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HEART DISEASE PREDICTION SYSTEM – MLOPS

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Assignment	End-to-End MLOps Pipeline
Dataset	UCI Heart Disease Dataset
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Repository	*https://github.com/rahulvg/MLOPS-Assignment-Group-41-*
Demo Video	Link

Group Info

Name	ID	Contribution
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Bharatam Sai Sachin	2024AA05847	100
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Problem Statement

The objective of this project is to design, develop, and deploy a scalable, reproducible, and production-ready machine learning system to predict the presence of heart disease based on patient health attributes.

The solution follows modern MLOps best practices, including experiment tracking, CI/CD automation, containerization, Kubernetes deployment, and monitoring.

1. Setup and Installation Instructions

1.1 Local Environment

Python Version: 3.10

Install Dependencies

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

Run Training File (Runs experiment with different parameter on Logistics Regression and Random Forest)

```
python train/train_experiment.py
```

Run all unit tests using Pytest

```
pytest
```

Create report using pytest

```
pytest --html=pytest_report.html
```

Launch MLflow UI (Local SQLite DB)

```
mlflow ui --backend-store-uri sqlite:///mlflow.db
```

Access MLflow at:

```
http://localhost:5000
```

1.2 Verification of Docker Build and Execution via GitHub Actions

Due to organizational restrictions that prevent local installation of Docker Desktop, the Docker image build and container execution were verified using **GitHub Actions**, which provides a Docker-enabled runner environment.

This ensures that containerization and execution are **reproducible, verifiable, and independent of local system constraints**.

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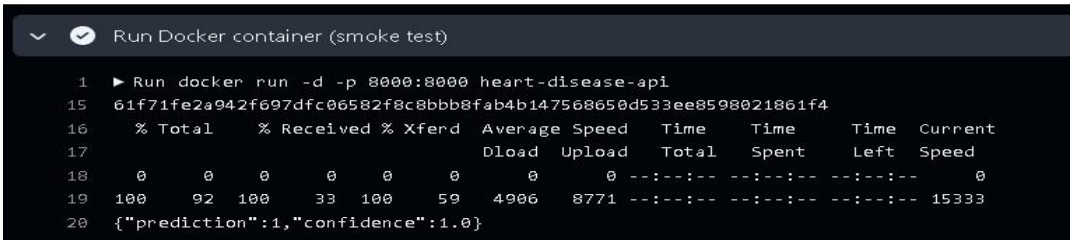
1. Navigate to the GitHub repository:
   https://github.com/rahulvg/MLOPS-Assignment-Group-41-
2. Click on the **Actions** tab in the repository.
3. Select the most recent workflow run under the **CI pipeline**.
4. Open the workflow run and inspect the following steps:
   - **Build Docker image**
     This step executes the Docker build command using the project's `Dockerfile`.
   - **Run Docker container and test API**
     This step starts the container and invokes the `/predict` endpoint using a sample JSON request.

Evidence of Successful Docker Execution

Within the GitHub Actions workflow logs, the following evidence can be observed:

- Docker build logs confirming successful image creation
- Container startup logs indicating the FastAPI service is running
- Successful HTTP response from the `/predict` endpoint returning a prediction and confidence score

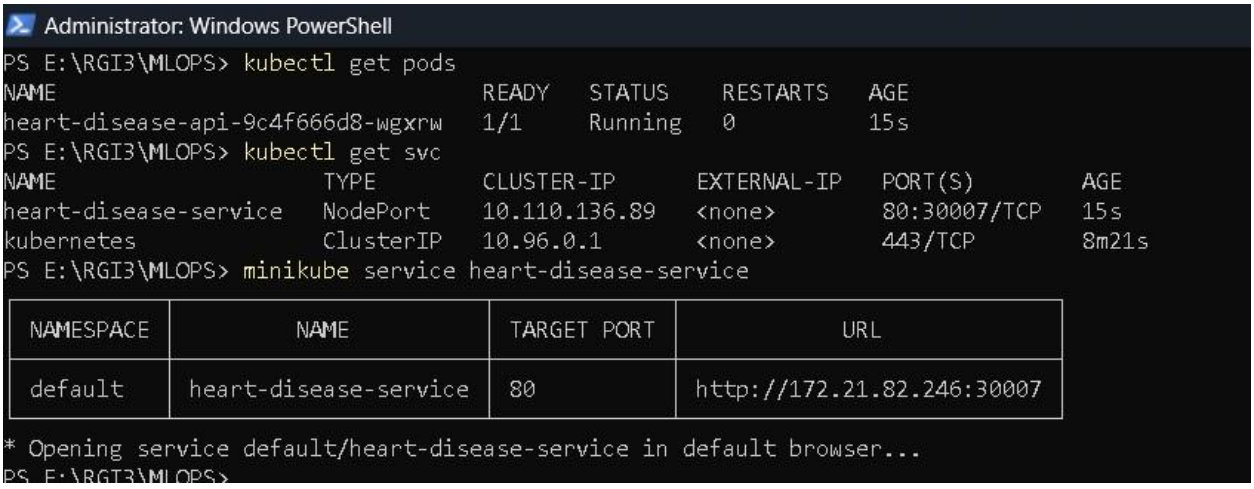
Screenshot of successful Docker run event



1.3 Kubernetes (Local Deployment with Minikube)

Start Minikube

```
minikube start --container-runtime=containerd
```



Inside Minikube

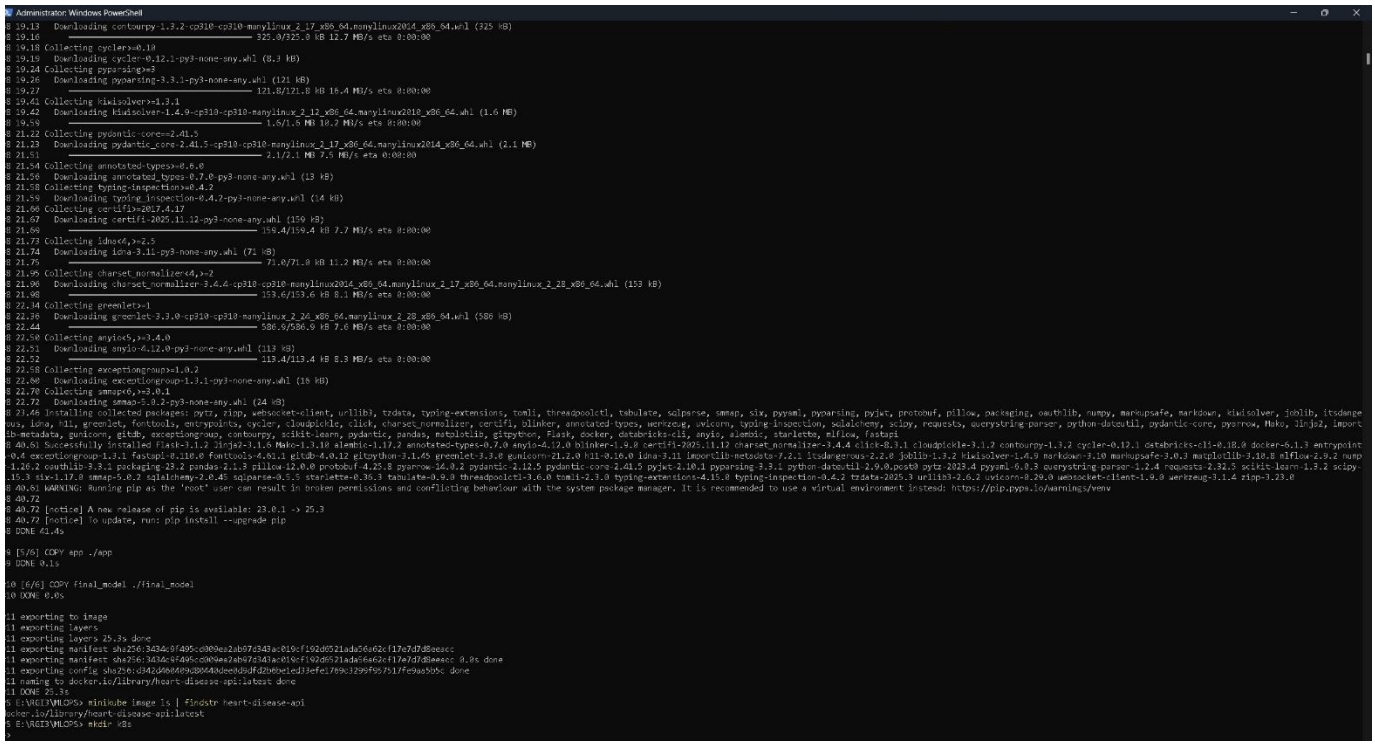
```
minikube image build -t heart-disease-api .
```

Deploy Application

```
kubectl apply -f k8s/deployment.yaml
kubectl apply -f k8s/service.yaml
```

Expose Service

```
minikube service heart-disease-service
```



2. Data Acquisition and Exploratory Data Analysis

2.1 Dataset

- Source: UCI Machine Learning Repository
- Format: CSV
- Task: Binary classification (presence or absence of heart disease)

2.2 Preprocessing

- Missing values handled
- Numerical features scaled using StandardScaler
- Target variable encoded
- Preprocessing implemented using a scikit-learn Pipeline

2.3 Exploratory Data Analysis (EDA) & Modelling choice

- Feature distributions analyzed using histograms
- Correlation heatmap used to study feature relationships
- Class balance verified

The modelling approach was guided by dataset characteristics, interpretability needs, and deployment stability.

Two models were evaluated:

- **Logistic Regression** – chosen as a strong, interpretable baseline for structured medical data
- **Random Forest** – included to capture non-linear relationships and feature interactions

All numerical features were standardized using **StandardScaler**, and preprocessing was implemented through a unified **scikit-learn Pipeline** to ensure reproducibility, prevent data leakage, and enable deployment-safe inference.

Hyperparameter Tuning

- Logistic Regression: `C ∈ {0.1, 1.0, 10.0}`
- Random Forest:
    - `n_estimators ∈ {100, 200}`
    - `max_depth ∈ {None, 10}`

Each configuration was logged as a separate experiment using **MLflow**.

Evaluation

Models were evaluated using **5-fold cross-validation** with the following metrics:

- Accuracy
- Precision
- Recall
- ROC-AUC

Final Model

Logistic Regression with C = 0.1 was selected due to:

- Consistent cross-validation performance
- Lower variance across folds
- Better generalization
- Simpler and more interpretable behavior

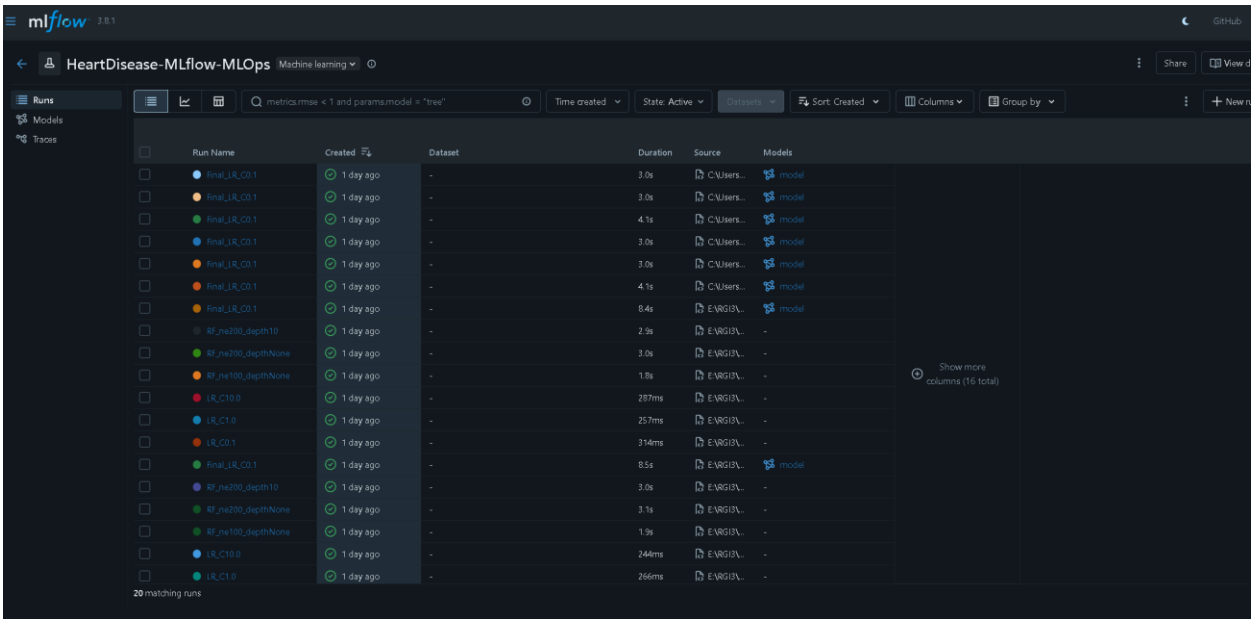
Its stability and ease of monitoring make it well-suited for a production-oriented MLOps pipeline.

3. Experiment Tracking

MLflow was integrated to track:

- Model parameters
- Cross-validation metrics
- Model artifacts

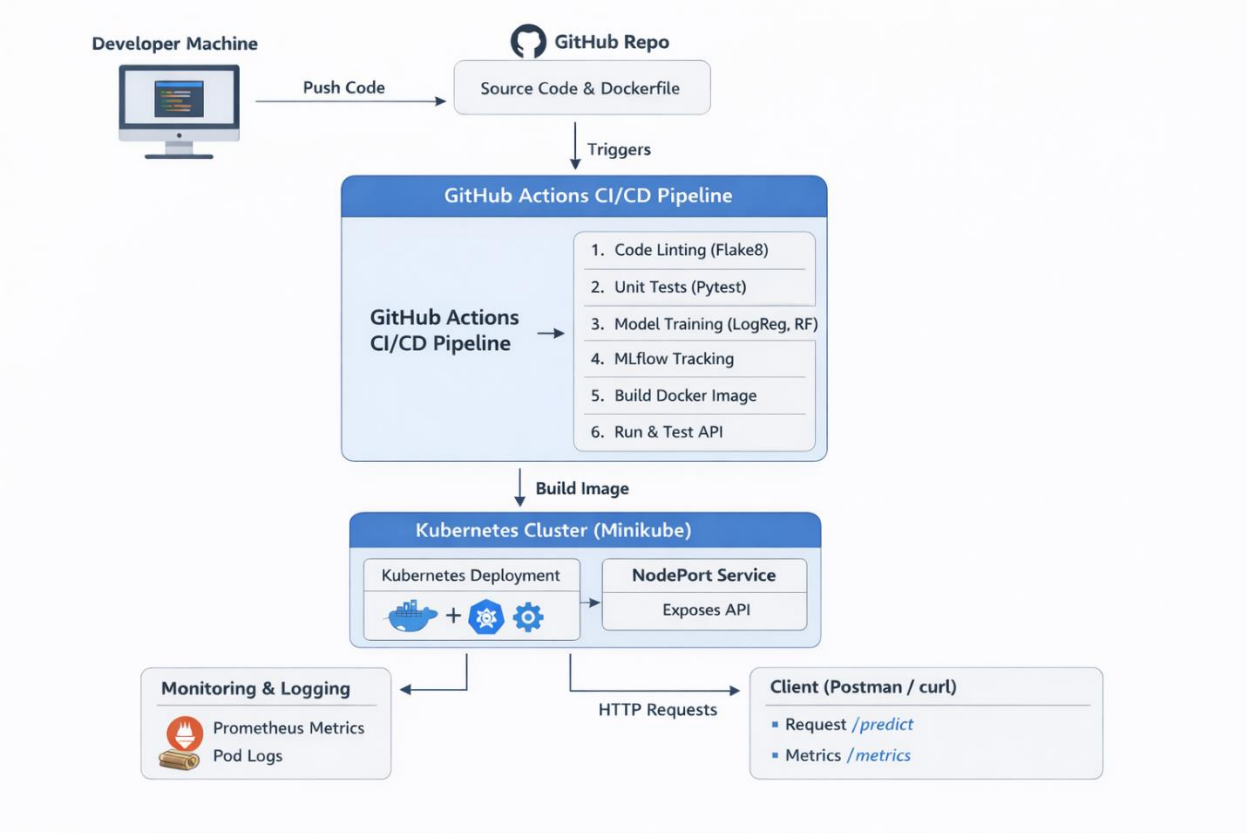
All experiments are logged under a dedicated MLflow experiment for easy comparison.



Model Packaging and Reproducibility

- Final model saved as a serialized scikit-learn Pipeline
- Model can be found at **final_model\heart_disease_lr_c01.pkl** in git repo.
- Preprocessing included within the model
- Reproducible inference guaranteed
- Dependencies listed in requirements.txt
- Artifacts stored and versioned using MLflow check **mlflow_experiment.db** in git repo

4. Architecture Diagram



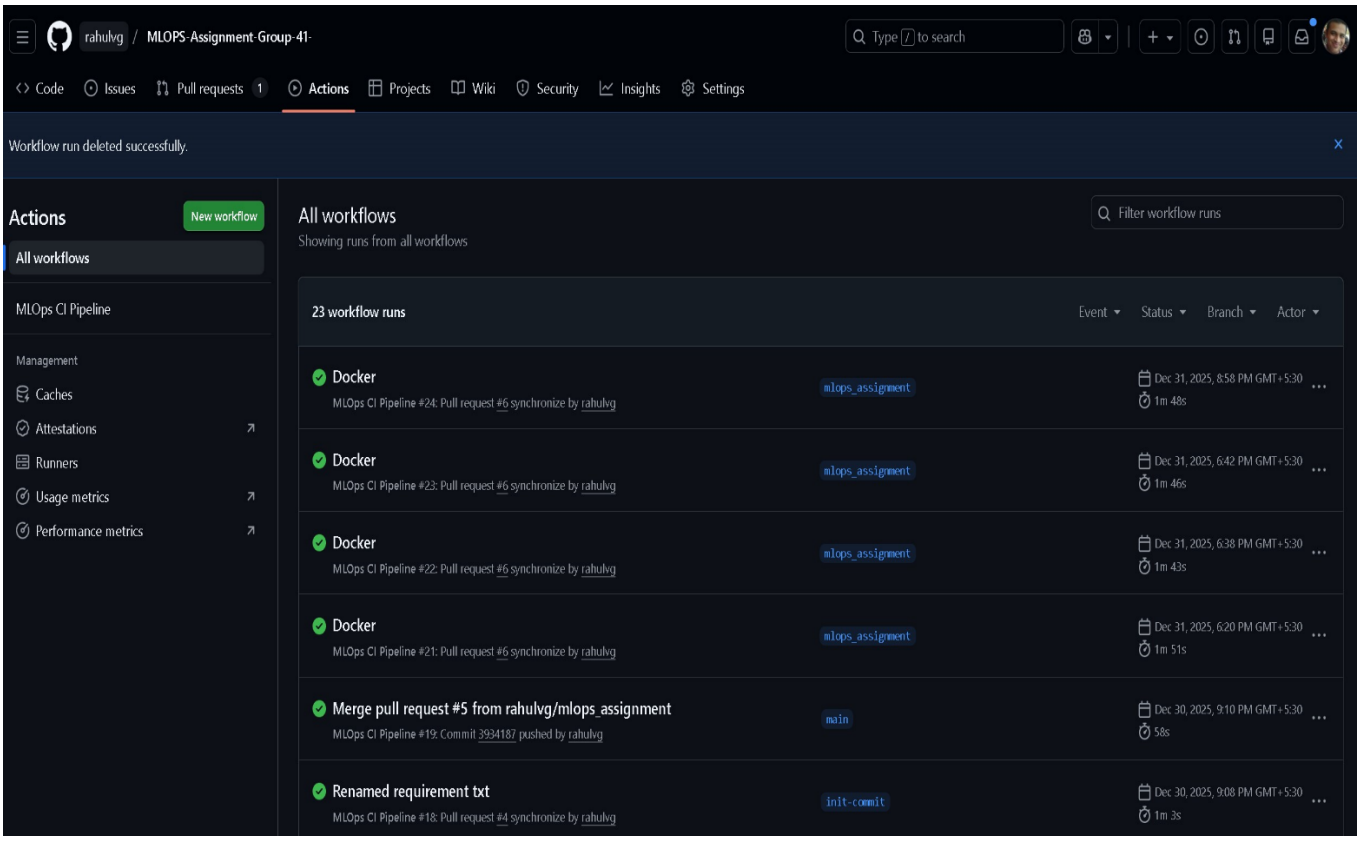
5. CI/CD Pipeline

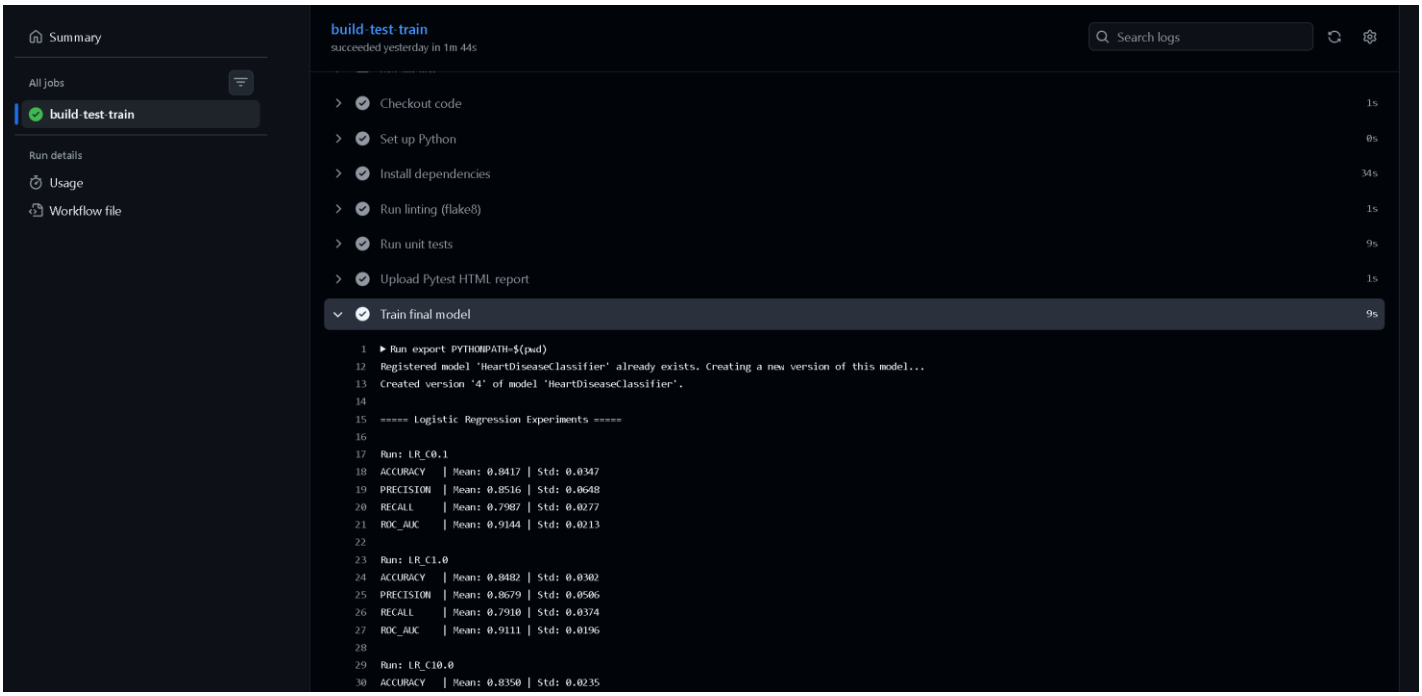
Tools Used

- GitHub Actions
- Pytest
- Flake8
- Docker

Pipeline Stages

- Code linting
- Unit testing
- Model training
- Docker image build
- API smoke testing




Summary
All jobs
build-test-train
Run details
Usage
Workflow file
build-test-train
succeeded yesterday in 1m 44s
Search logs
Checkout code 1s
Set up Python 0s
Install dependencies 34s
Run linting (flake8) 1s
Run unit tests 9s
Upload Pytest HTML report 1s
Train final model 9s
▶ Run export PYTHONPATH=$(pwd)
Registered model 'HeartDiseaseClassifier' already exists. Creating a new version of this model...
Created version '4' of model 'HeartDiseaseClassifier'.
===== Logistic Regression Experiments =====
Run: LR_C0.1
ACCURACY | Mean: 0.8417 | Std: 0.0347
PRECISION | Mean: 0.8516 | Std: 0.0648
RECALL | Mean: 0.7987 | Std: 0.0277
ROC_AUC | Mean: 0.9144 | Std: 0.0213
Run: LR_C1.0
ACCURACY | Mean: 0.8482 | Std: 0.0302
PRECISION | Mean: 0.8679 | Std: 0.0506
RECALL | Mean: 0.7910 | Std: 0.0374
ROC_AUC | Mean: 0.9111 | Std: 0.0196
Run: LR_C10.0
ACCURACY | Mean: 0.8350 | Std: 0.0235

6. Code Repository

https://github.com/rahulvg/MLOPS-Assignment-Group-41-

7. Containerization and Deployment

7.1 Dockerized API

- FastAPI-based service
- /predict endpoint
- Accepts JSON input
- Returns prediction and confidence score

7.2 Kubernetes Deployment

- Local Kubernetes using Minikube
- Deployment and NodePort Service manifests
- API tested using curl and Postman

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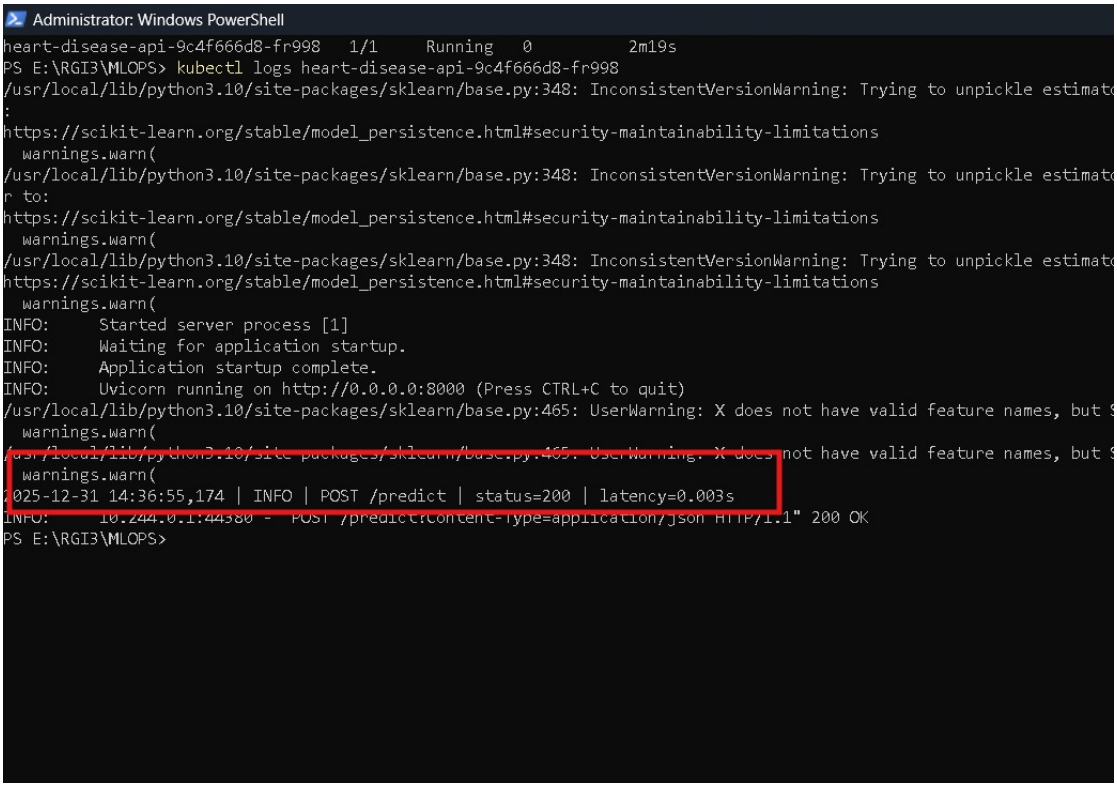
8. Monitoring and Logging

8.1 Logging

- Request-level logging implemented via FastAPI middleware
- Logs include endpoint, HTTP status, and latency
- Logs accessible via Kubernetes pod logs

8.2 Monitoring

- Prometheus-compatible /metrics endpoint exposed
- Metrics include request count and request latency
- Ready for Prometheus and Grafana integration


Administrator: Windows PowerShell
heart-disease-api-9c4f666d8-fr998 1/1 Running 0 2m19s
PS E:\RGI3\MLOPS> kubectl logs heart-disease-api-9c4f666d8-fr998
/usr/local/lib/python3.10/site-packages/sklearn/base.py:348: InconsistentVersionWarning: Trying to unpickle estimato
:
https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
warnings.warn(
/usr/local/lib/python3.10/site-packages/sklearn/base.py:348: InconsistentVersionWarning: Trying to unpickle estimato
r to:
https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
warnings.warn(
/usr/local/lib/python3.10/site-packages/sklearn/base.py:348: InconsistentVersionWarning: Trying to unpickle estimato
https://scikit-learn.org/stable/model_persistence.html#security-maintainability-limitations
warnings.warn(
INFO: Started server process [1]
INFO: Waiting for application startup.
INFO: Application startup complete.
INFO: Uvicorn running on http://0.0.0.0:8000 (Press CTRL+C to quit)
/usr/local/lib/python3.10/site-packages/sklearn/base.py:465: UserWarning: X does not have valid feature names, but S
warnings.warn(
/usr/local/lib/python3.10/site-packages/sklearn/base.py:465: UserWarning: X does not have valid feature names, but S
warnings.warn(
2025-12-31 14:36:55,174 | INFO | POST /predict | status=200 | latency=0.003s
INFO: 10.244.0.1:44380 - "POST /predict HTTP/1.1" 200 OK
PS E:\RGI3\MLOPS>

9. Architecture Overview

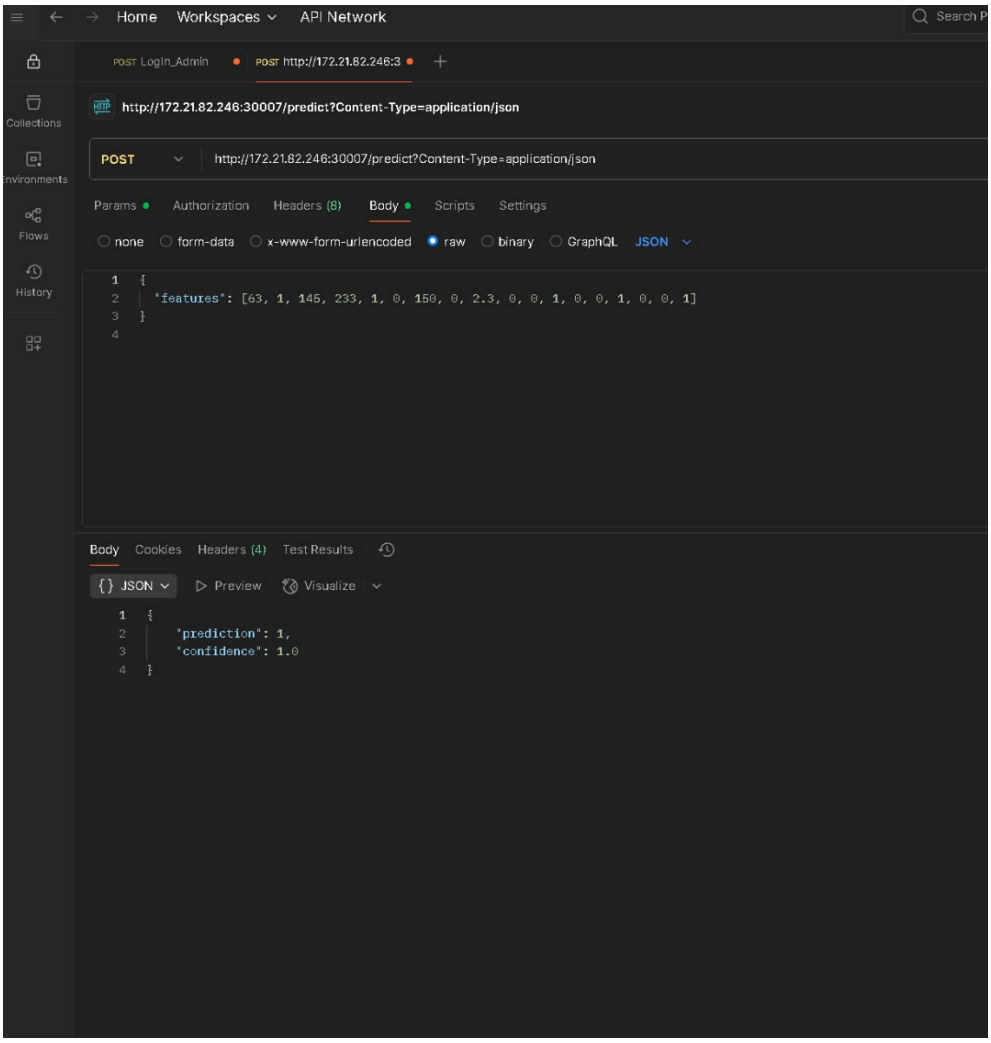
Client (Postman / curl)
→ FastAPI API (/predict, /metrics)
→ Scikit-learn Pipeline
→ Kubernetes Pod
→ NodePort Service

CI/CD is handled using GitHub Actions, and experiment tracking is handled using MLflow.

10. Run using CURL/Postman API

Curl Command

```
"curl -X POST http://127.0.0.1:30007/predict \
-H "Content-Type: application/json" \
-d '{"features":[63,1,145,233,1,0,150,0,2.3,0,0,1,0,0,1,0,0,1]}'"
```



11. Conclusion

This project demonstrates a complete, production-grade MLOps workflow covering data analysis, model development, experiment tracking, CI/CD automation, containerization, Kubernetes deployment, and monitoring.

The system is scalable, reproducible, and aligned with real-world MLOps practices.

Demo video

Google Drive Link for Demo Video

Github Link for demo video