Heart Disease Prediction: MLOps Pipeline Report

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GitHub Repository: suvamrx/MLOPS_Assignment1
Registry: `ghcr.io/suvamrx/heart-api`

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1. Setup & Installation

The system is designed for reproducibility using a containerized approach.

- **Dependencies:** Install required packages using:

  ```
  pip install -r requirements.txt
  ```

- **Training:** Run the training script to clean the raw data, save the processed CSV, and generate the model.joblib artifact:

  ```
  python scripts/train.py
  ```

- **Kubernetes Deployment:** Deploy the API to your local Kubernetes cluster using the provided manifests:

  ```
  kubectl apply -f kubernetes/deployment.yaml
  kubectl apply -f kubernetes/service.yaml
  ```

What these commands actually do:

1. **`python scripts/train.py`**: This executes the script we modified earlier. It looks for the raw CSV, cleans it, saves the new `processed_heart_disease.csv`, and trains the model.
2. **`kubectl apply -f ...`**: This tells Kubernetes to read your configuration files. The `deployment.yaml` creates the pods (the "brain"), and the `service.yaml` creates the network path so you can actually visit the API in your browser.

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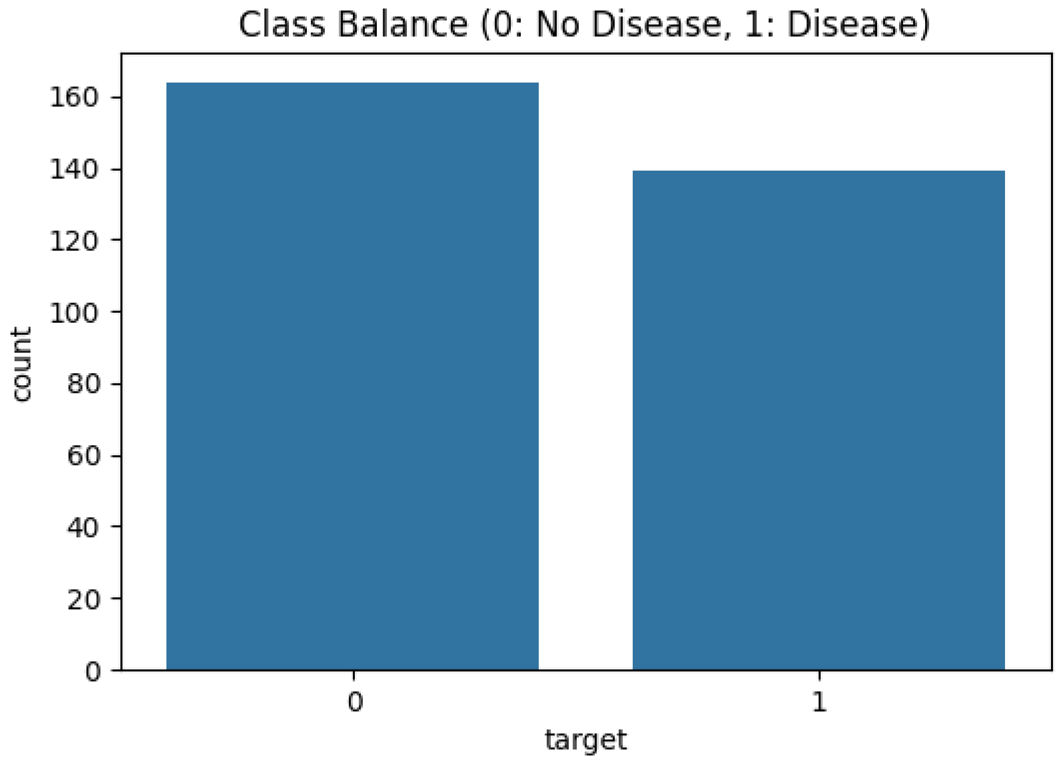
2. EDA and Modelling Choices

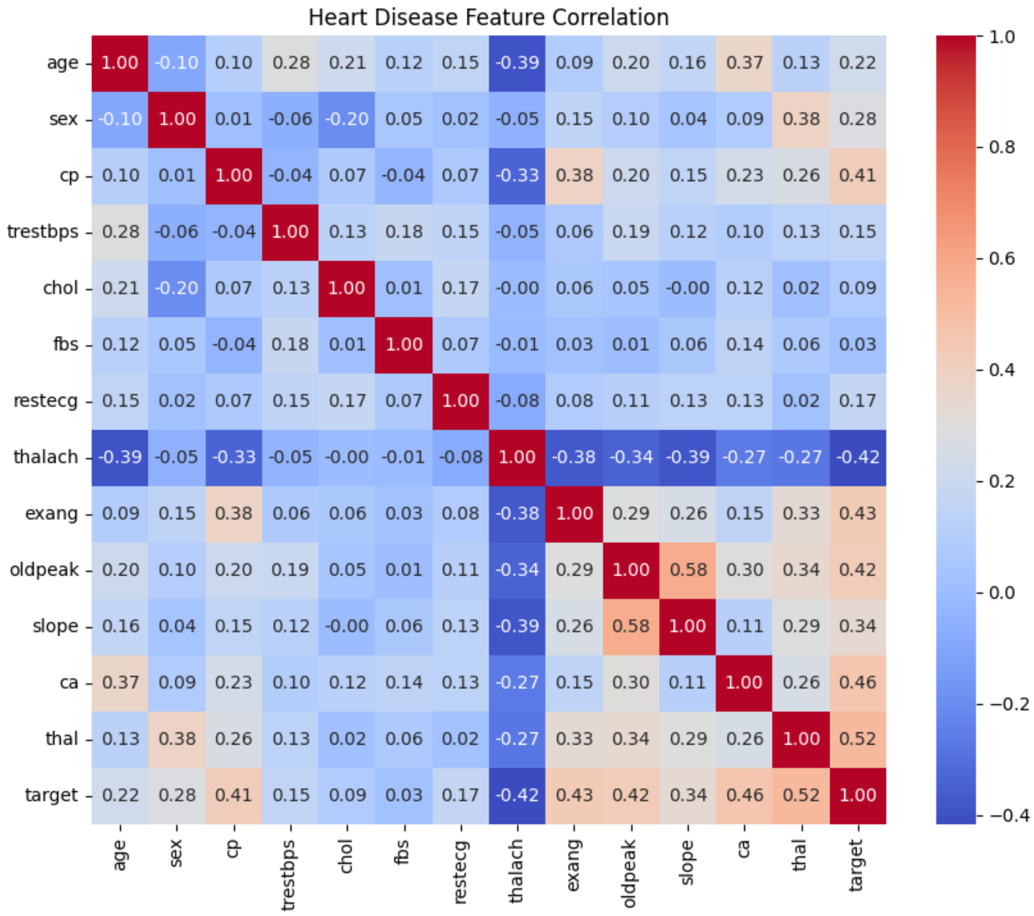
Exploratory Data Analysis (EDA)

Before training, I conducted an analysis of the UCI Heart Disease dataset to understand feature distributions and target relationships.

- **Class Balance:** As shown in the bar chart below, the dataset is relatively balanced between 'No Disease' (0) and 'Disease' (1). This balance ensures that the model evaluation metrics like Accuracy and Precision are reliable.



- **Feature Correlation:** The heatmap reveals significant correlations. Features such as `cp` (chest pain type), `thal`, and `ca` show strong positive correlations with heart disease, while `thalach` (maximum heart rate achieved) shows a strong negative correlation.



Modelling Choices

To meet the project requirements, a robust machine learning pipeline was constructed:

- **Data Cleaning:** Missing values (marked as '?') were handled using median imputation to maintain data integrity without losing samples.
- **Preprocessing Pipeline:** I implemented a `ColumnTransformer` to ensure training-serving consistency:
  - **Numerical Features:** Normalized using `StandardScaler` to ensure the model isn't biased by feature scales (e.g., Age vs. Cholesterol).
  - **Categorical Features:** Transformed using `OneHotEncoder` to convert text/categories into machine-readable format.
- **Algorithms Compared:** 1. **Logistic Regression:** Used as a baseline for high interpretability. 2. **Random Forest Classifier:** Selected for production as it effectively captures the non-linear interactions between health features found during EDA.

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3. Experiment Tracking Summary

To manage the model lifecycle and ensure reproducibility, **MLflow** was used to track all training experiments.

Experiment Details

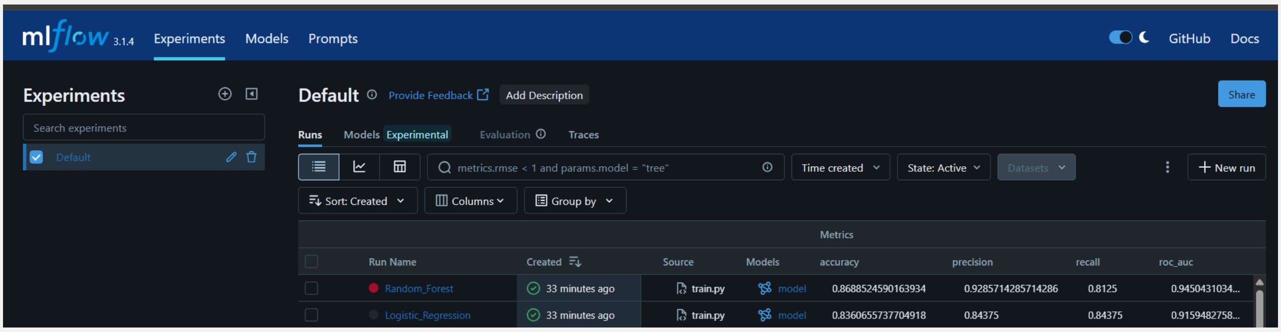
- **Tool Used:** MLflow Tracking UI.

- **Parameters Logged:** Model hyperparameters (e.g., `n_estimators` for Random Forest, `max_iter` for Logistic Regression).
- **Metrics Tracked:** Accuracy, Precision, Recall, and ROC-AUC.
- **Artifacts:** For every run, the system logged the `model.joblib` and the cleaned `processed_heart_disease.csv` dataset.

Performance Results

The comparison between the baseline and the optimized model is summarized below:

Model	Accuracy	Precision	Recall	ROC-AUC
Logistic Regression	0.836	0.843	0.843	0.915
Random Forest	**0.868**	**0.928**	**0.812**	**0.945**

> **Analysis:** The Random Forest model was selected for the production deployment due to its superior accuracy (86.8%) and excellent ROC-AUC (0.945), indicating strong discriminative power (ability to distinguish between diseased and healthy patients). This model was successfully registered and dumped to `model.joblib` for deployment.
> 
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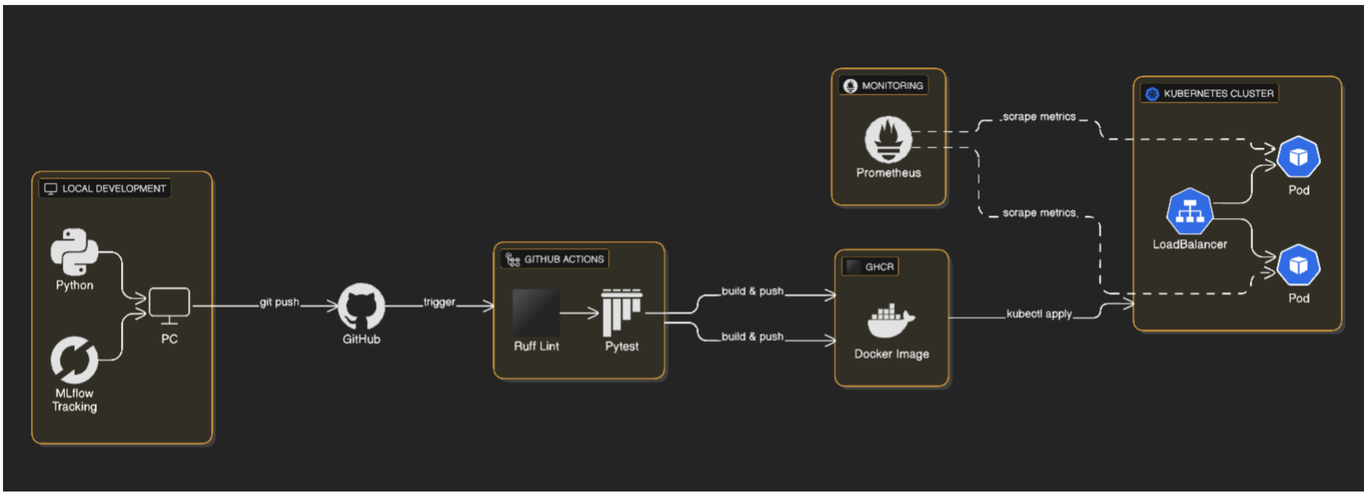
4. Architecture Diagram

The system architecture follows a production-grade **"Push-to-Deploy"** MLOps pattern. This design ensures that every update to the model or API is automatically validated, containerized, and orchestrated.



Architecture Overview

The pipeline is designed to eliminate "manual hand-offs." By integrating **MLflow** at the research stage and **GitHub Actions** at the deployment stage, we ensure that only models that pass quality gates (Ruff/Pytest) reach the **Kubernetes** production environment. This creates a closed-loop system where data science and software engineering are synchronized.

Component Breakdown:

1. **Development (Local Machine):** The project starts with local Python development. Training experiments, including hyperparameters and metrics, are tracked locally using **MLflow** to ensure reproducibility.
2. **Source Control (GitHub):** The repository serves as the "Single Source of Truth." Any code push to the `main` branch triggers the automated CI/CD pipeline.
3. **CI/CD Pipeline (GitHub Actions):** * **Static Analysis:** Runs **Ruff** to catch syntax errors and maintain code quality.
    - **Unit Testing:** Runs **Pytest** to ensure API endpoints and data logic are functional before deployment.
4. **Container Registry (GHCR):** Once tests pass, the application is packaged into a Docker image and pushed to the **GitHub Container Registry (GHCR)**.
5. **Orchestration (Kubernetes):** * The **Docker Desktop Kubernetes** cluster pulls the latest image from GHCR.
    - A **Deployment** manifest manages **2 Pod replicas** for high availability and self-healing.
    - A **Service (LoadBalancer)** provides a stable entry point for user prediction requests.
6. **Observability:** The API integrates `prometheus-fastapi-instrumentator` to expose real-time technical metrics via the `/metrics` endpoint, allowing for continuous monitoring of system health.

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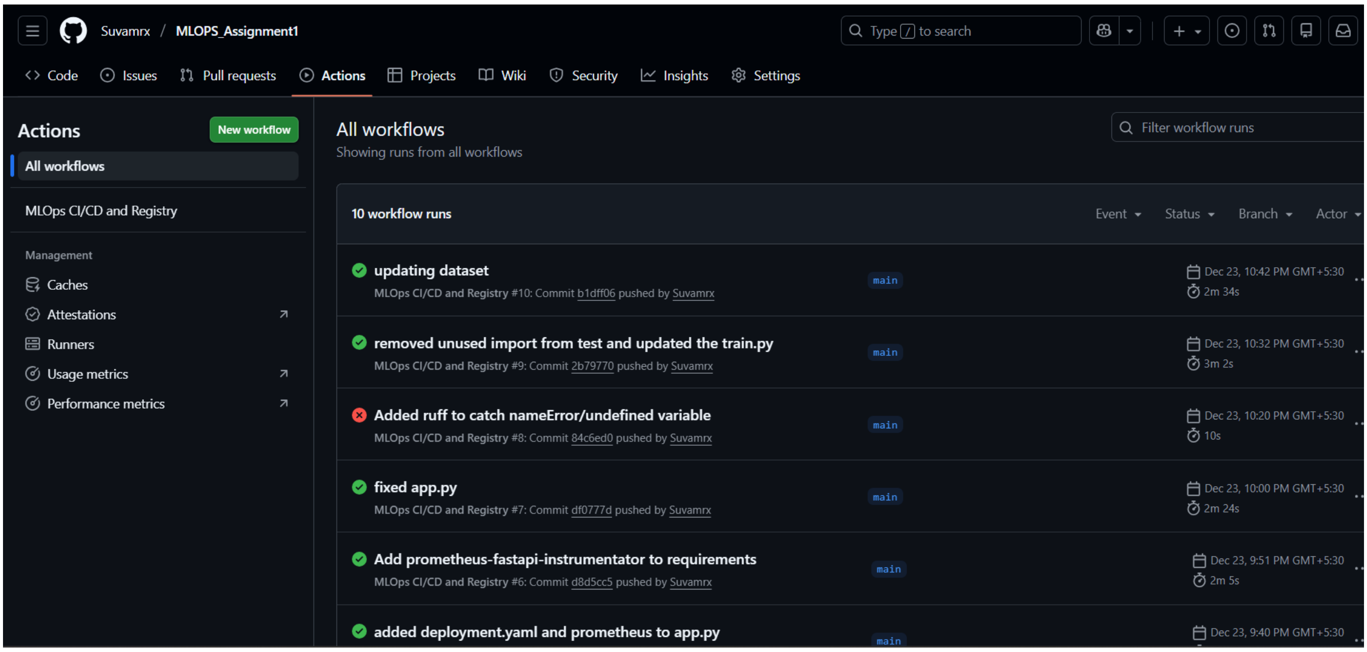
5. CI/CD and Deployment Workflow Proof

This section provides visual evidence that the pipeline is fully operational, meeting the requirements for automated testing, high availability, and observability.

Requirement: Fail-Fast CI/CD (GitHub Actions)

The GitHub Actions pipeline is configured as a "quality gate." If the code fails linting (Ruff) or testing (Pytest), the build is terminated immediately, preventing broken code from reaching the registry.



Requirement: High Availability (Kubernetes)

To ensure the Heart Disease Prediction API remains available even if a container crashes, the Kubernetes deployment is configured with two active replicas.

- **Pods:** Two running instances of the API.
- **Service:** A LoadBalancer providing a stable entry point.

```
(mlops_env) C:\Users\LENOVO\MLOPS_Assignment1>kubectl apply -f deployment.yaml
deployment.apps/heart-disease-deployment created
service/heart-api-service created

(mlops_env) C:\Users\LENOVO\MLOPS_Assignment1>kubectl get pods
NAME                                        READY   STATUS    RESTARTS   AGE
heart-disease-deployment-7d797b877d-blj4g   1/1     Running   0          17s
heart-disease-deployment-7d797b877d-dxbz9   1/1     Running   0          17s

(mlops_env) C:\Users\LENOVO\MLOPS_Assignment1>
```

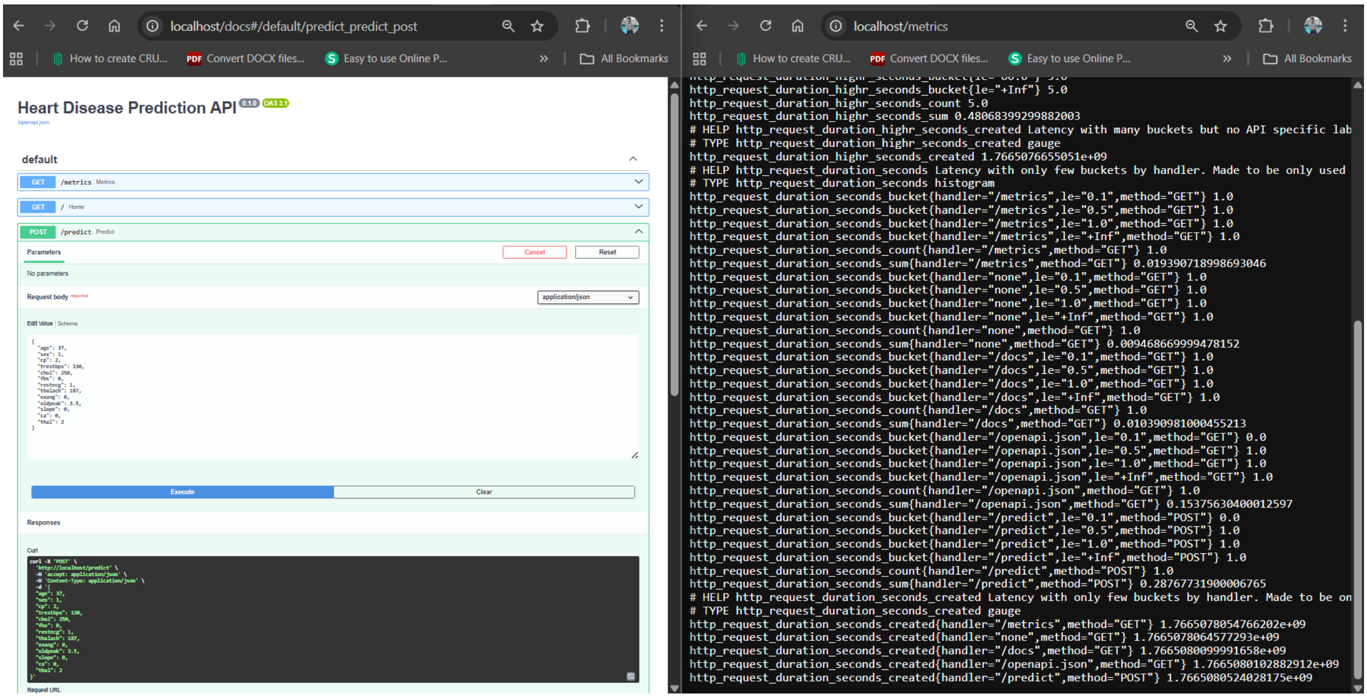
```
(mlops_env) C:\Users\LENOVO\MLOPS_Assignment1>kubectl get services
NAME                TYPE           CLUSTER-IP      EXTERNAL-IP   PORT(S)        AGE
heart-api-service   LoadBalancer   10.105.82.172   localhost     80:30912/TCP   112s
kubernetes          ClusterIP      10.96.0.1       <none>        443/TCP        4m33s

(mlops_env) C:\Users\LENOVO\MLOPS_Assignment1>
```

```
(mlops_env) C:\Users\LENOVO\MLOPS_Assignment1>kubectl get svc heart-api-service
NAME                TYPE           CLUSTER-IP      EXTERNAL-IP   PORT(S)        AGE
heart-api-service   LoadBalancer   10.105.82.172   localhost     80:30912/TCP   13m
```

```
(mlops_env) C:\Users\LENOVO\MLOPS_Assignment1>kubectl describe svc heart-api-service
Name:                     heart-api-service
Namespace:                default
Labels:                   <none>
Annotations:              <none>
Selector:                 app=heart-api
Type:                     LoadBalancer
IP Family Policy:         SingleStack
IP Families:              IPv4
IP:                       10.105.82.172
IPs:                      10.105.82.172
LoadBalancer Ingress:     localhost
Port:                     <unset>  80/TCP
TargetPort:               8000/TCP
NodePort:                 <unset>  30912/TCP
Endpoints:                10.1.0.6:8000,10.1.0.7:8000
Session Affinity:         None
External Traffic Policy:  Cluster
Internal Traffic Policy:  Cluster
Events:                   <none>
```

Requirement: Real-time Monitoring & Metrics

The API exposes technical performance metrics using the Prometheus format. This allows for real-time monitoring of request latency, error rates, and system resource usage.



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6. Conclusion

The implemented MLOps pipeline successfully bridges the gap between manual data science experimentation and automated cloud-native deployment. By leveraging **MLflow** for experiment tracking and **Kubernetes** for orchestration, the system is prepared for scalable production use with high reliability.

Final Repository Link: https://github.com/suvamrx/MLOPS_Assignment1