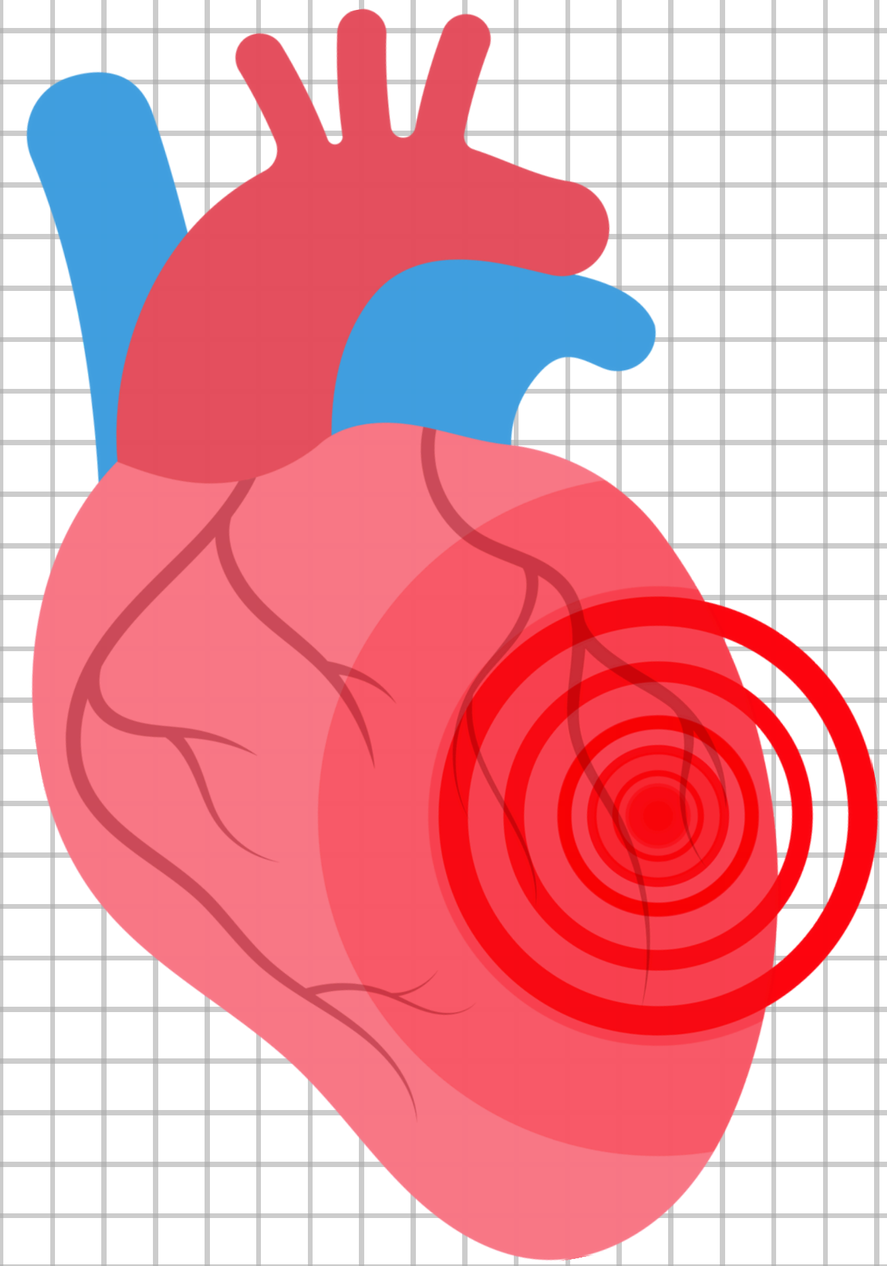


HEART DISEASE PREDICTION

Nguyen Hoang Tung	22BA13318
Pham Cong Duyet	23BI14136

TABLE OF CONTENT

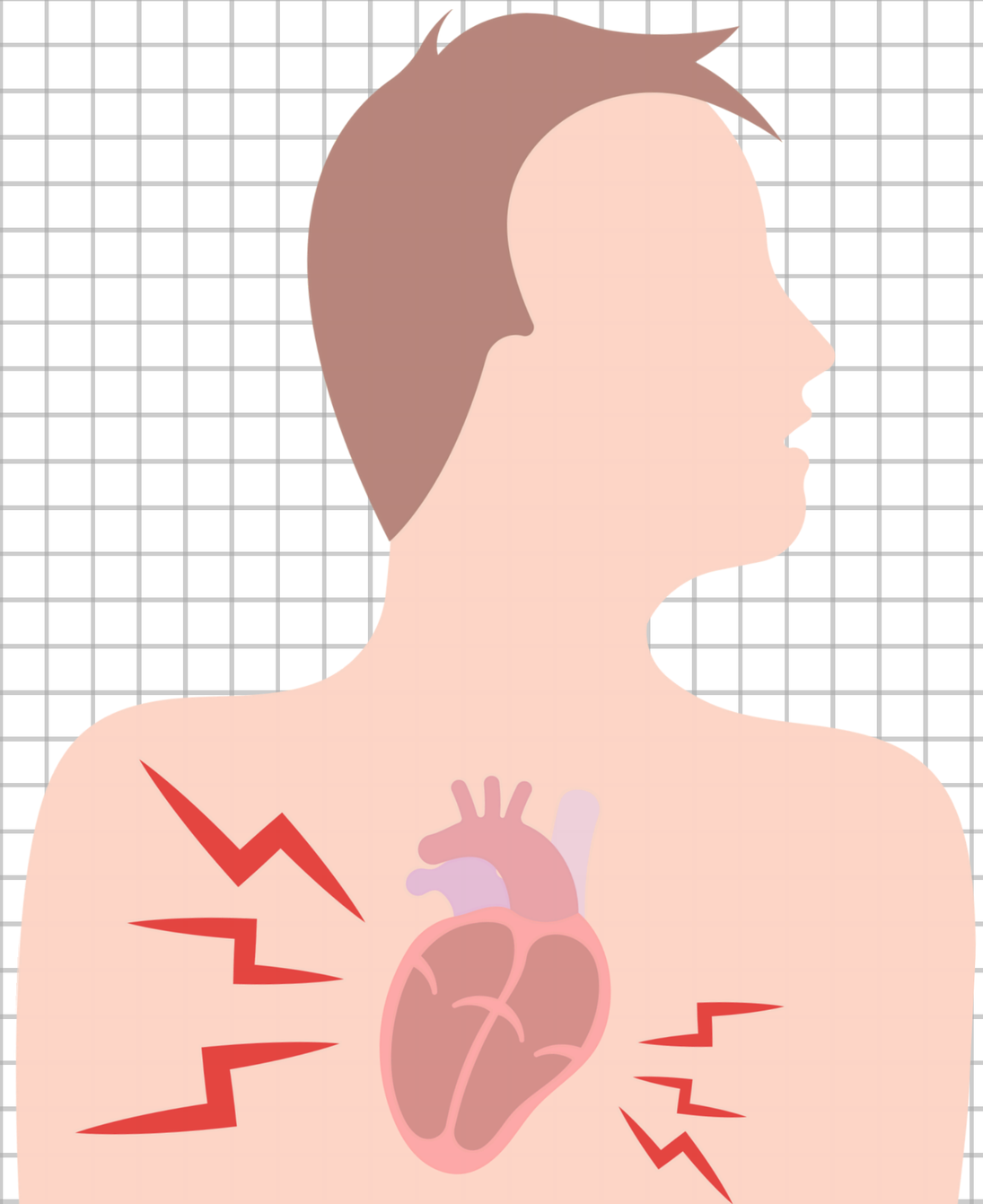
I. INTRODUCTION

Motivation

- Heart disease is one of the leading causes of death worldwide (~17.9 million deaths/year – WHO)
- In Viet Nam, 1 in 4 adults has high blood pressure.
- Heart disease ranks among the top causes of death and hospitalization.
- Many cases are detected late, leading to costly and less effective treatmen

Business Problem

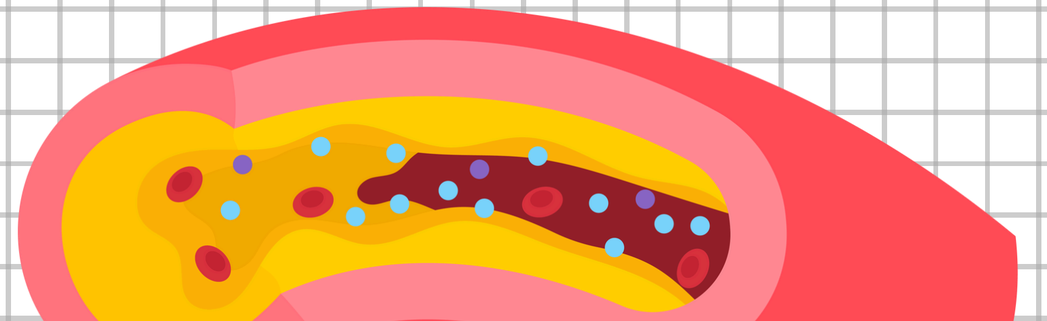
- Early Detection: Identify high-risk patients for timely treatment or lifestyle advice.
- Cost Reduction: Early intervention → fewer emergency cases & long-term treatment costs.
- In Viet Nam, data-driven models help optimize limited medical resources.
- Support evidence-based decision-making for hospitals and healthcare managers.



GOALS

- Collect and preprocess patient data.
- Explore and analyze the dataset to find patterns and risk factors.
- Train and evaluate multiple ML models to predict heart disease.
- Compare performance and select the best model.
- Build a simple Flask web interface for user-friendly predictions.

DATA COLLECTION AND MAGAGEMENT



DATA COLLECTION AND MAGAGEMENT

Data Collection

📊 Dataset Overview

- Source: Kaggle – Heart Failure Prediction Dataset (Fedesoriano, 2021)
- Samples: 918 records
- Features: 12 attributes (demographic + clinical)

🎯 Target Variable

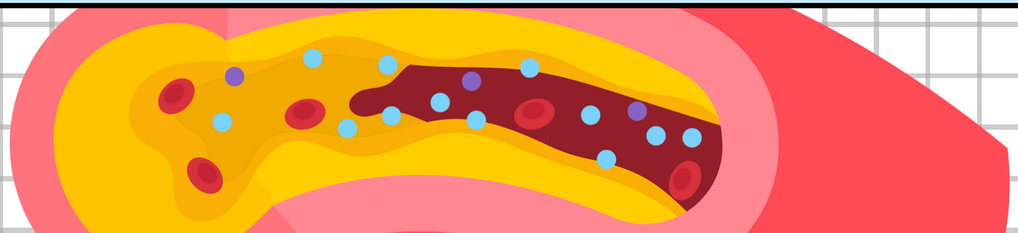
- HeartDisease is the output class used for prediction.
- 1 indicates disease presence; 0 indicates normal condition.

🧠 Key Features

- Age: patient's age (years)
- Sex: gender (M: Male, F: Female)
- ChestPainType: type of chest pain (TA, ATA, NAP, ASY)
- RestingBP: resting blood pressure (mmHg)
- Cholesterol: serum cholesterol level (mg/dl)
- FastingBS: fasting blood sugar (1 if >120 mg/dl, else 0)
- RestingECG: resting ECG result (Normal, ST, LVH)
- MaxHR: maximum heart rate achieved (60–202 bpm)
- ExerciseAngina: exercise-induced angina (Y/N)
- Oldpeak: ST depression induced by exercise (numeric)
- ST_Slope: slope of peak exercise ST segment (Up, Flat, Down)
- HeartDisease: target variable (1 = heart disease, 0 = normal)

DATASET

Age	Sex	CPT	R.BP	Chol	F.BS	R.ECG	MaxHR	EA	Oldpeak	Slope	HS
40	M	ATA	140	289	0	NORMAL	172	N	0	UP	0
49	f	NAP	160	180	0	NORMAL	156	N	1	FLLAT	1
37	M	ATA	130	283	0	ST	98	N	0	UP	0
48	F	ASY	138	214	0	NORMAL	108	Y	1.5	FLAT	1



DATA COLLECTION AND MAGAGEMENT

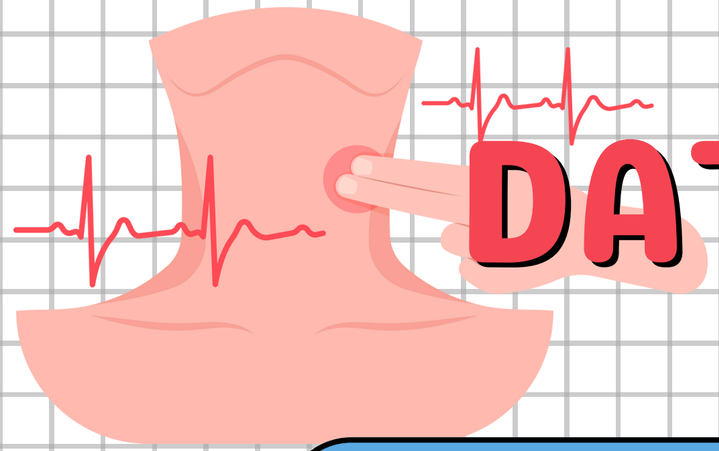
Data management

Data Cleaning

- Identified invalid or unrealistic values in the dataset.
- RestingBP: one record = 0 → replaced with median (since BP can’t be 0).
- Cholesterol: 172 records = 0 → replaced using KNN Imputer to estimate realistic values from similar patients.
- Other features (Age, Sex, ChestPainType, RestingECG, etc.) were clean and consistent.
- This step ensured data reliability and reduced bias during model training.

Data Processing

- Handled categorical variables that machine learning models can’t process directly.
  - Binary Encoding:
    - Sex: M→1, F→0
    - ExerciseAngina: Y→1, N→0
  - One-Hot Encoding:
    - ChestPainType, RestingECG, ST_Slope → converted to multiple dummy columns.
- Result: dataset transformed into fully numerical and standardized format for modeling. It consists of 19 columns including the target column.



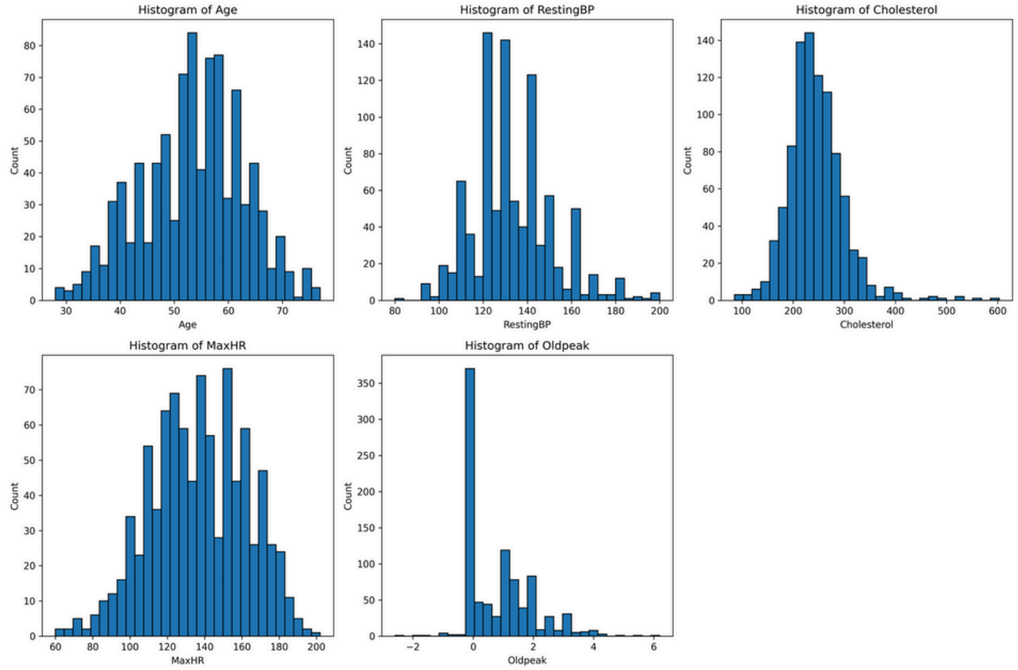
DATA VISUALIZATION

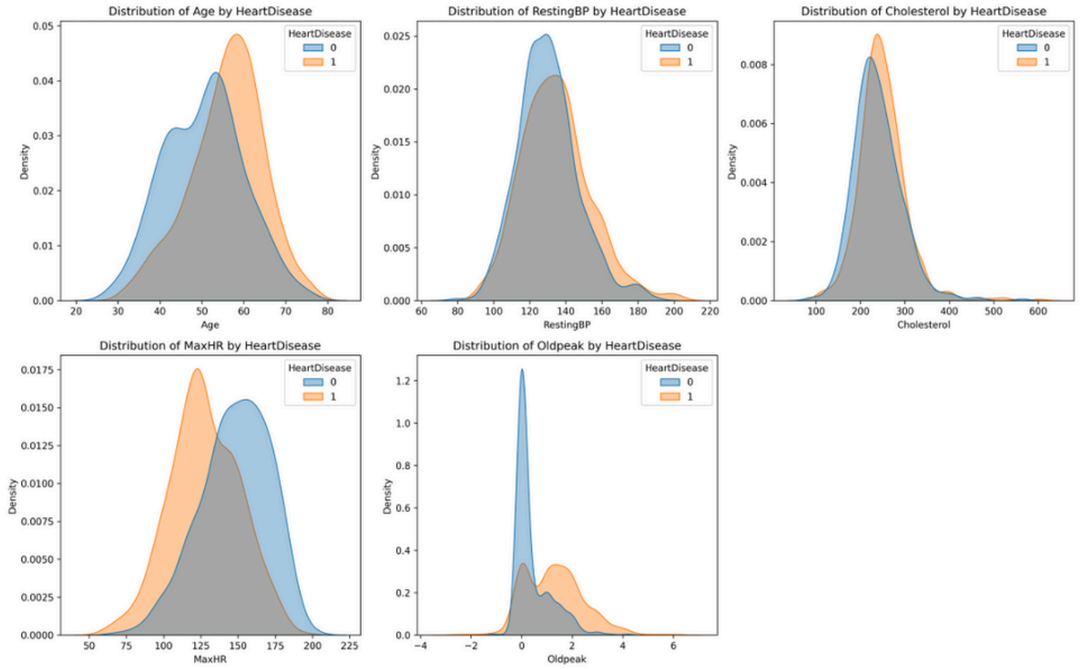
Visualization Goals

- Explore the data distribution of key variables
- Compare categorical features
- Identify patterns and potential predictors of heart disease

Visualization Methods

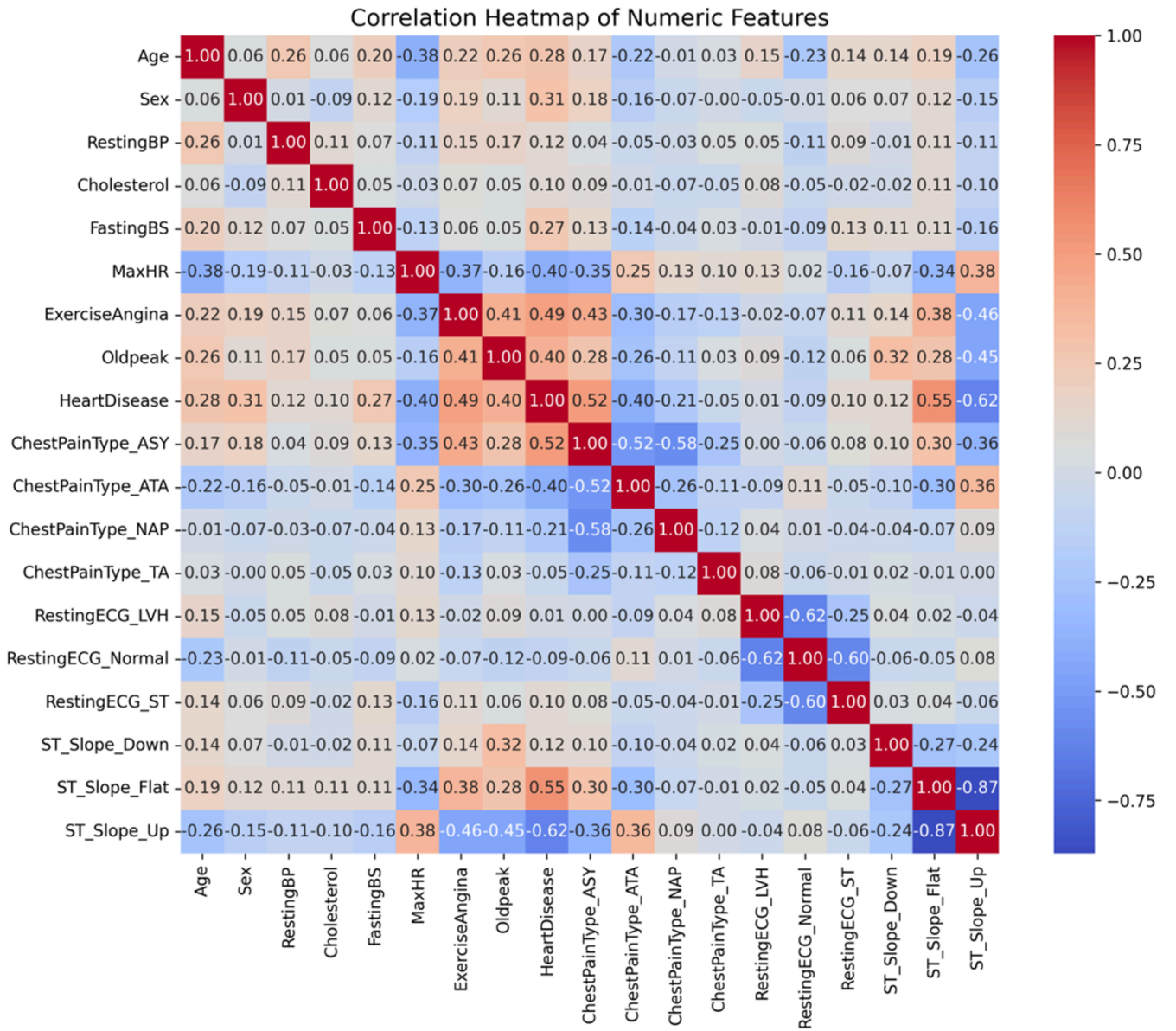
- Histograms
- KDE plots
- Countplots
- Boxplots
- Correlation heatmap



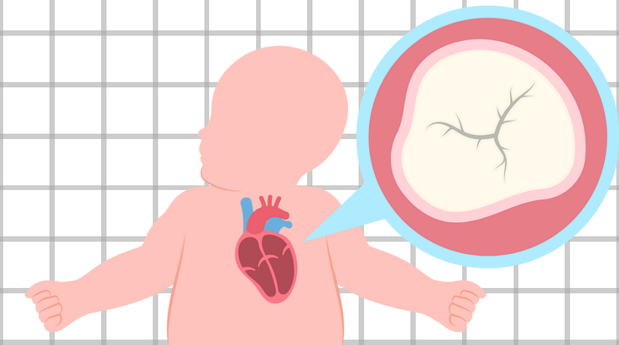


- **Age**
  - Distribution: Concentrated between 45–65 years, with diseased patients peaking around 55–65.
  - Insight: Middle-aged and older adults have higher exposure to risk factors → higher heart disease prevalence.
- **RestingBP**
  - Distribution: Most values around 120–140 mmHg, similar across both groups.
  - Insight: Hypertension is common but not highly discriminative in this dataset.
- **Cholesterol**
  - Distribution: Right-skewed; most below 300 mg/dl, few extreme cases >400.
  - Insight: Overlaps between groups; may be affected by medication or lifestyle, thus limited predictive power.
- **MaxHR**
  - Distribution: Approximately normal, centered 120–160 bpm; diseased patients cluster below 140 bpm.
  - Insight: Lower MaxHR reflects reduced exercise tolerance — a strong clinical marker of coronary disease.
- **Oldpeak**
  - Distribution: Most healthy patients ≈ 0; diseased patients show higher values (up to >4).
  - Insight: ST depression (Oldpeak) strongly indicates myocardial ischemia — one of the most powerful predictors.

- Oldpeak shows the strongest positive correlation with heart disease →
- Higher ST depression reflects ischemia, making it one of the most powerful predictors.
- ST_Slope variables reveal clear patterns:
- Flat slope (r = +0.55) → strongly associated with diseased patients.
- Upsloping (r = −0.60) → dominant in healthy cases → protective indicator.
- ExerciseAngina (r = +0.49) also stands out →
- Exercise-induced chest pain is a key clinical signal of coronary artery blockage.
- MaxHR (r = −0.40) →
- Lower maximum heart rate during exertion indicates reduced cardiac reserve and higher disease likelihood.
- Age (r = +0.28) →
- Heart disease prevalence increases steadily with age, reflecting accumulated vascular risks.
- RestingBP, Cholesterol, FastingBS →
- Traditional medical risk factors but show weak correlation here — likely due to treatment effects or limited sample variation.

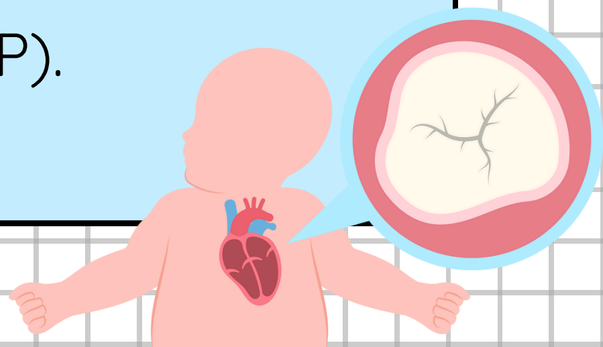


MODEL DEVELOPMENT



Data Preparation

- Dataset divided 80/20, stratified by HeartDisease to maintain class balance and ensure reproducibility.
- Scale continuous features with **StandardScaler**.
- Automates preprocessing before model fitting.
- Prevents leakage and supports model flexibility (Logistic Regression, SVM, RF, XGBoost).
- Cross-Validation:
- Stratified K-Fold (k=5) ensures balanced label distribution → robust evaluation.
- Transformed features re-combined into DataFrame →
- enables post-hoc analysis (e.g., Permutation Importance, SHAP).



SUMMARY OF RESULT

Model	CV ROC-AUC	TEST ROC-AUC	Accuracy
LR	0.9221	0.9320	0.88
SVC	0.9201	0.9366	0.86
RF	0.9290	0.9229	0.86
XGB	0.9328	0.9318	0.89

SUMMARY OF RESULT

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Logistic Regression (LR)
→ Achieved the high accuracy (0.88) and a strong ROC-AUC (0.9320).
→ Results are highly consistent between CV and test sets, indicating stable generalization.

Support Vector Machine (SVC)
→ Reached the highest Test ROC-AUC (0.9366), showing superior discriminative ability.
→ However, accuracy (0.86) is slightly lower, and performance variation between CV and test sets suggests less stability.

Random Forest (RF)
→ Produced a solid CV ROC-AUC (0.9290) and comparable Test ROC-AUC (0.9229), showing acceptable generalization.
→ Minor performance gap indicates slight overfitting tendency, but still performs reliably across datasets.

XGBoost (XGB)
→ Demonstrated the most balanced and consistent performance overall.
→ Achieved the highest CV ROC-AUC (0.9328) and a strong Test ROC-AUC (0.9318) with accuracy = 0.89.
→ Results are stable across folds and test sets, proving excellent robustness and generalization.

🎯 **Conclusion**

- Logistic Regression → Best for simplicity, interpretability, and solid accuracy.
- SVC → Strongest discriminative ability, ideal when precision is prioritized.
- Random Forest → Reliable ensemble with mild overfitting risk.
- XGBoost → Best trade-off between accuracy, stability, and robustness → recommended final model.

🔹 **Top Predictive Features**

ST_Slope (Up, Flat) and ChestPainType_ASY show the strongest impact on model performance.

→ When shuffled, they cause the largest ROC-AUC drop, confirming that ECG patterns and chest pain symptoms are the most decisive factors.

→ These features represent the functional response of the heart under stress, aligning with medical evidence of ischemia and abnormal cardiac activity.

ExerciseAngina, Oldpeak, and MaxHR appear in the mid-to-high importance range.

→ These are exercise-related ECG indicators, capturing how the heart performs during exertion.

→ Their consistent ranking across SHAP and permutation analyses reinforces their clinical relevance in detecting reduced cardiac function.

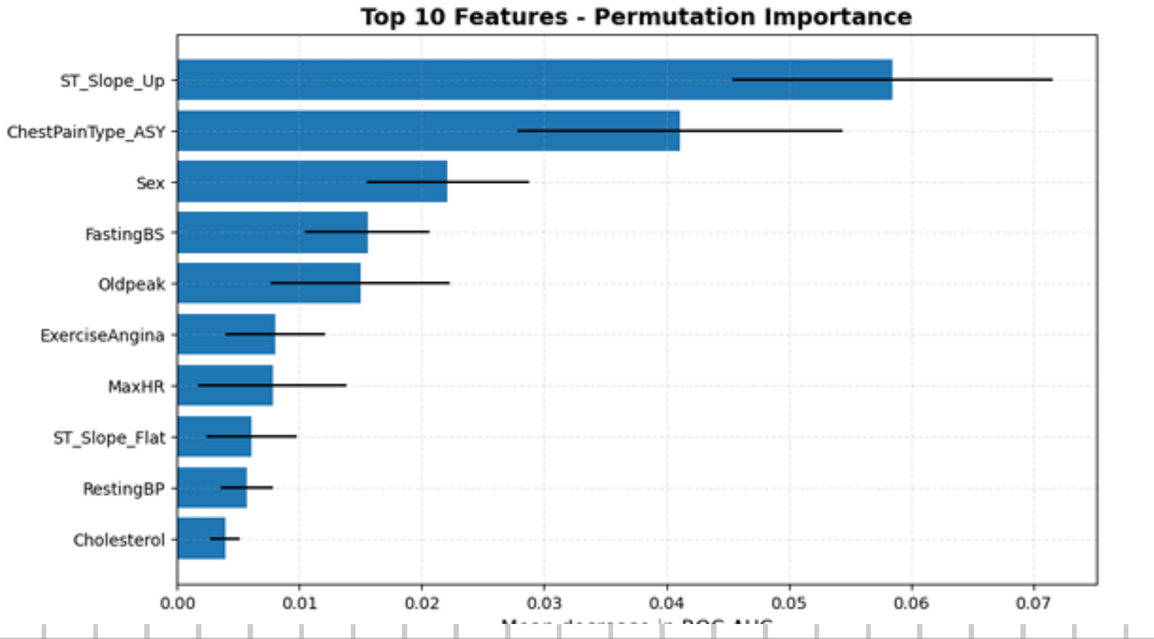
🔹 **Moderate Predictors**

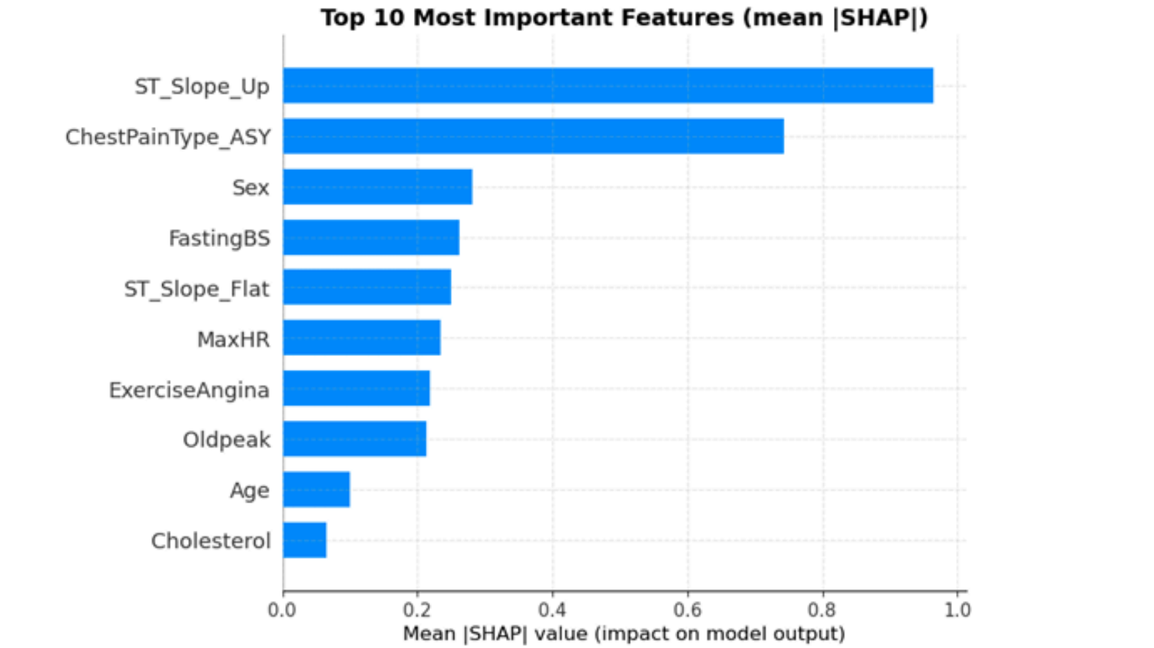
Sex and FastingBS show moderate contributions, suggesting that biological and metabolic differences still play a role but are secondary to ECG-based measures.

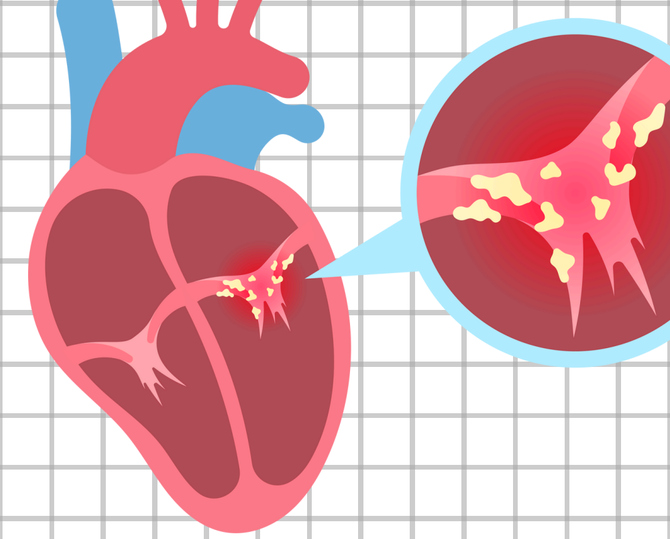
🔹 **Low-Contributing Features**

Age, Cholesterol, and RestingBP contribute minimally to prediction accuracy.

→ This may be due to dataset composition (controlled or medicated patients) or the model's tendency to rely on dynamic physiological signals rather than static clinical measurements.







USER INTERFACE

app.py

- The trained XGBoost pipeline was exported as xgb_pipeline.pkl using Joblib (faster and more efficient than Pickle).
- A Flask-based web app was developed for heart disease prediction.
- Users input clinical data (age, sex, blood pressure, cholesterol, ECG results, etc.).
- Results are displayed on the web page (index.html).
- If invalid data is entered, the app shows an error message instead of breaking.

index.html

- Developed using HTML and Bootstrap 5 for simplicity, responsiveness, and modern UI styling.
- Blue gradient background, white rounded form with shadow, and blue buttons for a clean, medical-themed aesthetic.
- Contains 11 main fields — Age, Sex, RestingBP, Cholesterol, MaxHR, Oldpeak, FastingBS, ExerciseAngina, ChestPainType, ST_Slope, RestingECG.
- Includes tooltips to explain each field's meaning and assist user input.
- User Experience Enhancements:
- Displays a loading spinner while processing predictions.
- Results (probability + Positive/Negative label) appear in a dedicated result box below the form.

CONCLUSION

🧩 1. Project Overview

- Objective: Develop a machine learning–based system for predicting the probability of heart disease.
- Core contribution: Integrating a robust classification model (XGBoost) with a user-friendly web interface, demonstrating the potential of ML in healthcare.
- Results:
- → High model performance on structured data.
- → Real-time prediction via Flask web app enhances accessibility.

⚙️ 2. System Implementation

- Backend: Flask application connected to the XGBoost model saved via Joblib for fast loading.
- Frontend: Built with HTML and Bootstrap, featuring tooltips, validation, and a loading spinner.
- Process: User inputs → validation → transformation → prediction (Positive/Negative + probability).
- Demonstrates how ML can support real-time, interpretable healthcare decision-making.

💡 3. Key Insights

- The model performs stably and generalizes well to unseen data.
- The interface design ensures ease of use, even for non-technical users.
- The project proves the practical value of predictive analytics in modern healthcare.

🚀 4. Future Work

1. Data Expansion: Add more samples and clinical variables to improve model robustness.
2. Explainability (SHAP): Integrate model explainability to help clinicians understand prediction logic.
3. Cloud Deployment: Move the system to a cloud environment for scalability and accessibility.
4. Integration with EHR: Combine with Electronic Health Record (EHR) systems for personalized medical support.

🎯 5. Final Remark

This project successfully built a reliable and interpretable heart disease prediction system while laying the foundation for further integration of machine learning, web development, and healthcare analytics — bridging the gap between data science and clinical decision support.


Q&A