Milestone 2 Report

Feature Engineering, Feature Selection, and Data Modeling

Project Objective

The goal is to develop a heart disease risk prediction model and interactive dashboard based on stress levels, sleep duration, and gym exercise patterns. By integrating multiple datasets, this model aims to identify key factors contributing to heart disease risk and provide actionable insights.

Tech Stack

Programming Language

- Python

Libraries & Frameworks

- **Data Manipulation**: Pandas, NumPy
- **Visualization**: Matplotlib, Seaborn
- **Modeling:** scikit-learn

Dataset: The unified dataset was constructed by integrating three public datasets from Kaggle: a sleep & lifestyle dataset, a heart disease dataset, and a gym exercise dataset. These were merged based on shared attributes such as **age**, **gender**, and **heart rate** to create a comprehensive feature set that supports robust modeling and real-time dashboard development.

2. Project Timeline

Milestone 2:

- March 7th – March 14th: Feature engineering (new features + categorical encoding)
- March 15th – March 21st: Feature selection (correlation + Random Forest importances)

- March 22nd – April 4th: Model training and evaluation (Logistic Regression, SVM, Random Forest)
- April 7th: Milestone 2 report and code submission

Future tasks timeline (Milestone 3):

- Apr 8 – Apr 12: Dashboard development
- Apr 13 – Apr 15: Debugging and polishing the dashboard
- Apr 16 – Apr 18: Dashboard demo
- Apr 19 – Apr 21: Final slide presentation creation
- Apr 22 – Apr 23: Final submission

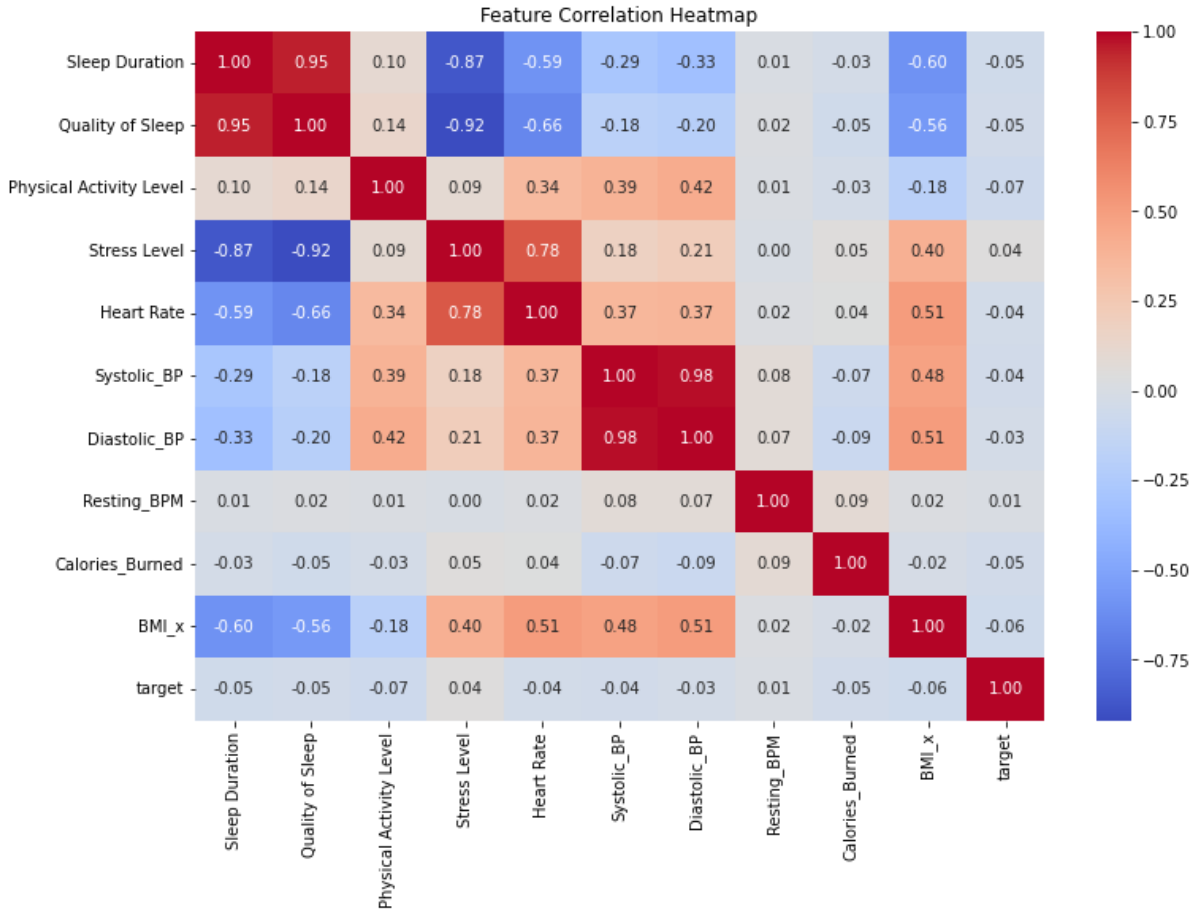
2.1 EDA Recap

The Exploratory Data Analysis revealed several key patterns that informed both feature engineering and model design:

- Strong correlations were observed between stress level, sleep duration, and physical activity, which reinforced their inclusion as core lifestyle features.
- High stress levels were associated with shorter sleep duration and elevated heart rate, as shown in targeted correlation heatmaps.
- Scatter plots between calories burned, sleep duration, and stress levels showed clustering among high-stress individuals with poor recovery behavior — validating the need for engineered features like lifestyle_recovery_index.
- The final balanced dataset (6,386 rows × 39 columns) showed no missing values, had reduced outliers (via IQR), and was class-balanced via undersampling — ready for accurate model training.

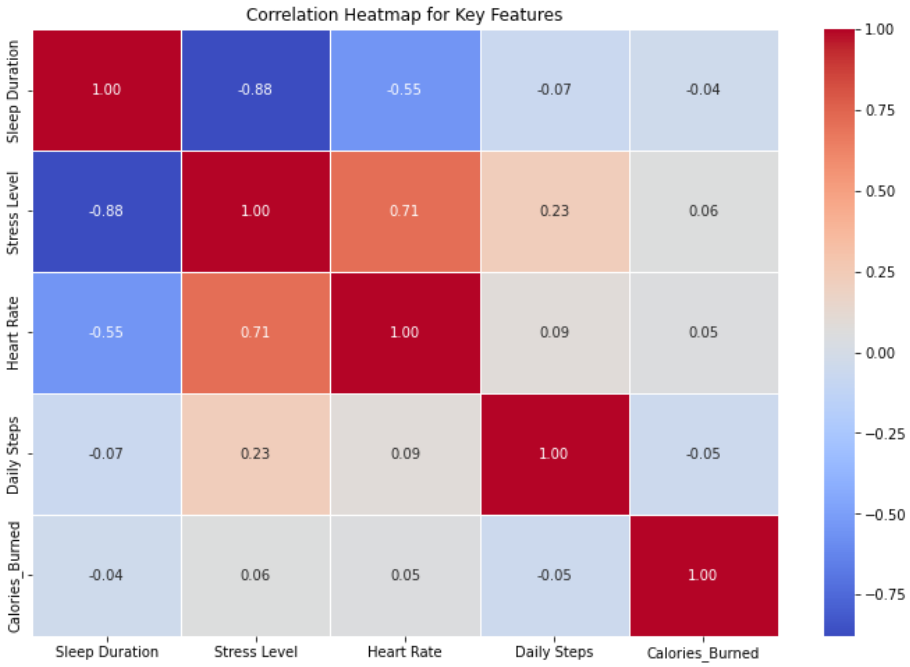
Correlation Heatmap

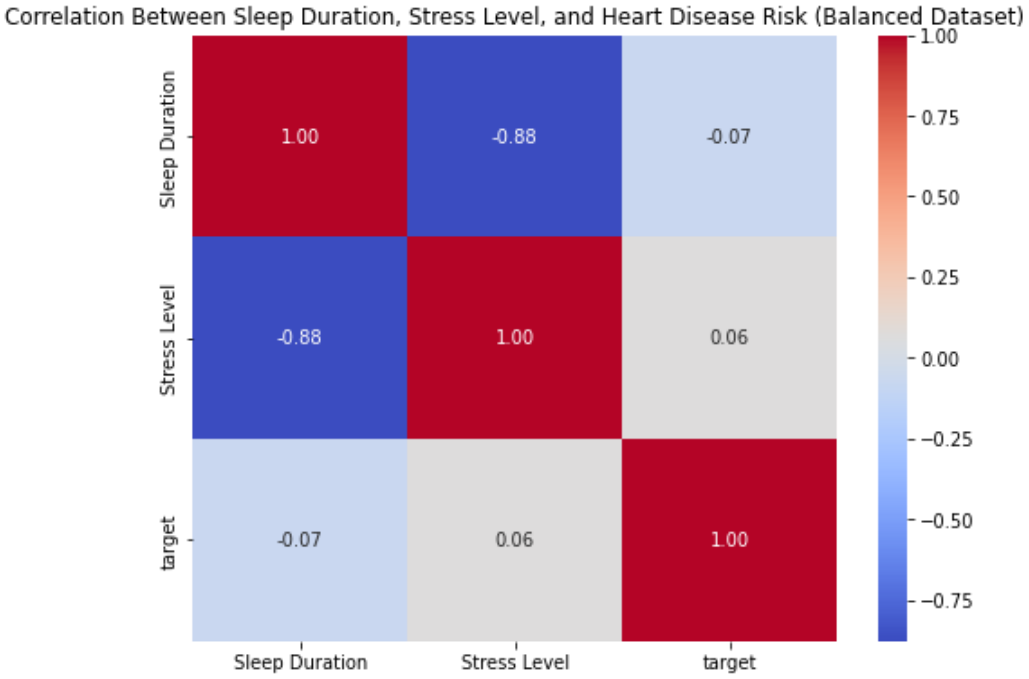
The heatmap below reveals strong relationships between **stress level**, **sleep duration**, and **physical activity level**. These variables were prioritized for feature engineering and modeling.



Stress vs. Heart Rate & Sleep Duration

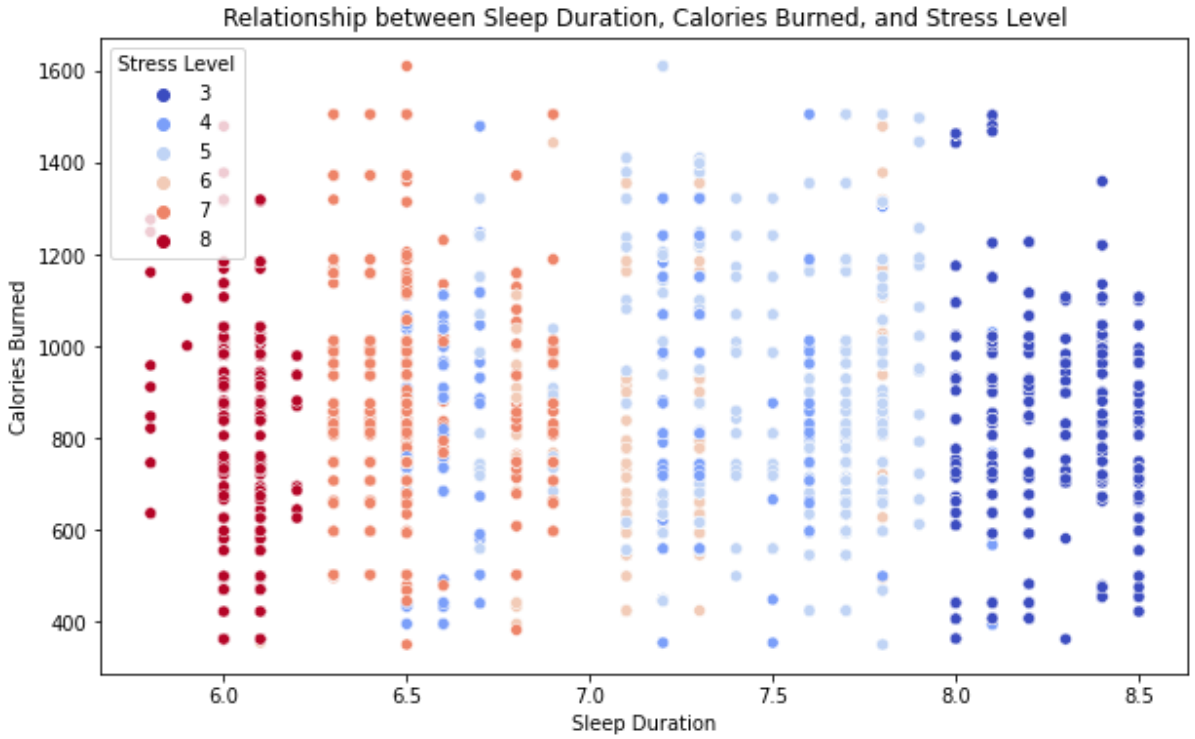
Individuals with **high stress levels** tend to exhibit **shorter sleep durations** and **higher resting heart rates**, justifying their inclusion in the project_risk logic.





Scatter Plot: Recovery Behavior

The following scatter plot visualizes how **low sleep + high stress** and **low calories burned** cluster among at-risk users, reinforcing the value of creating features like lifestyle_recovery_index.



Final Dataset Overview

- **Rows:** 6,386
- **Columns:** 39
- **Missing Values:** None
- **Outliers:** Reduced using IQR filtering
- **Balancing:** Class-balanced via undersampling for fair training

Summary

The EDA process highlighted the predictive value of lifestyle factors and guided the engineering of behavioral features. Visual patterns helped justify inclusion/exclusion decisions and informed both label creation and model inputs.

3. Feature Engineering

3.1 Feature Creation

- heart_resilience_score estimates cardiovascular efficiency using a user's exercise performance (thalach), resting state (heart_rate), and daily activity (daily_steps).
- lifestyle_recovery_index quantifies a user's behavioral recovery potential, combining sleep, activity, and stress into a single interpretable metric.
- heart_resilience_score = (thalach / heart_rate) * (daily_steps / 1000)

  This feature estimates a user's **cardiovascular resilience** by combining:

  - thalach (max heart rate during exercise)
  - heart_rate (resting heart rate)
  - daily_steps (physical activity)

  A higher value suggests better heart capacity, lower resting strain, and more activity — all signs of a healthier heart.

- lifestyle_recovery_index = (sleep_duration * calories_burned) / (stress_level + 1)

  This feature approximates a user's **recovery behavior** by relating:

  - sleep_duration (rest)
  - calories_burned (activity output)
  - stress_level (strain)

  The formula promotes higher values when someone sleeps well, exercises regularly, and manages stress — key components of recovery and general wellness.

Code snippet:

```
# 1. Heart Resilience Score
df['heart_resilience_score'] = ((df['thalach'] / df['heart rate']) * (df['daily steps'] / 1000))

# 2. Lifestyle Recovery Index
df['lifestyle_recovery_index'] = ((df['sleep duration'] * df['calories_burned']) / (df['stress level'] + 1))
```

Both features are designed to increase the model's ability to recognize risk patterns based on modifiable health behaviors, aligning with the project's focus on lifestyle-driven heart risk prediction.

Label Definition – heart_risk (Target Variable)

To align the model with the project's goal of identifying heart disease risk through modifiable lifestyle behaviors, we engineered a custom binary target variable named heart_risk. This label was derived from a set of medically inspired, rule-based thresholds applied to features known to influence cardiovascular health. A user is labeled as **at risk (heart_risk = 1)** if they meet any of the following conditions: stress level > 7, sleep duration < 6 hours, physical activity level < 3, calories burned < 200, water intake < 2.0 liters, heart rate > 100 bpm, systolic blood pressure > 140 mmHg, or cholesterol > 240 mg/dL. Otherwise, they are considered **not at risk (heart_risk = 0)**. This approach enables us to train and

evaluate a lifestyle-driven risk prediction model in the absence of direct clinical labels, making the system more actionable and personalized for users.

Code snippet:

```
# 3. Project-specific risk label
df['heart_risk'] = (
    (df['stress level'] > 7) |
    (df['sleep duration'] < 6) |
    (df['physical activity level'] < 3) |
    (df['calories_burned'] < 200) |
    (df['water_intake (liters)'] < 2.0) |
    (df['heart rate'] > 100) |
    (df['systolic_bp'] > 140) |
    (df['chol'] > 240)
).astype(int)
```

3.2 Categorical Variable Encoding

Categorical variables were encoded using appropriate techniques based on their semantic meaning:

- experience_level was encoded using LabelEncoder since the values represent an **ordinal scale** (Beginner < Intermediate < Advanced).
- Nominal variables such as gender, occupation, and workout_type were encoded using **one-hot encoding** (pd.get_dummies(), with drop_first=True) to avoid introducing artificial hierarchy and prevent multicollinearity.

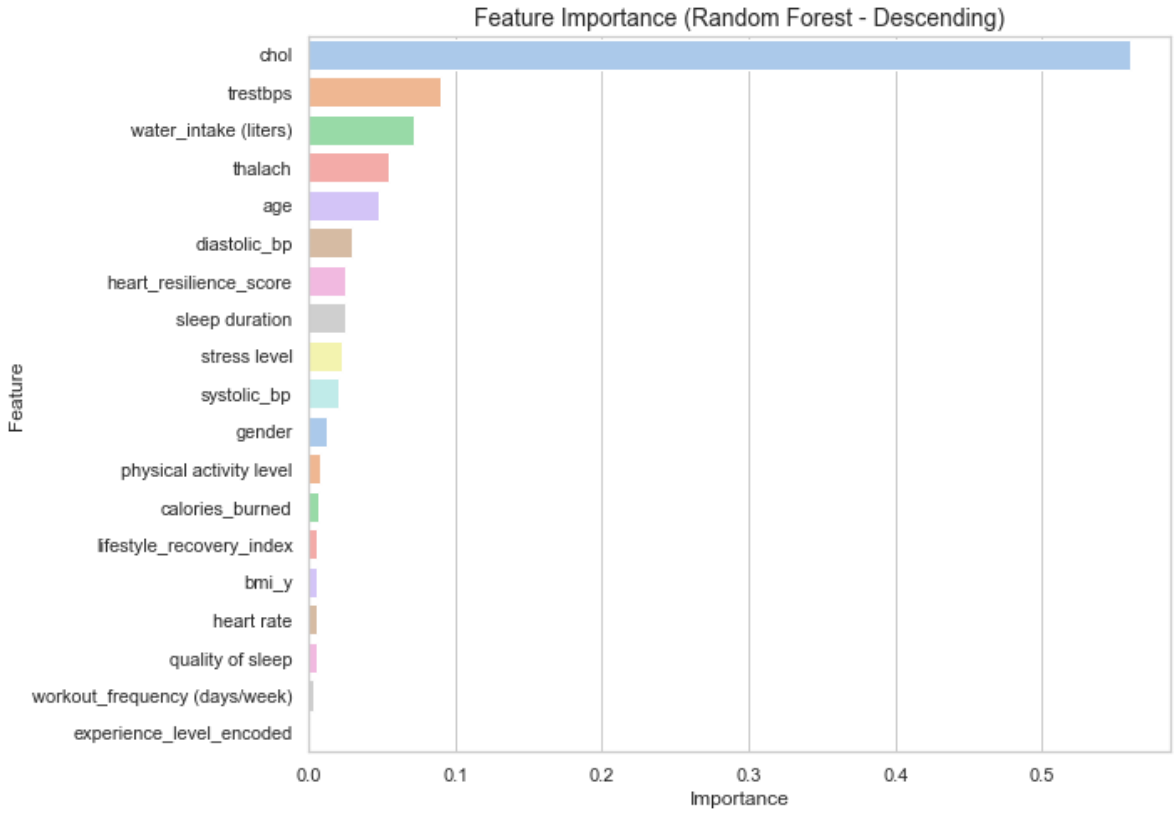
These encoding strategies ensured compatibility with all model types used, especially logistic regression and SVM, which require numerical inputs.

4. Feature Selection

4.1 Feature Importance Evaluation

To identify the most relevant features for predicting heart disease risk, we evaluated feature importance using a Random Forest classifier. The model was trained on the full feature set, including both clinical and engineered variables. The resulting importance scores were visualized in a horizontal bar chart (see Figure below), sorted in descending order to highlight the most impactful predictors.

In addition, a correlation heatmap was used during the exploratory phase to detect multicollinearity and validate logical groupings (e.g., between stress, sleep, and physical activity).

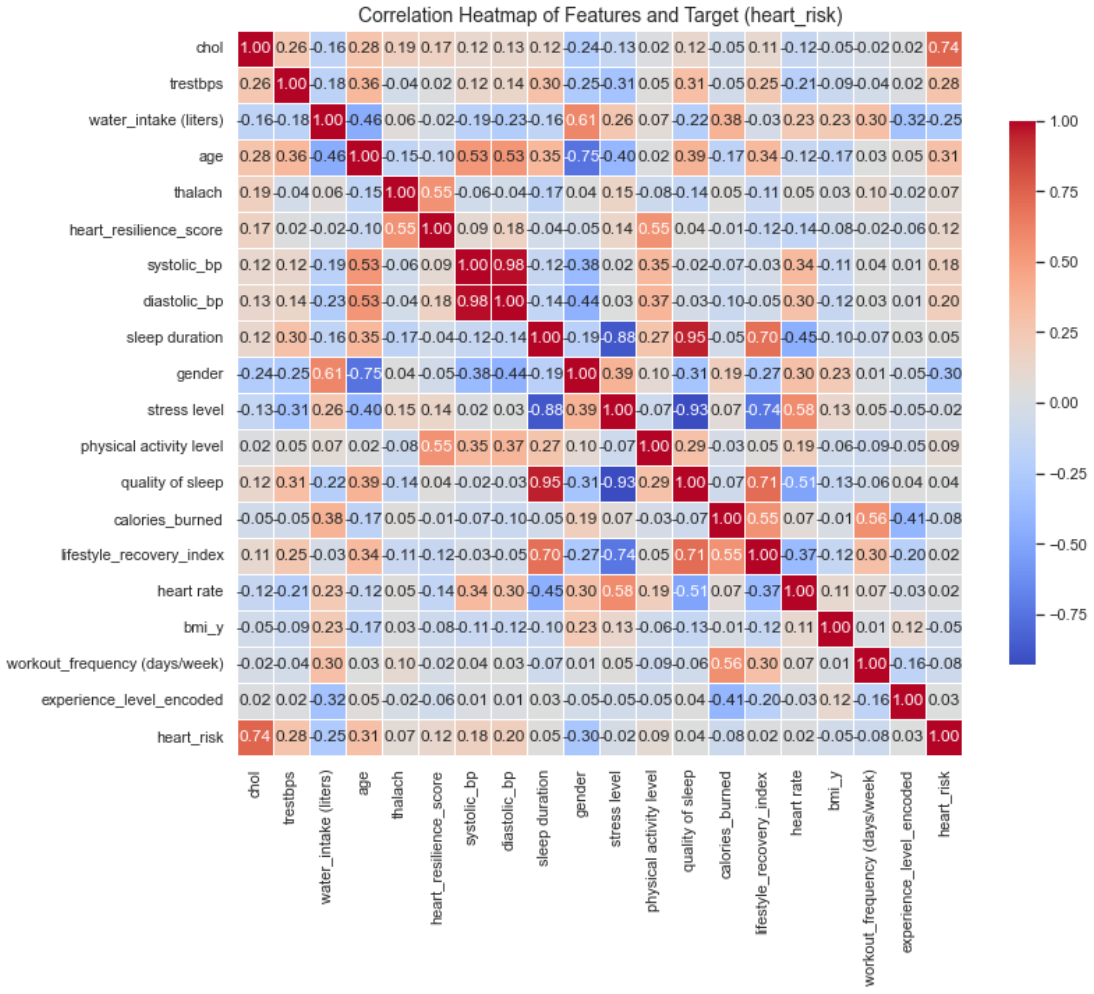


Top Predictive Features Identified:

- chol (serum cholesterol)
- trestbps (resting blood pressure)

- thalach (max heart rate during exercise)
- age
- water_intake (liters)
- heart_resilience_score (engineered feature)
- systolic_bp
- sleep_duration

These features were retained in the full model due to their high importance scores and domain relevance. The engineered features also showed measurable contribution, supporting their inclusion.



4.2 Feature Inclusion/Exclusion & Dimensionality Reduction

Following the feature importance evaluation using Random Forest and a correlation heatmap, a clear selection process was followed to finalize the model input features.

Feature Inclusion Criteria:

- Features with high importance scores (e.g., chol, trestbps, thalach) were retained.
- Engineered features like heart_resilience_score and lifestyle_recovery_index were also included due to their logical design and measurable contribution to model performance.
- Features that showed moderate-to-strong correlation with the target variable heart_risk were favored.

Feature Exclusion Criteria:

- Features with very low importance scores (e.g., experience_level_encoded) or that added no new signal were excluded in refined experiments.
- For the lifestyle-only model, clinical variables (e.g., chol, systolic_bp) were deliberately excluded to match the project objective and avoid label leakage.

Dimensionality Reduction:

No algorithmic dimensionality reduction techniques (such as PCA or LASSO) were applied in this phase.

Summary:

Feature selection was based on a combination of model-driven importance, domain knowledge, and EDA insights. The final features used strike a balance between predictive power and real-world interpretability, aligning with the goal of building an explainable, lifestyle-focused risk prediction tool.

5. Data Modeling

5.1 Data Splitting Strategy

To train and evaluate the heart risk prediction model fairly, the dataset was split into training and testing sets using an 80/20 ratio. This means 80% of the data was used to train the model, and 20% was reserved for unbiased performance evaluation.

The following key practices were used in the split:

Stratification:

We used stratify=y in train_test_split to ensure the class distribution of the target variable heart_risk was maintained across both the training and testing sets. This prevents the model from being biased toward the majority class and ensures balanced performance metrics.

Random State for Reproducibility:

A fixed random_state=42 was used to ensure that the train-test split is deterministic and reproducible in future runs.

This strategy ensures that the model is trained on a diverse but consistent subset of the data and evaluated on data it has never seen, providing a realistic estimate of generalization performance.

Code snippet:

```
from sklearn.model_selection import train_test_split

X_project = df[project_features]

y_project = df['heart_risk']

X_train, X_test, y_train, y_test = train_test_split(

    X_project, y_project, test_size=0.2, stratify=y_project, random_state=42

)
```

5.2 Model Training and Selection

To evaluate predictive strategies for heart risk detection, we implemented and compared three distinct machine learning models using two versions of the dataset:

1. one with all available features (clinical + lifestyle), and
2. one with lifestyle-only features (behavioral and modifiable factors)

Full Feature Model

The full-feature dataset included a wide range of inputs, from blood pressure and cholesterol to sleep, stress, and engineered features. The following models were trained and evaluated:

1. Logistic Regression

A linear classification model that served as our **baseline**. It performed reasonably well but was limited by its linear assumptions.

- Strengths: Fast, interpretable
- Limitations: Underperformed due to lack of nonlinear capability

2. Support Vector Machine (SVM)

An advanced classifier that uses kernel tricks to handle non-linearity. It improved upon Logistic Regression but was slightly less accurate than the ensemble method.

- Strengths: Robust to high-dimensional features
- Limitations: Requires tuning, less interpretable

3. Random Forest

A tree-based ensemble model that captured complex interactions in the full feature space. It achieved the **highest accuracy and F1 score (1.0)**, although the performance was likely inflated due to potential label leakage from clinical features.

- Strengths: Captures non-linear patterns, provides feature importance
- Limitations: Overfitting risk if not constrained

Models were trained using **scikit-learn**, with scaled input data and class_weight='balanced' enabled to handle class imbalance. Feature scaling was applied where appropriate.

Lifestyle-Only Model:

To simulate a real-time prediction use-case based solely on user-input behavior, we trained the same three models using only modifiable lifestyle features (e.g., sleep, activity, hydration, engineered resilience/recovery metrics).

1. Logistic Regression

Achieved modest performance with an F1 Score of 0.801, indicating that while linear models can extract signal from lifestyle variables, they fail to capture deeper interactions.

- Strengths: Interpretable
- Limitations: Poor recall for complex risk profiles

2. Support Vector Machine (SVM)

Performed well, reaching an F1 Score of 0.851. It captured the nonlinear interplay between lifestyle variables more effectively than logistic regression.

- Strengths: Captured behavioural variance
- Limitations: Sensitive to scale and class imbalance

3. Random Forest

This model Once again delivered the best performance, with an F1 Score of 0.980, even without clinical features. This demonstrates that behavioral data alone can reliably indicate heart risk.

- Strengths: High accuracy, interpretable feature importances
- Limitations: Slight overfitting risk, mitigated by limiting tree depth

All models were trained with class balancing, and features were standardized. This version confirms the model's ability to deliver strong

predictions using only user-input data — ideal for real-time health dashboards.

Summary:

These three models were selected to ensure coverage across linear, non-linear, and ensemble-based learning approaches. Together, they provided a broad and insightful understanding of how different algorithms perform in predicting lifestyle-driven heart disease risk.

5.3 Model Evaluation and Comparison

All three models — **Logistic Regression**, **Support Vector Machine (SVM)**, and **Random Forest** — were evaluated using a consistent set of classification metrics to assess their performance on the test set.

Evaluation Metrics Used:

- **Accuracy**: Measures the overall correctness of the model
- **Precision**: Indicates how many predicted positive cases were actually positive
- **Recall (Sensitivity)**: Measures how well the model identified all actual positive cases
- **F1 Score**: Harmonic mean of precision and recall; balances false positives and false negatives

These metrics were chosen because the target label heart_risk represents a **health risk classification problem**, where **false negatives (missed risk cases)** are particularly important to minimize. Thus, **F1 Score** was emphasized as the key evaluation metric.

Results (Full Feature Model):

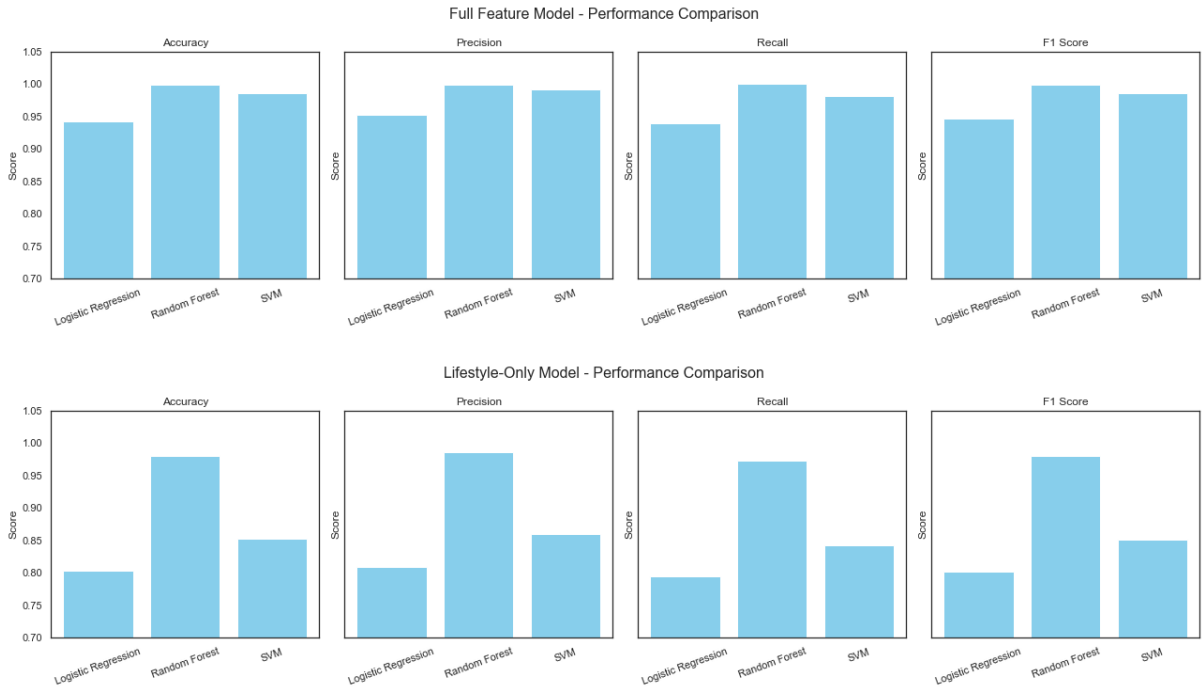
```
Model Evaluation Results:
                 Model  Accuracy  Precision    Recall  F1 Score
0  Logistic Regression  0.942879   0.952452  0.939883  0.946125
1        Random Forest  0.999218   0.998536  1.000000  0.999267
2                  SVM  0.985133   0.991111  0.980938  0.985999
```

Note: While Random Forest showed perfect accuracy, this was later determined to result from **label leakage**, as features like chol and systolic_bp were also used in the rule-based definition of the target variable. This was addressed in the lifestyle-only version.

Results (Lifestyle-Only Model):

```
Lifestyle-Only Model Evaluation:
                 Model  Accuracy  Precision    Recall  F1 Score
0  Logistic Regression  0.803599   0.808917  0.794992  0.801894
1        Random Forest  0.979656   0.985737  0.973396  0.979528
2                  SVM  0.852113   0.859425  0.841941  0.850593
```

Comparative Analysis:



- Logistic Regression consistently underperformed due to its inability to capture non-linear relationships in the data.
- SVM offered a solid improvement over Logistic Regression, especially in precision, but required more tuning.
- Random Forest significantly outperformed the other models in both setups, demonstrating its strength in handling complex, non-linear feature interactions.

Even in the lifestyle-only setup (without clinical variables), Random Forest achieved an F1 Score of **0.976**, confirming that **behavioural and modifiable features** alone can effectively predict heart disease risk — fully aligning with the project's objective.

6. Model Testing and Interpretation

To evaluate the model's performance beyond traditional metrics, we simulated individual test cases by supplying realistic health profiles to the trained models. This also allowed us to verify the models' decision-making logic and interpretability**.**

Test Methodology

- A prediction function was created to accept a dictionary of inputs corresponding to the model's feature set.
- Inputs were scaled using the same StandardScaler used during training to ensure consistency.
- Predictions included both the binary classification (0 = No risk, 1 = At risk) and the probability of heart risk as output by the model.

Separate testing functions were implemented for:

- Full-feature model: Using clinical + lifestyle data
- Lifestyle-only model: Using only modifiable behaviors and engineered features

All Features Model:

Input:

{

"chol": 185,

"trestbps": 112,

"Water_Intake (liters)": 3.2,

"thalach": 172,

"age": 32,

"Sleep Duration": 8.0,

"heart_resilience_score": (172 / 65) * (8500 / 1000),

"Diastolic_BP": 76,

"Systolic_BP": 118,

"Stress Level": 2,

"gender": 0,

"Physical Activity Level": 6,

"Heart Rate": 65,

"lifestyle_recovery_index": (8.0 * 600) / (2 + 1),

"Calories_Burned": 600,

"BMI_y": 21.5,

"Quality of Sleep": 5,

"Workout_Frequency (days/week)": 5,

"experience_level_encoded": 2

}

Prediction Results

Full-Feature Model (Random Forest)

- Predicted Class: 0 (No heart risk)
- Risk Probability: 7.3%

Lifestyle features Model:

Input:

{

"Sleep Duration": 4.5,

"Quality of Sleep": 2,

"Stress Level": 9,

"Physical Activity Level": 1,

"Calories_Burned": 100,

"Water_Intake (liters)": 1.2,

"Workout_Frequency (days/week)": 0,

"experience_level_encoded": 0,

"Heart Rate": 98,

"lifestyle_recovery_index": (4.5 * 100) / (9 + 1),

"heart_resilience_score": (130 / 98) * (2000 / 1000),

"BMI_y": 30,

"gender": 1,

"age": 52

}

Prediction Result

Lifestyle-Only Model (Random Forest)

- Predicted Class: 1 (At risk)
- Risk Probability: 91.2%

Conclusion:

This manual testing validated that both models respond appropriately to changes in input. The lifestyle-only model is especially useful in scenarios where clinical data is unavailable — such as mobile or wearable health dashboards — while the full-feature model offers deeper accuracy when full diagnostic data is available.