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.

2.1 EDA Recap

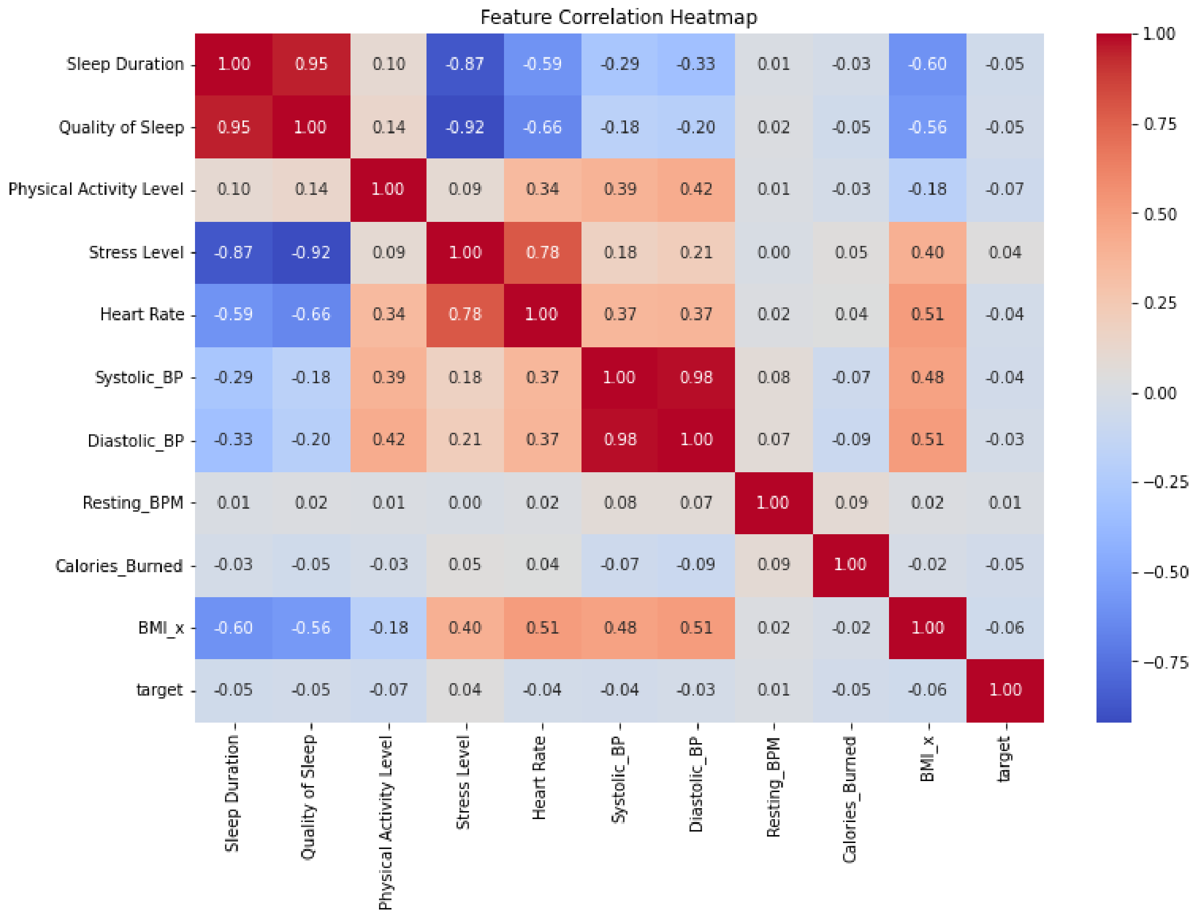
The Exploratory Data Analysis revealed several key patterns that informed both feature engineering and model design:

- 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.

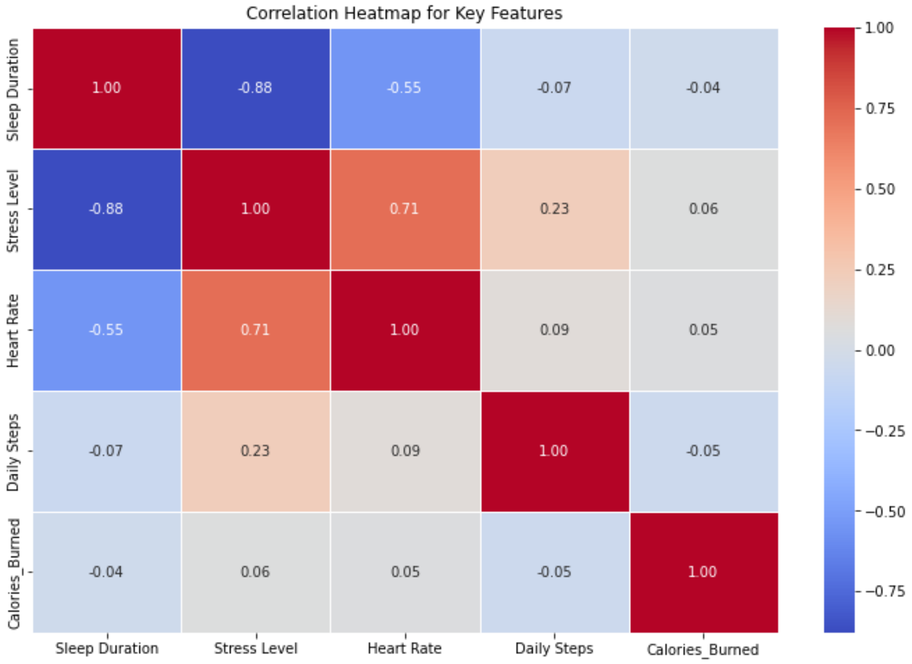
Correlation Heatmap

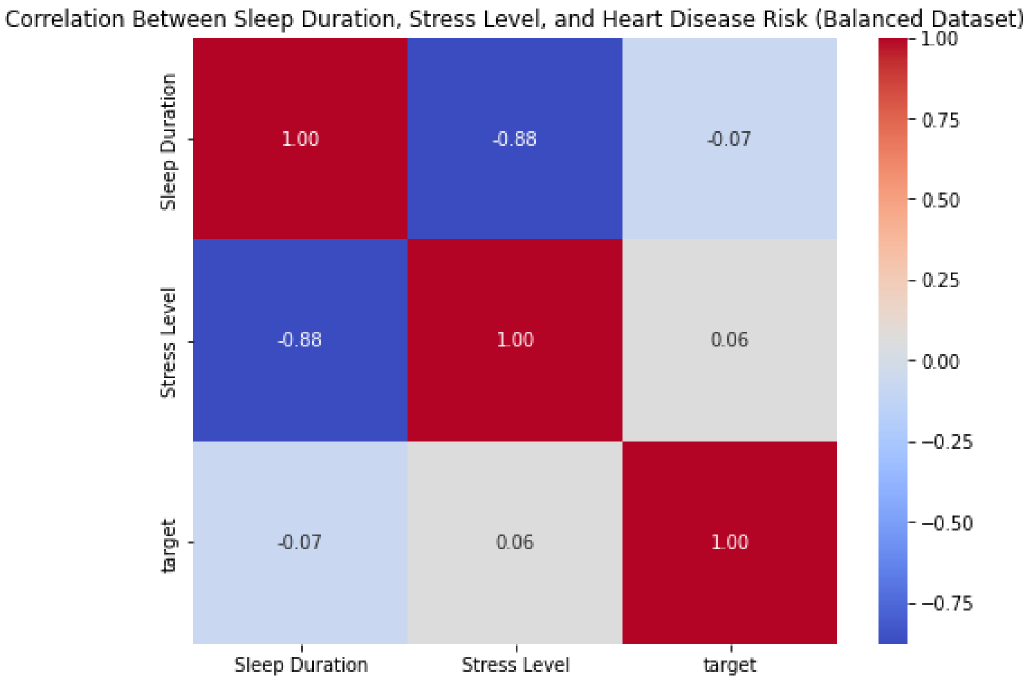
The heatmap below reveals strong relationships between **stress level**, **sleep duration**, and **physical activity level**. These variables were prioritized for feature engineering and modeling.



Stress vs. Heart Rate & Sleep Duration

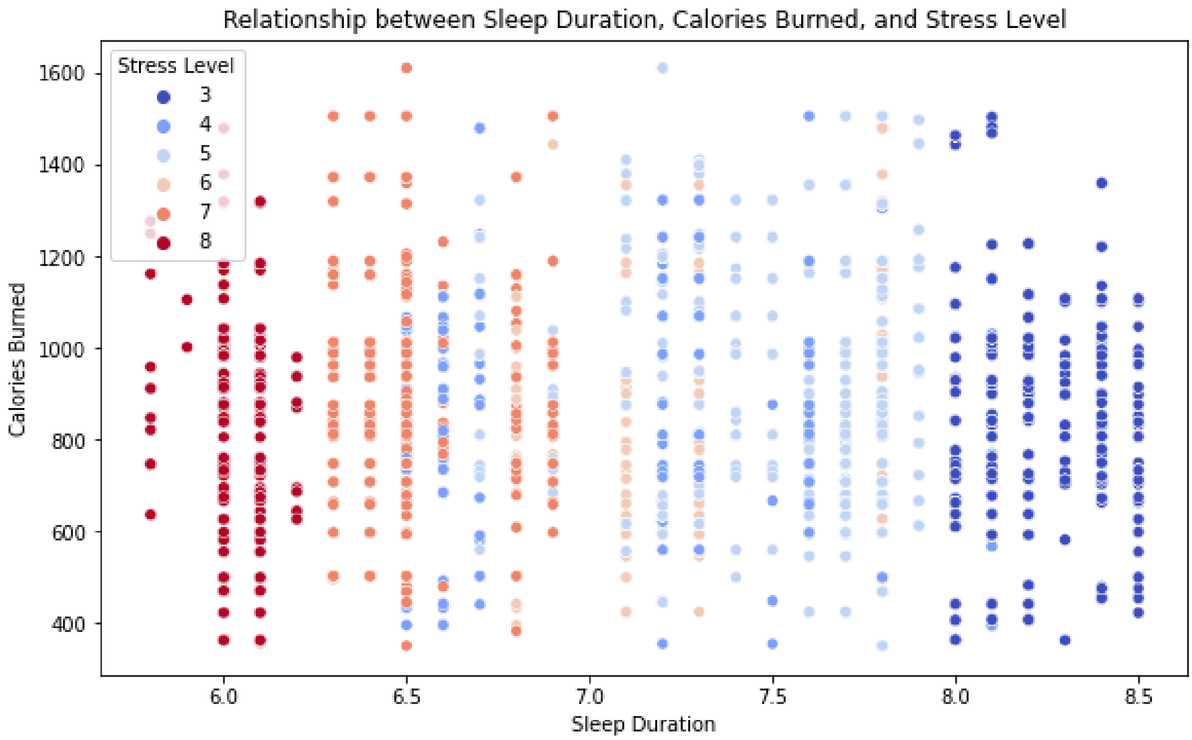
Individuals with **high stress levels** tend to exhibit **shorter sleep durations** and **higher resting heart rates**, justifying their inclusion in the project_risk logic.





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.

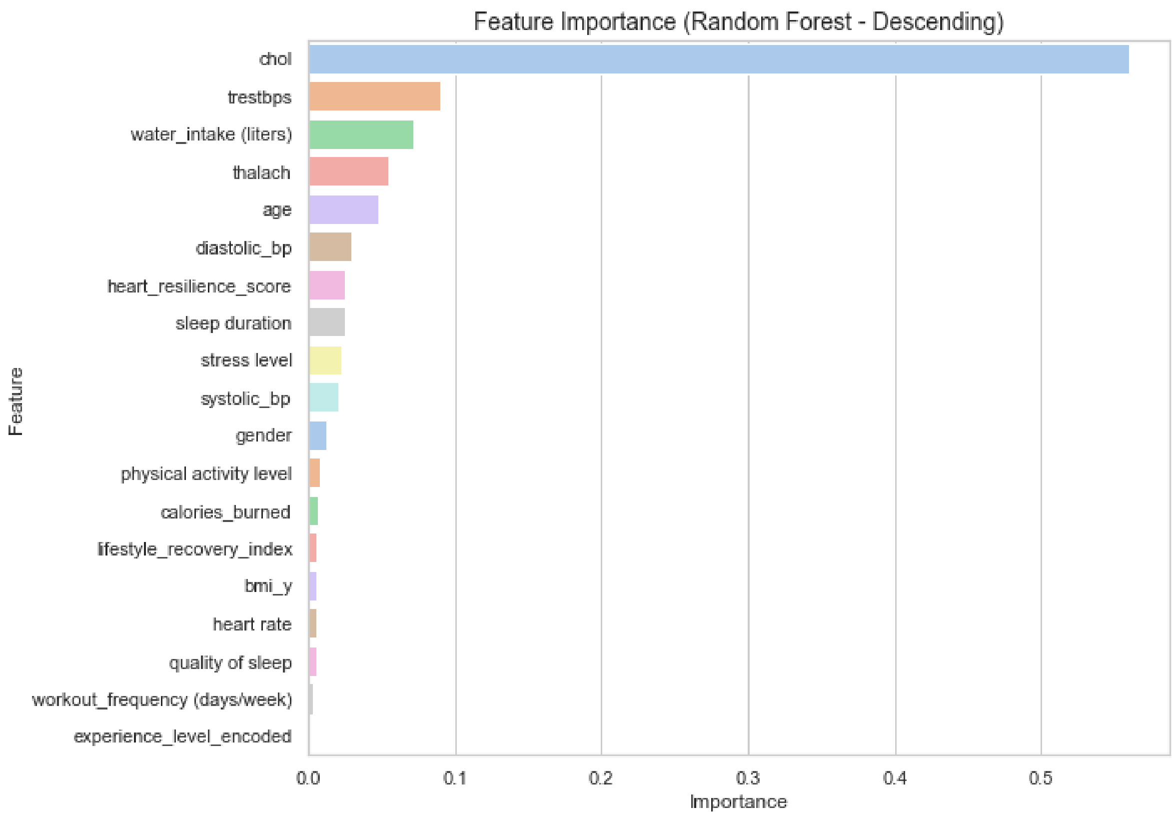
These encoding strategies ensured compatibility with all model types used, especially logistic regression and SVM, which require numerical inputs.

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.

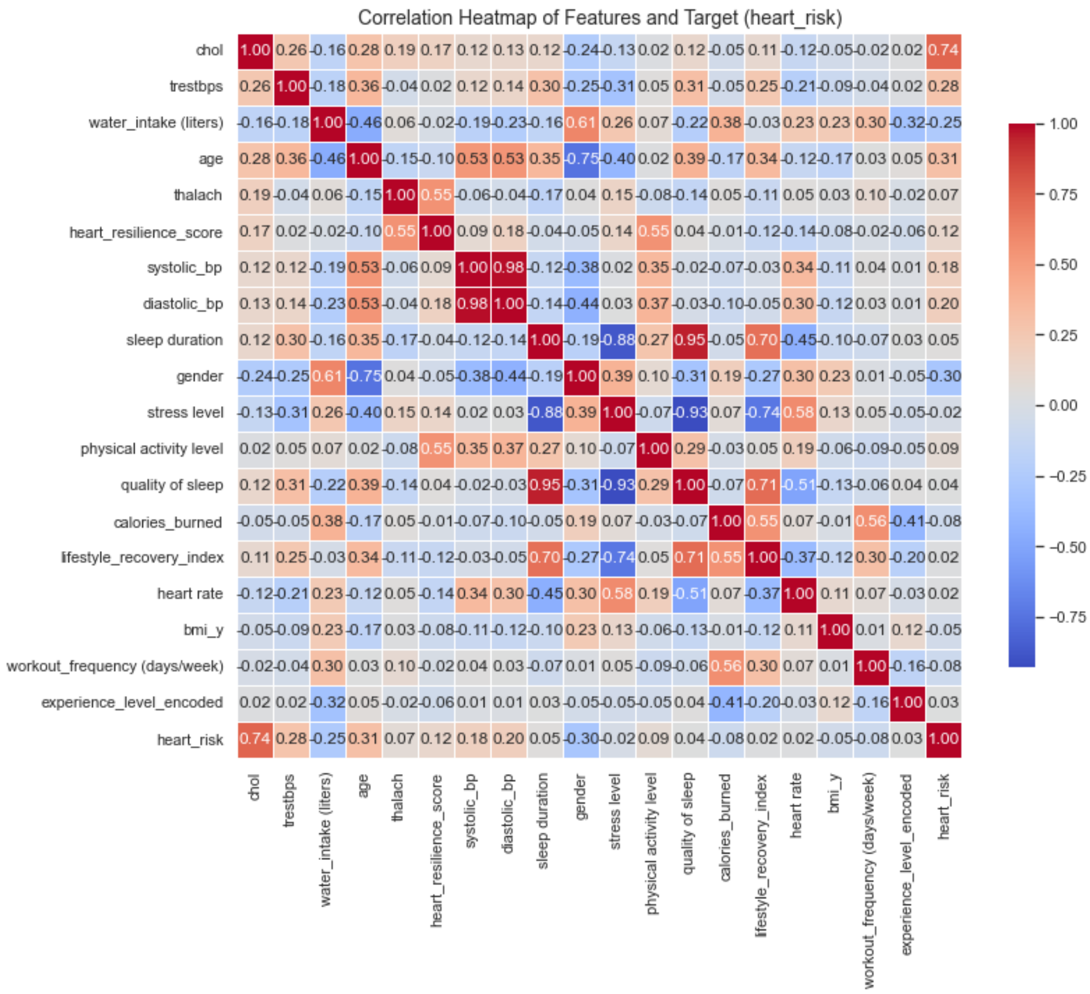
In addition, a correlation heatmap was used during the exploratory phase to detect multicollinearity and validate logical groupings (e.g., between stress, sleep, and physical activity).



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

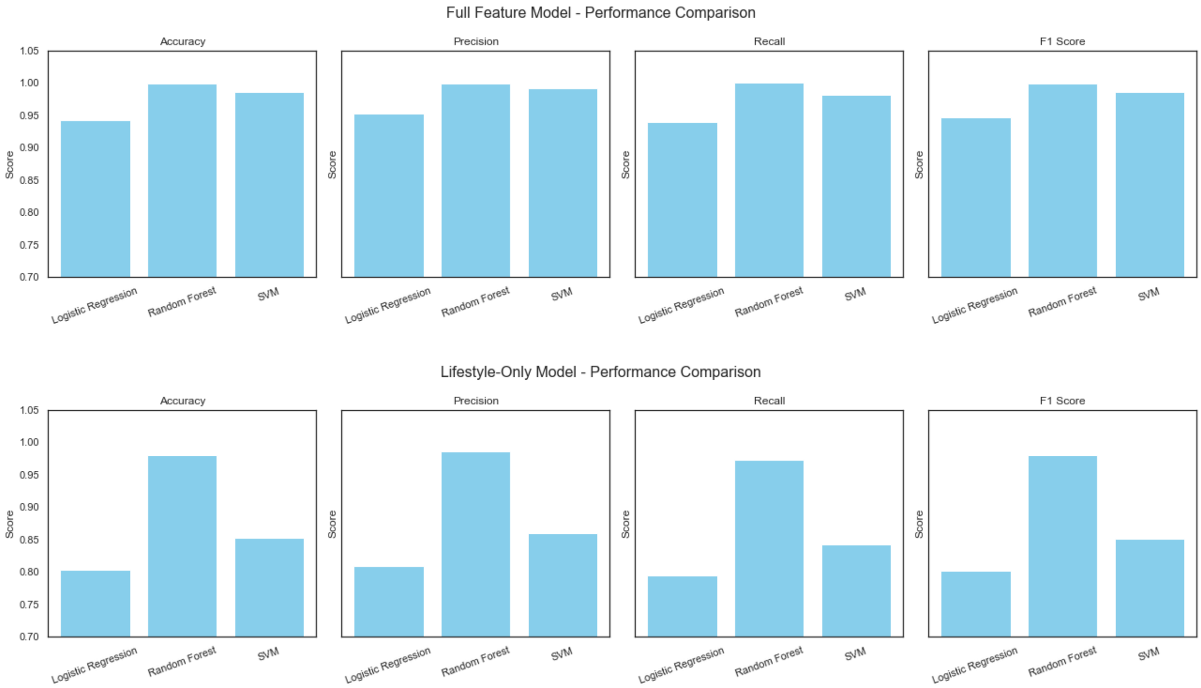
Note: While Random Forest showed perfect accuracy, this was later determined to result from **label leakage**, as features like chol and systolic_bp were also used in the rule-based definition of the target variable. This was addressed in the lifestyle-only version.

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%

7. Tool Summary (Dashboard Overview)

Tool Overview:

An interactive heart disease risk prediction dashboard was developed using Streamlit, combining both clinical and lifestyle inputs to provide personalized risk assessments. The tool is designed to assist users in understanding their potential heart disease risk through data-driven insights and engaging visualizations.

Key Functionalities:

1. **Dynamic User Input Interface:**
    - Users enter 19 parameters, including:
        - Clinical: Cholesterol, Resting BP, Systolic/Diastolic BP, Max Heart Rate, etc.
        - Lifestyle: Sleep Duration, Physical Activity, Calories Burned, Water Intake, etc.

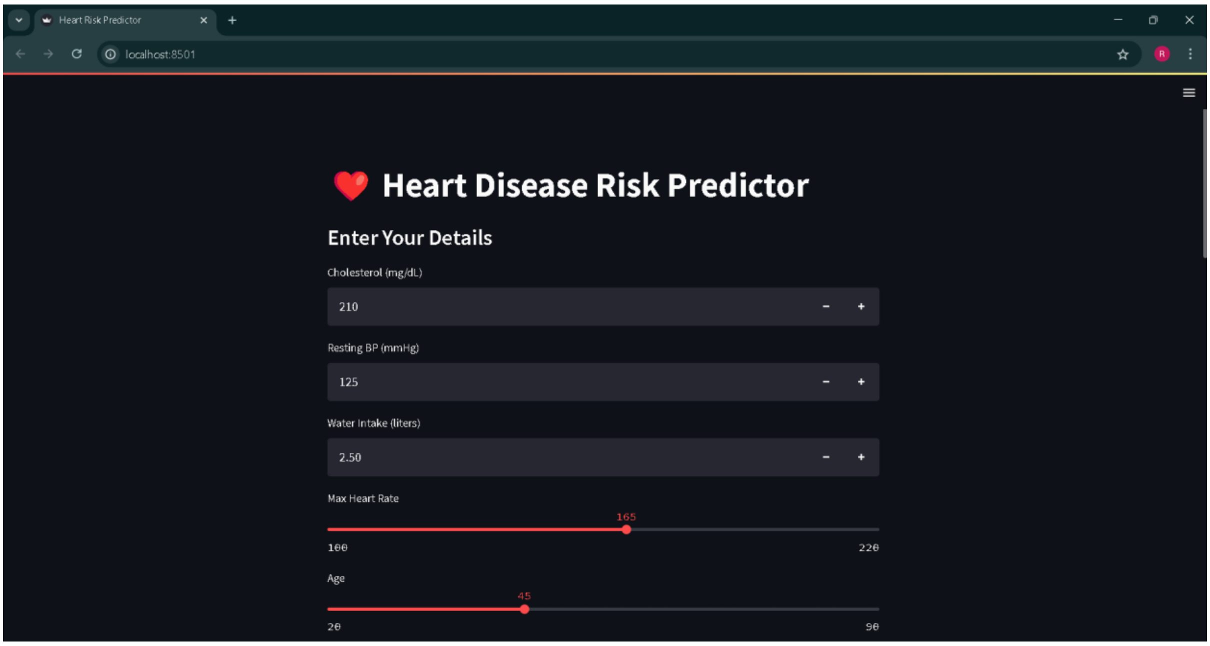
- User-friendly sliders, number inputs, and selection menus ensure easy interaction.

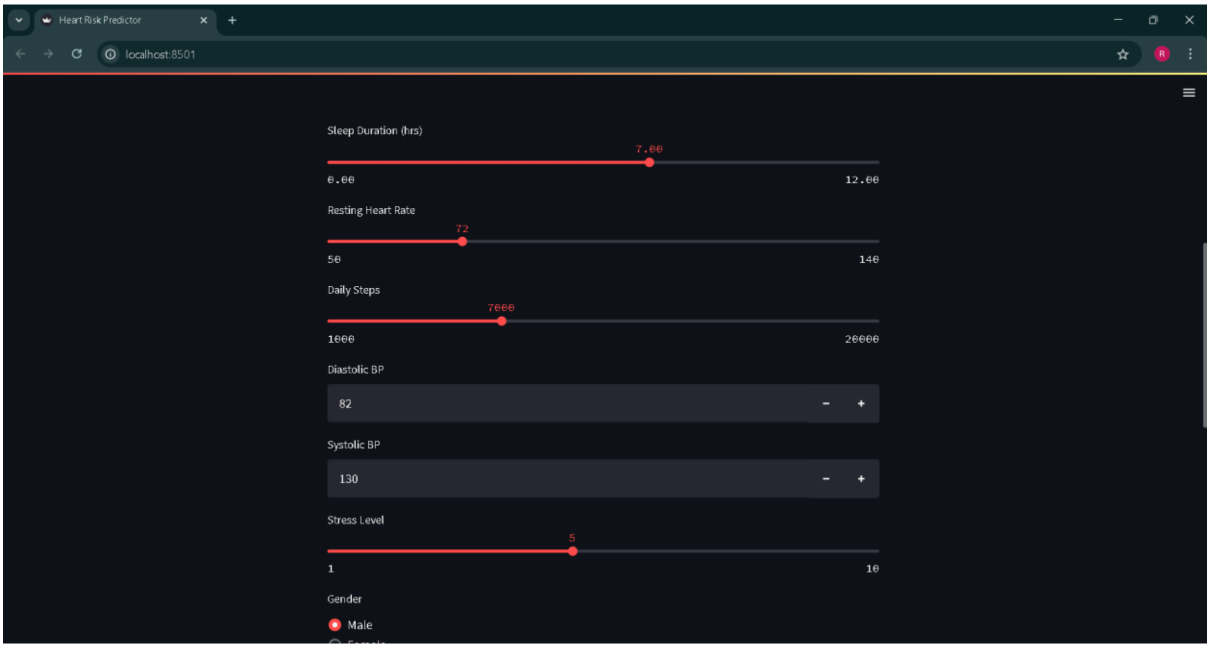
2. **Real-Time Prediction:**
   - Utilizes a Random Forest Classifier trained on a balanced dataset with 19 features.
   - Returns:
     - Binary classification: At Risk / Not at Risk
     - Probability of Risk: Confidence percentage for transparency.

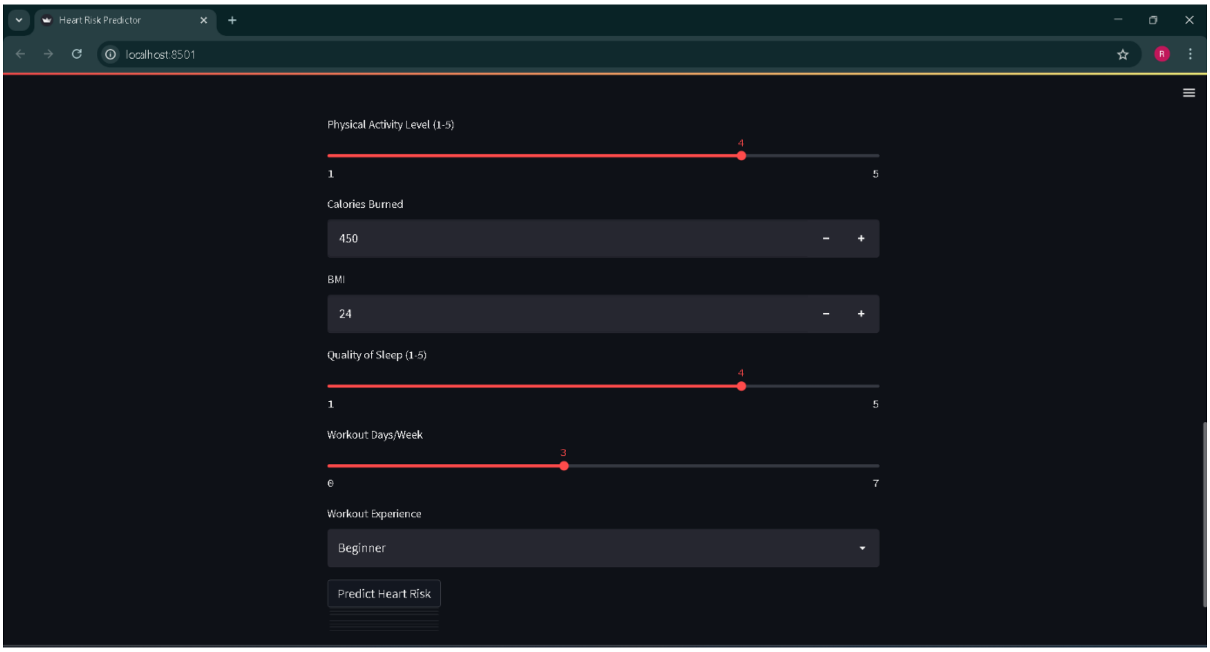
3. **Personalized Health Comparison:**
   - Visual side-by-side bar chart compares user inputs to ideal health benchmarks.
   - Key metrics compared include:
     - Cholesterol, Blood Pressure, Heart Rate
     - Sleep Duration, BMI, Stress Level, etc.
   - Enables users to easily identify areas for potential improvement.

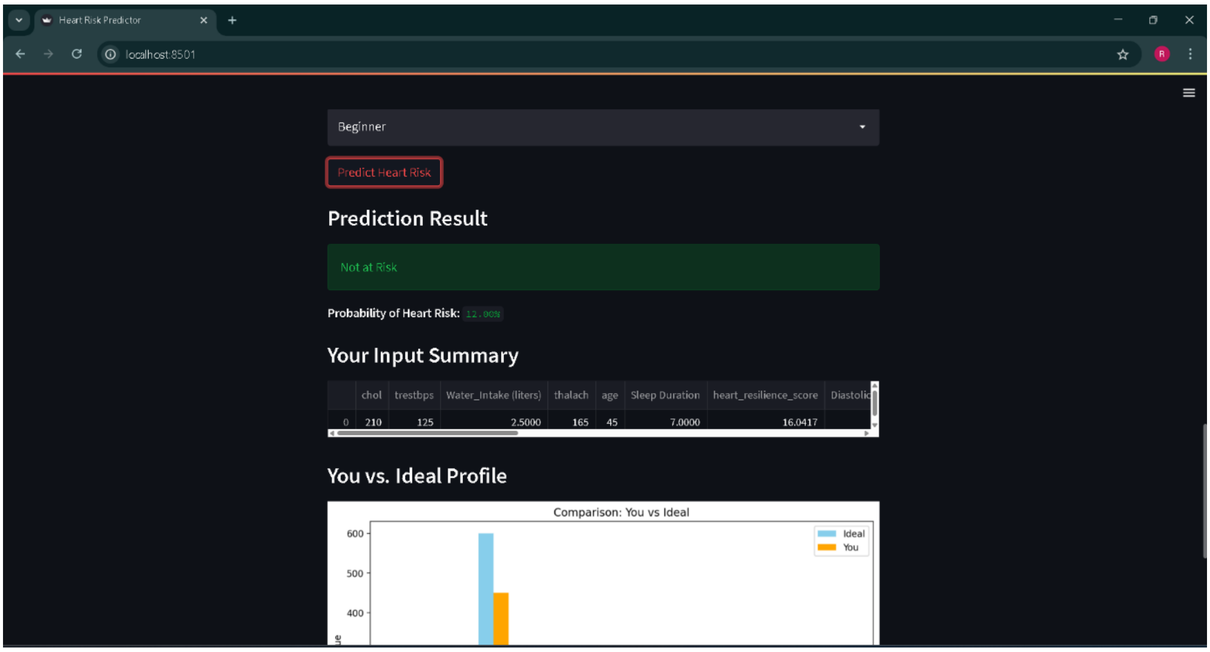
4. **Input Summary Table:**
   - After prediction, a dataframe view of all entered inputs is displayed.
   - Ensures full transparency and allows users to review their data.

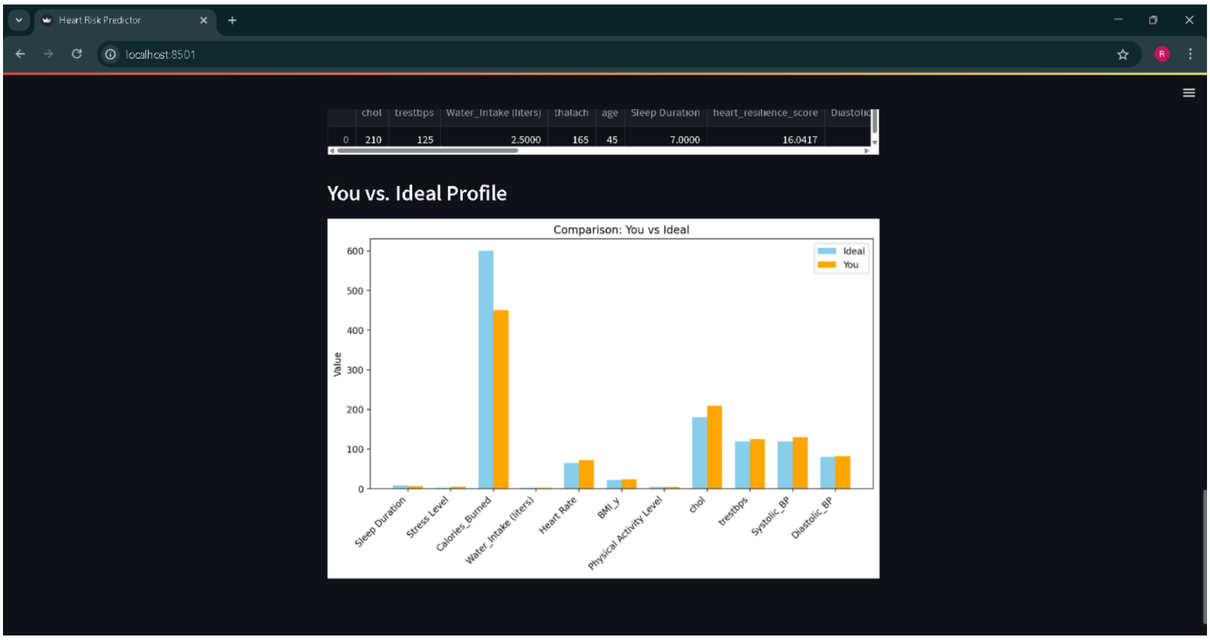
5. **Screenshots of Tool:**
   - Dashboard Home with Inputs and Prediction Result
     - Screenshot showing the dashboard interface with input fields filled and a prediction displayed.
     - Highlights: “Not at Risk” result with 12% risk probability.
   - Comparison Chart: You vs Ideal Profile
     - Bar chart comparing user's key health metrics (e.g., BMI, BP, Cholesterol) to ideal targets.
   - Shows clear visual gaps where improvement might be needed.
   - Input Summary Table
     - A snapshot of the tabular summary of the user's inputs, reinforcing the transparency of the tool.


Heart Risk Predictor
localhost:8501
Heart Disease Risk Predictor
Enter Your Details
Cholesterol (mg/dL)
210
Resting BP (mmHg)
125
Water Intake (liters)
2.50
Max Heart Rate
165
100
220
Age
45
20
90


Heart Risk Predictor
localhost:8501
Sleep Duration (hrs)
7.00
0.00
12.00
Resting Heart Rate
72
50
140
Daily Steps
7000
1000
20000
Diastolic BP
82
Systolic BP
130
Stress Level
5
1
10
Gender
Male


Heart Risk Predictor
localhost:8501
Physical Activity Level (1-5)
4
1
5
Calories Burned
450
BMI
24
Quality of Sleep (1-5)
4
1
5
Workout Days/Week
3
0
7
Workout Experience
Beginner
Predict Heart Risk


Heart Risk Predictor
localhost:8501
Beginner
Predict Heart Risk
Prediction Result
Not at Risk
Probability of Heart Risk: 12.00%
Your Input Summary
chol trestbps Water_Intake (liters) thalach age Sleep Duration heart_resilience_score Diastolic
0 210 125 2.5000 165 45 7.0000 16.0417
You vs. Ideal Profile
Comparison: You vs Ideal
600
500
400
Ideal
You



Limitations

1. Lifestyle-Only Model Accuracy:
    - The lifestyle-only model, although practical for user-driven inputs, achieved lower predictive accuracy (~97.9%) compared to the full-feature model (99.9%).
    - Limitation: Lifestyle data alone lacks the depth to fully capture medical risk, especially in the absence of clinical variables like cholesterol, blood pressure, and heart rate.
2. Potential Overfitting in Full-Feature Model:
    - The full-feature model's very high performance may indicate overfitting, especially due to possible label leakage or data imbalances.
    - Model calibration or cross-validation could improve generalizability.
3. Lack of Genetic & Family History Data:
    - The model does not incorporate hereditary factors or genetic predispositions, which are significant contributors to heart disease risk.

4. Synthetic Feature Sensitivity:
    - Features like heart_resilience_score and lifestyle_recovery_index are based on derived metrics and could vary widely, potentially introducing noise.
5. Dataset Constraints:
    - The dataset was pre-balanced using downsampling, which may not reflect real-world population distributions.

Conclusion:

The project successfully delivered a powerful and interactive Heart Disease Risk Prediction Tool by merging clinical and lifestyle data. Through detailed data analysis, model training, and user-focused dashboard development, the tool empowers individuals to understand and assess their heart risk in real-time.

The Random Forest model trained on all features demonstrated superior predictive performance, validating the need to integrate both clinical and lifestyle metrics for accurate health assessments. While the lifestyle-only model offered accessible insights, its lower accuracy underlined the importance of a holistic data approach.

This tool serves as a foundation for promoting data-driven health awareness. Future improvements will focus on data enrichment, model calibration, and expanding the tool's interpretability and accessibility.

LLM Usage Declaration

ChatGPT was used for assistance with feature engineering ideas, code optimization, and Streamlit visualization suggestions. All outputs were reviewed, adapted, and integrated independently into the project.

1. Feature Engineering Ideas:

- Prompt: "Suggest ideas for creating new features for heart disease prediction by combining health metrics, gym activity data, and heart-related parameters."
- Used For: Generating concepts like:
  - heart_resilience_score: capturing cardiovascular efficiency by combining max heart rate, resting heart rate, and steps taken.
  - lifestyle_recovery_index: balancing gym activity (calories burned), sleep quality, and stress levels to reflect recovery potential.

2. Code Optimization Suggestions:

- Prompt: "How can I optimize model training and scaling for health datasets?"
- Used For: Structuring train-test split and applying StandardScaler efficiently.

3. Model Performance Results Aggregation

- Prompt: "How to collect accuracy, precision, recall, F1 score into a DataFrame for multiple models?"
- Adapted Code:

```
results = []
for name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)
    results.append({
        "Model": name,
        "Accuracy": accuracy_score(y_test, y_pred),
```

```
        "Precision": precision_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "F1 Score": f1_score(y_test, y_pred)
    })

results_df = pd.DataFrame(results)
```

4. Streamlit Page Layout Customization

- **Prompt**: "How to set a custom layout and page title in Streamlit?"
- **Applied**:

Code:

```
st.set_page_config(page_title="Heart Risk Predictor", layout="centered")
```

5. Streamlit Comparison Chart

- **Prompt**: "How can I compare user inputs to ideal values in Streamlit with matplotlib?"
- **Used This Logic**:

Code:

```
fig, ax = plt.subplots(figsize=(10, 5))
ax.bar(x - width/2, compare_df["Ideal"], width, label="Ideal", color="skyblue")
ax.bar(x + width/2, compare_df["You"], width, label="You", color="orange")
st.pyplot(fig)
```