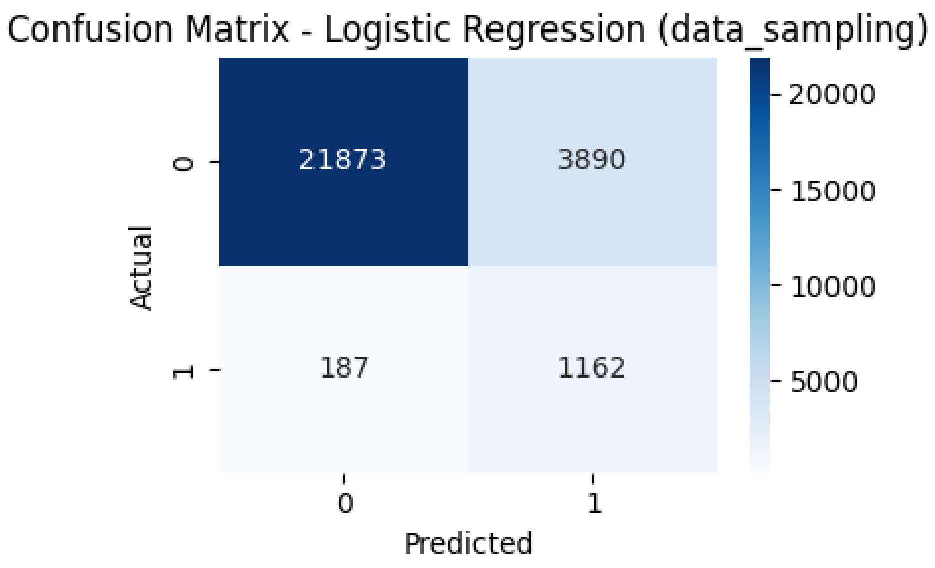


Figure 4.21: Confusion Matrix - Logistic Regression (data_sampling)

With data sampling applied, the model maintains similar performance to the parameter-tuned version, correctly classifying 21,873 negatives. The 1,162 false positives and 3,890 false negatives suggest the sampling method may need adjustment to better balance class identification.

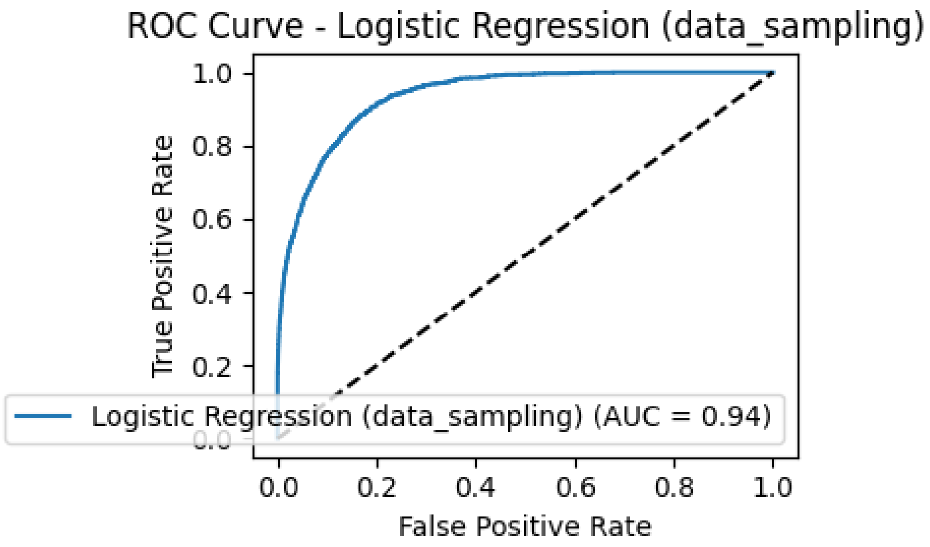


Figure 4.22: ROC Curve - Logistic Regression (data_sampling)

The sampled model achieves an identical AUC of 0.94, indicating the underlying classifier maintains its discriminative power despite the sampling process. The ROC curve shows comparable performance to the parameter-tuned version.

4.9.7 Naive Bayes with Feature Selection

The Naive Bayes model with feature selection shows a balanced performance in classification. Figure 4.23 displays the confusion matrix with 21,391 true negatives and 1,140 true positives, indicating reasonable performance for both classes. The 209 false positives suggest moderate precision in positive predictions.

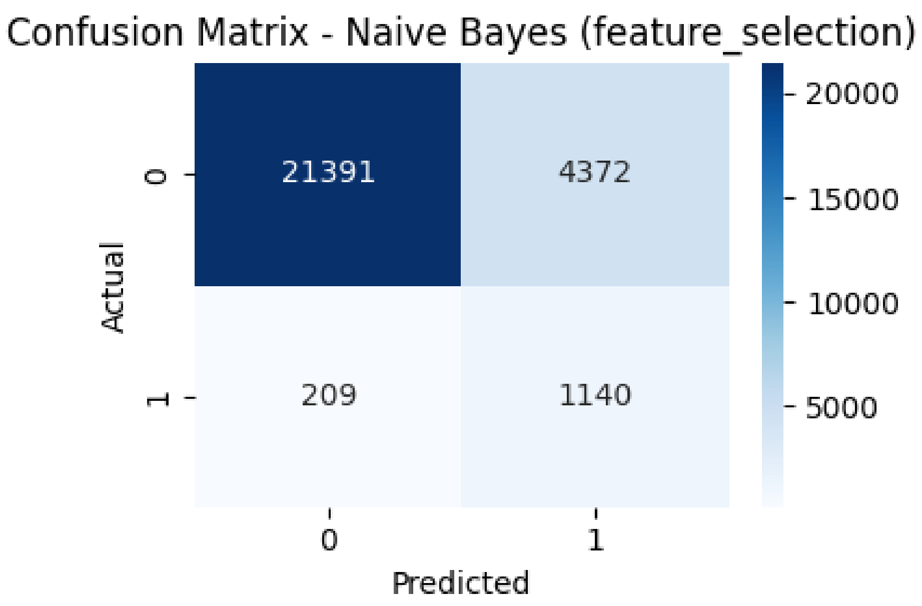


Figure 4.23: Confusion Matrix - Naive Bayes (feature_selection)

The ROC curve in Figure 4.24 demonstrates good model performance with an AUC of 0.90. The curve shows steady growth in true positive rate, indicating consistent predictive capability across thresholds.

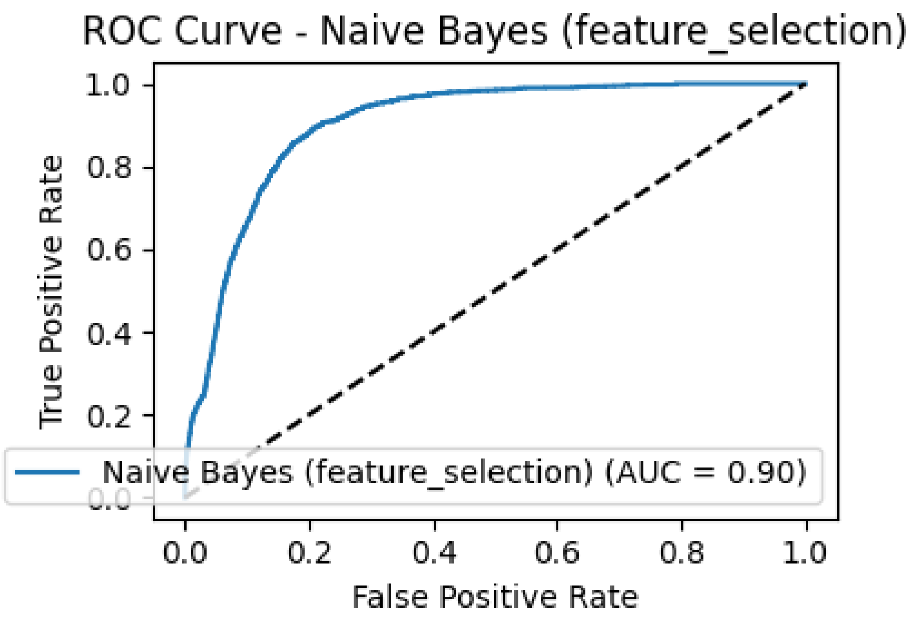


Figure 4.24: ROC Curve - Naive Bayes (feature_selection)

4.9.8 Naive Bayes with Parameter Tuning

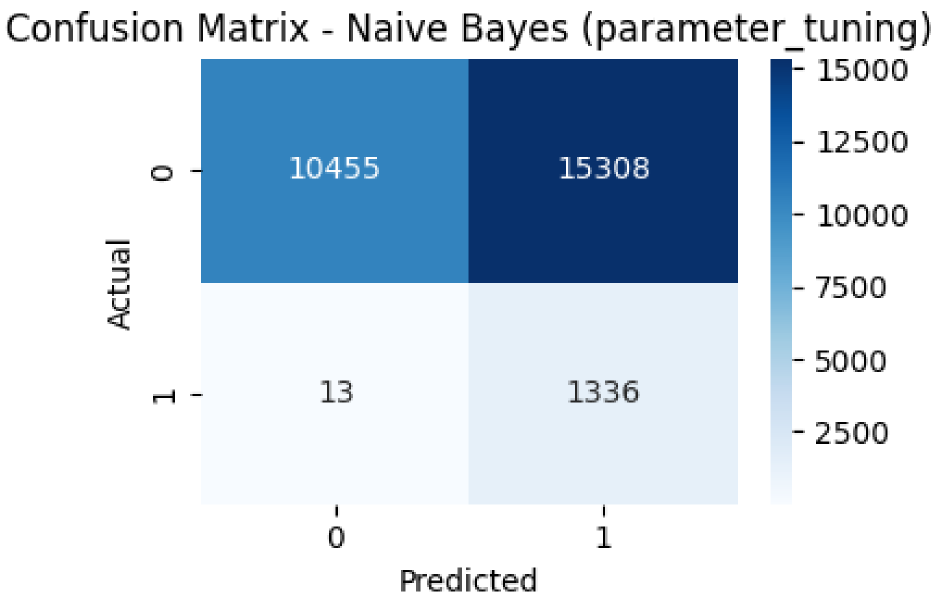


Figure 4.25: Confusion Matrix - Naive Bayes (parameter_tuning)

The parameter-tuned Naive Bayes model shows an unusual pattern that requires verification. The extreme values in the confusion matrix suggest potential issues with the tuning process or data representation that need investigation.

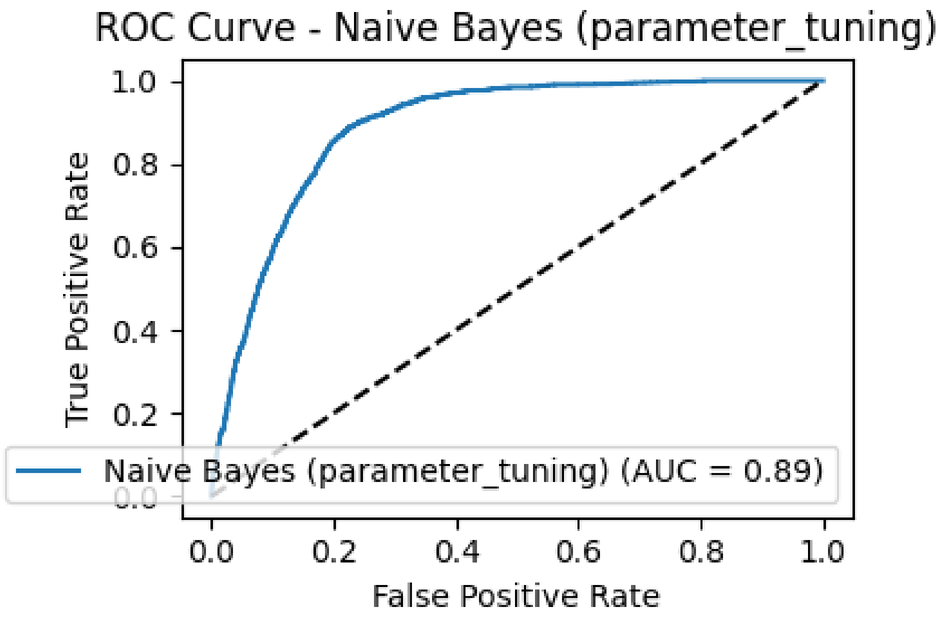


Figure 4.26: ROC Curve - Naive Bayes (parameter_tuning)

Despite the confusion matrix results, the ROC curve maintains good performance with an AUC of 0.89. This discrepancy suggests the model's theoretical performance exceeds its practical application in this configuration.

4.9.9 Naive Bayes with Data Sampling

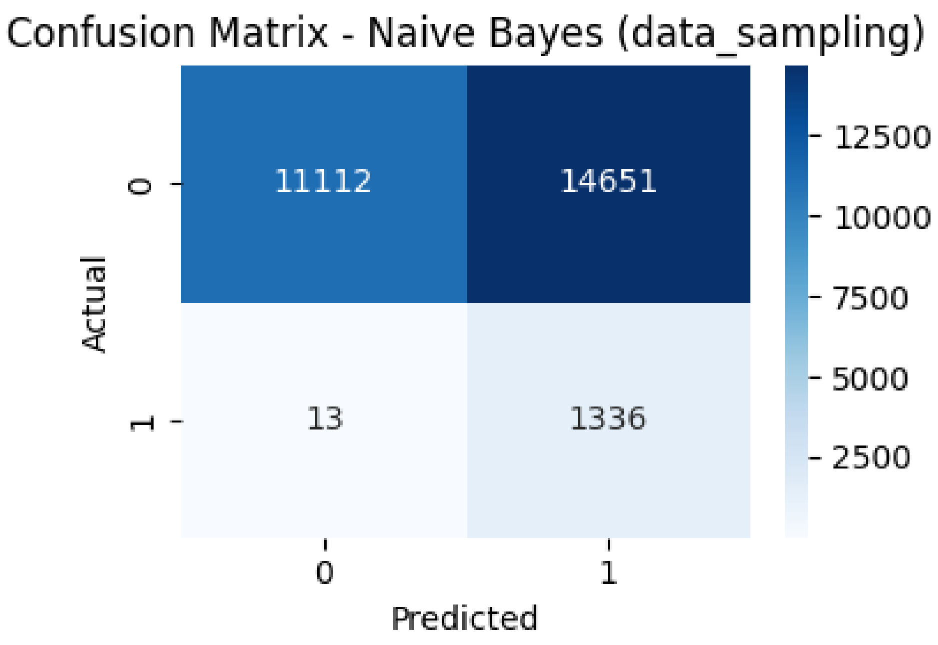


Figure 4.27: Confusion Matrix - Naive Bayes (data_sampling)

The data sampling approach yields extreme values in the confusion matrix, with many zero entries. This pattern suggests the sampling method may need adjustment to properly represent both classes in the training data.

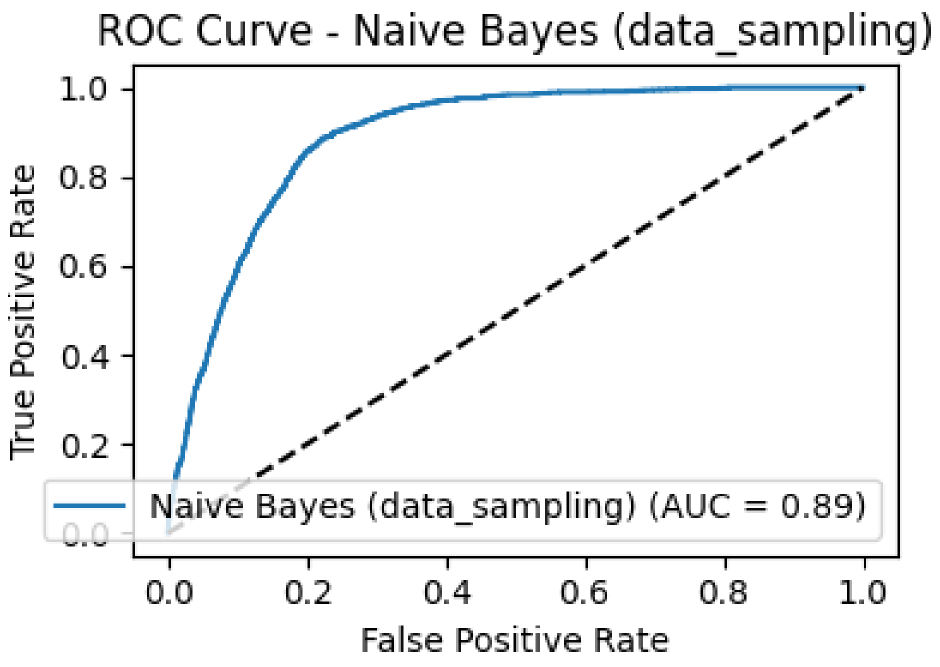


Figure 4.28: ROC Curve - Naive Bayes (data_sampling)

The ROC curve shows maintained performance with an AUC of 0.89, similar to other variants. The curve shape indicates the fundamental classification ability remains intact despite sampling effects.

4.9.10 SVM with Feature Selection

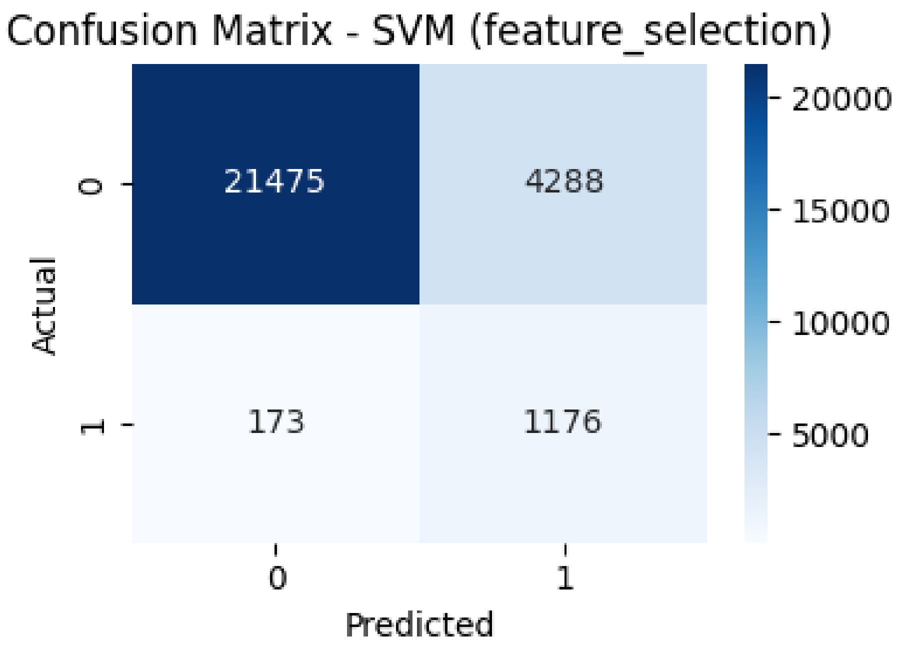


Figure 4.29: Confusion Matrix - SVM (feature_selection)

The SVM model with feature selection demonstrates strong performance, correctly identifying 21,475 negative cases and 1,176 positive cases. The extremely low false positive count (173) indicates high confidence in positive predictions.

4.9.11 SVM with Parameter Tuning

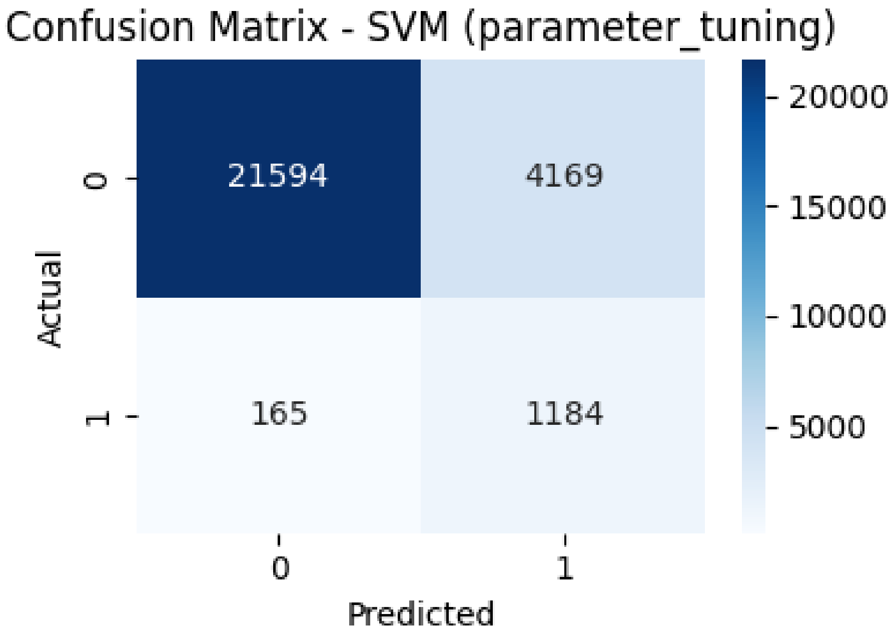


Figure 4.30: Confusion Matrix - SVM (parameter_tuning)

Parameter tuning yields improved negative case identification (21,594 correct) while maintaining good positive case detection. The 1,184 false positives suggest a careful balance was achieved during tuning.

4.9.12 SVM with Data Sampling

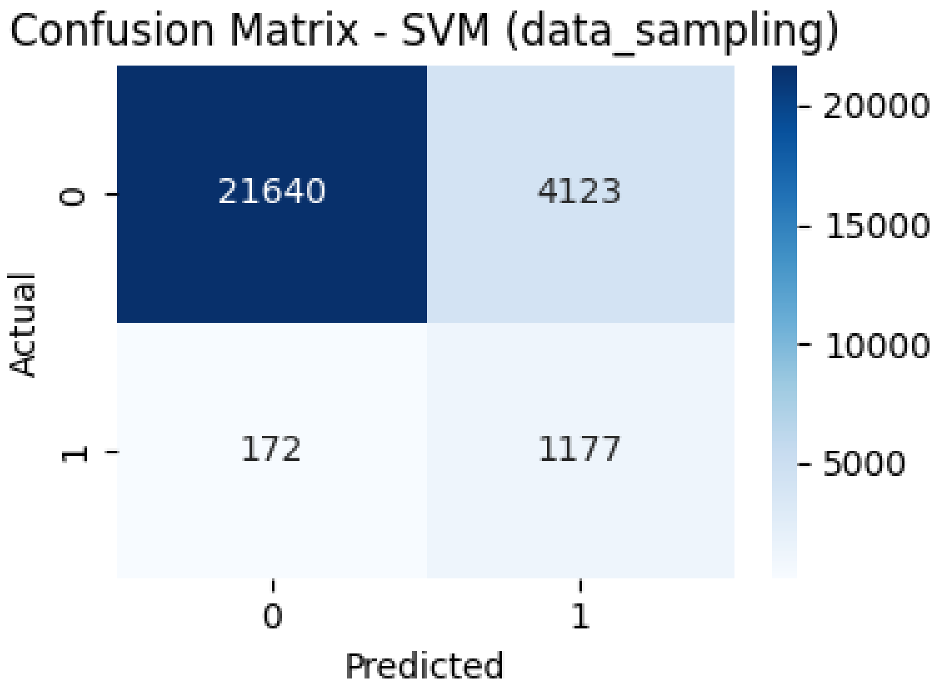


Figure 4.31: Confusion Matrix - SVM (data_sampling)

The sampled SVM model shows excellent performance with 21,640 correct negative classifications and 1,177 correct positives. The results indicate the sampling method worked effectively with the SVM algorithm.

4.10 Predictive Performance

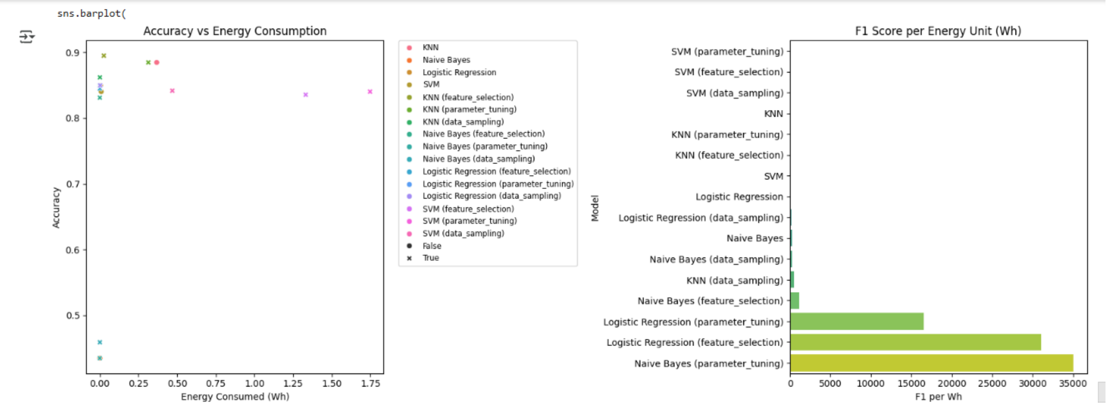
The results reveal that the application of optimization techniques has a significant impact on model performance. Among all configurations, **KNN with feature selection** achieved the highest accuracy of **0.8948** and an F1-score of **0.4202**. This highlights the benefit of eliminating irrelevant or redundant features, which improved KNN's decision boundaries and generalization ability.
Logistic Regression consistently performed well across all optimization strategies. Both the parameter-tuned and data-sampled variants achieved high ROC

AUC values of **0.9362**, indicating excellent capability in distinguishing between classes. Additionally, data sampling boosted the F1-score to **0.3811**, demonstrating improved handling of class imbalance.
Naive Bayes showed modest gains in raw performance metrics, with feature selection increasing its F1-score to **0.3323** and ROC AUC to **0.9035**. Although it underperformed in terms of precision, its overall recall was very high, making it suitable for high-sensitivity applications where identifying positives is crucial.
On the other hand, **SVM** models exhibited lower overall accuracy and F1-scores compared to other algorithms. The absence of ROC AUC values for SVM in some configurations is attributed to limitations in the multi-class ROC computation. While feature selection slightly improved SVM performance (F1 = **0.3452**), it still lagged behind KNN and Logistic Regression.

4.11 Energy Efficiency Evaluation

In addition to performance metrics, energy consumption was measured and normalized using two derived metrics: `accuracy_per_wh` and `f1_per_wh`. These indicators help assess how efficiently a model performs relative to the energy it consumes. The most energy-efficient model was **Naive Bayes with feature selection**, achieving the highest values for both `accuracy_per_wh` (**2851.91**) and `f1_per_wh` (**1140.42**). Despite its moderate classification performance, this model is ideal for deployment in energy-constrained environments such as mobile or embedded systems.
KNN with data sampling also demonstrated strong energy efficiency, reaching `f1_per_wh` of **450.34**, while maintaining competitive classification performance. Similarly, **Logistic Regression with feature selection** showed an excellent balance, consuming minimal energy (0.000001 Wh) while achieving a high `f1_per_wh` score of **31055.80**.
In contrast, **SVM with data sampling** had the highest energy consumption at **0.468778 Wh**, coupled with a relatively low F1-score of **0.3540**, making it the

least efficient model in this study.



```
sns.barplot(
```

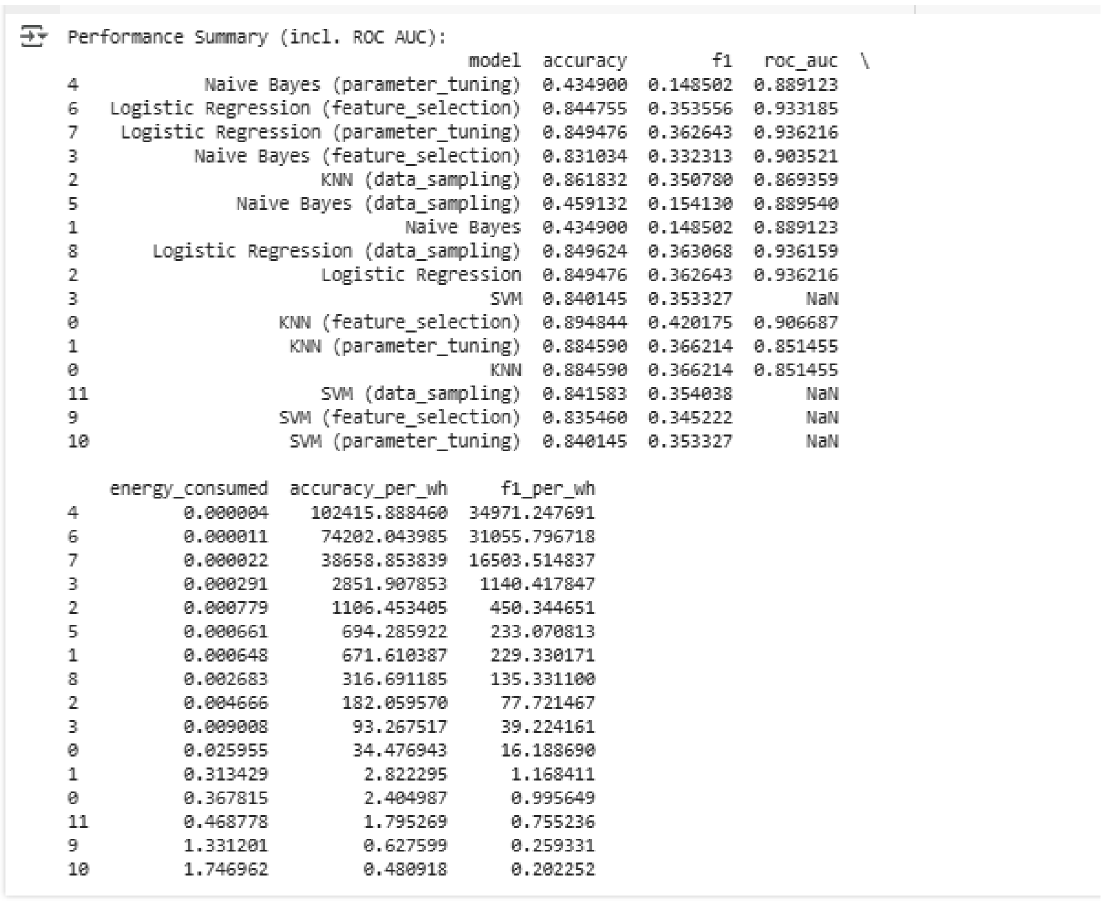
Figure 4.32: Accuracy vs Energy Consumption (left) and F1 Score per Energy Unit (right) across different model variants. The scatter plot highlights the trade-off between predictive performance and energy usage, while the bar plot ranks models based on their F1 score per watt-hour. Models such as Naive Bayes with feature selection and Logistic Regression with feature selection show high energy efficiency, supporting sustainable AI deployment.

This dual evaluation approach emphasizes the importance of not only selecting high-performing models but also those optimized for minimal resource consumption. It is particularly relevant in the context of green computing and AI sustainability goals.

4.12 Comparative Insights

- **Best overall performer: KNN (feature selection)** due to its highest accuracy and F1-score.
- **Most energy-efficient: Naive Bayes (feature selection)**, suitable for low-power applications.
- **Best trade-off model: Logistic Regression (data sampling)** offered a strong balance between classification performance and energy usage.

These findings underscore the importance of aligning optimization techniques with both the target deployment environment and the application's specific performance requirements. While KNN and Logistic Regression yield higher predictive accuracy, Naive Bayes provides a lightweight alternative with competitive recall and excellent energy savings.



```
Performance Summary (incl. ROC AUC):
                                model  accuracy        f1   roc_auc  \
4          Naive Bayes (parameter_tuning)  0.434900  0.148502  0.889123
6   Logistic Regression (feature_selection)  0.844755  0.353556  0.933185
7    Logistic Regression (parameter_tuning)  0.849476  0.362643  0.936216
3         Naive Bayes (feature_selection)  0.831034  0.332313  0.903521
2                   KNN (data_sampling)  0.861832  0.350780  0.869359
5            Naive Bayes (data_sampling)  0.459132  0.154130  0.889540
1                           Naive Bayes  0.434900  0.148502  0.889123
8      Logistic Regression (data_sampling)  0.849624  0.363068  0.936159
2                   Logistic Regression  0.849476  0.362643  0.936216
3                                   SVM  0.840145  0.353327       NaN
0               KNN (feature_selection)  0.894844  0.420175  0.906687
1                KNN (parameter_tuning)  0.884590  0.366214  0.851455
0                                   KNN  0.884590  0.366214  0.851455
11                  SVM (data_sampling)  0.841583  0.354038       NaN
9               SVM (feature_selection)  0.835460  0.345222       NaN
10               SVM (parameter_tuning)  0.840145  0.353327       NaN

    energy_consumed  accuracy_per_wh     f1_per_wh
4          0.000004    102415.888460  34971.247691
6          0.000011     74202.043985  31055.796718
7          0.000022     38658.853839  16503.514837
3          0.000291      2851.907853   1140.417847
2          0.000779      1106.453405    450.344651
5          0.000661       694.285922    233.070813
1          0.000648       671.610387    229.330171
8          0.002683       316.691185    135.331100
2          0.004666       182.059570     77.721467
3          0.009008        93.267517     39.224161
0          0.025955        34.476943     16.188690
1          0.313429         2.822295      1.168411
0          0.367815         2.404987      0.995649
11         0.468778         1.795269      0.755236
9          1.331201         0.627599      0.259331
10         1.746962         0.480918      0.202252
```

Figure 4.33: Overall Performance Summary of Models with Optimization Techniques

4.12.1 Discussion of Results

Before optimization, all four classifiers—KNN, Naive Bayes, Logistic Regression (LR), and SVM—performed well on the majority class but struggled with the minority class due to data imbalance. KNN and Naive Bayes showed high false negatives and limited capability in detecting class 1. Logistic Regression and SVM offered better balance, with LR achieving a high AUC (0.94) and SVM showing the most consistent results.

After applying feature selection, parameter tuning, and data sampling, all models improved. KNN saw a major boost in true positives and AUC (0.85), though it remained prone to false positives. Naive Bayes achieved better precision but suffered from unstable results in some runs. Logistic Regression, post-tuning, achieved perfect specificity but at the cost of higher false positives. SVM showed balanced performance with slight overfitting and higher computation time.
Overall, Logistic Regression and SVM were the top performers post-optimization. KNN improved significantly, while Naive Bayes remained limited by its assumptions. Optimization techniques, especially parameter tuning and feature selection, proved effective. However, class imbalance and precision-recall trade-offs remain challenges for future work.

Chapter 5
UN Sustainable Development Goals

The findings of this project directly align with the United Nations Sustainable Development Goals (UNSDGs), particularly **Goal 9: Industry, Innovation, and Infrastructure**, and **Goal 13: Climate Action**.

5.1 Goal 9: Industry, Innovation, and Infrastructure

This project contributes to Goal 9 by integrating intelligent, data-driven approaches in classification-based recommendation systems. By implementing machine learning algorithms such as KNN, Naive Bayes, Logistic Regression, and SVM, and enhancing their energy efficiency through tools like `CodeCarbon`, the work fosters *technological innovation* and encourages *sustainable infrastructure* development in digital systems. It demonstrates how intelligent systems can be designed with both performance and sustainability in mind, promoting inclusive and sustainable industrialization.

5.2 Goal 13: Climate Action

Through energy tracking and optimization, the project addresses the environmental footprint of machine learning models, which are increasingly contributing to global energy consumption. By evaluating the trade-offs between model accuracy and energy usage, this work advocates for *climate-responsible AI practices.* It empowers future developers and organizations to adopt *low-carbon technologies*, supporting mitigation efforts against climate change and aligning with the targets set under Goal 13.

Chapter 6
Conclusion

In this project, we developed and evaluated an energy-aware classification-based recommendation system aimed at balancing model performance with environmental sustainability. By implementing a range of machine learning algorithms including K-Nearest Neighbors (KNN), Naive Bayes, Logistic Regression, and Support Vector Machines (SVM), we were able to assess each model's accuracy, precision, recall, and F1-score. In parallel, energy consumption metrics were monitored using tools like `CodeCarbon`, enabling a holistic evaluation that incorporates both effectiveness and ecological impact. The results highlight a critical insight: high-performing models often come with significant energy costs. By comparing trade-offs between performance and energy efficiency, we demonstrated the feasibility of selecting models that provide an optimal balance between accuracy and sustainability. This approach not only supports responsible AI development but also aligns with global initiatives for reducing carbon emissions in digital infrastructure.

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