CARDIO TRACK - MACHINE LEARNING CANVAS

PREDICTION TASK

Cardio Track ML system performs a binary classification task based on clinical data from individual patients, with the goal of predicting the presence or absence of heart disease. Specifically, the model analyzes each patient's clinical features and risk factors to estimate the likelihood of developing heart failure.
There are two possible prediction outcomes: Positive, when the patient shows indicators of heart failure, and Negative, when no signs of disease are detected.

DECISIONS

The system's predictions support cardiologists and public health institutions (ASL).
For positive cases, cardiologists can order further tests, start monitoring, and define personalized treatments.
Aggregated results help public health institutions plan resources, prioritize facilities, and promote prevention and lifestyle improvements for long-term cardiovascular health.

VALUE PROPOSITION

The main end users are cardiologists and local health authorities (ASL).

For cardiologists, the system provides a reliable tool to assist in the early diagnosis of heart failure.
For health authorities, it enables more efficient management of healthcare resources by optimizing the distribution of diagnostic and therapeutic services.

Overall, Cardio Track ML system aims to support prevention and early detection of heart failure, improving patient outcomes and reducing mortality rates.

DATA COLLECTION

Data collection will be a continuous and evolving process. Real and high quality clinical data will be carefully labeled and verified by domain experts, ensuring data quality and consistency.

New patient data collected through standardized clinical protocols will periodically update and improve the model, allowing it to adapt and learn over time.

DATA SOURCES

The ML system will rely on a publicly available dataset that includes clinical parameters from both healthy individuals and patients diagnosed with heart failure.
The reference dataset is the Heart Failure Prediction Dataset, available on Kaggle:
https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction.

IMPACT SIMULATION

Before release, the model will undergo rigorous validation on an independent test set to verify its accuracy, reliability, and stability. Deployment will proceed only after the model demonstrates strong performance and full compliance with fairness and transparency requirements. Given the healthcare setting, we require high precision for the target class (minimizing false positives), with the decision threshold selected to meet a predefined precision target.

MAKING PREDICTIONS

Predictions will be made on-demand, triggered whenever new or updated clinical data becomes available in the hospital database.
Real-time processing is not required, but timely inference will support the decision-making workflow.
All computations will be executed on-premises, using the existing hospital IT infrastructure to ensure data privacy and security.

BUILDING MODELS

Cardio Track ML system will use a single main model in production. Model updates will occur periodically as new data is integrated, or when a new version demonstrates statistically significant improvements in the key metrics: accuracy, precision, recall, and F1-score.

FEATURES

The Heart Failure Prediction Dataset already provides a complete set of clinical features, so there is no need to extract them directly from medical exams or diagnostic reports.
The dataset includes the following features: Age, Sex, ChestPainType, RestingBP, Cholesterol, FastingBS, RestingECG, MaxHR, ExerciseAngina, Oldpeak, and ST_Slope. These features capture key cardiovascular risk factors such as hypertension, diabetes, hyperlipidemia, obesity, and other pre-existing heart conditions, making the dataset suitable for the early heart failure diagnosis.

MONITORING

After deployment, system performance will be continuously monitored to detect potential drifts or degradations over time. Key metrics include accuracy, sensitivity, specificity, and F1-score, reviewed at regular intervals.
Clinician feedback could also be collected to assess usability, clinical relevance, and practical impact, ensuring continuous model improvement and alignment with realworld medical needs.