Heart Disease Prediction System – MLOps

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

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**.

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:

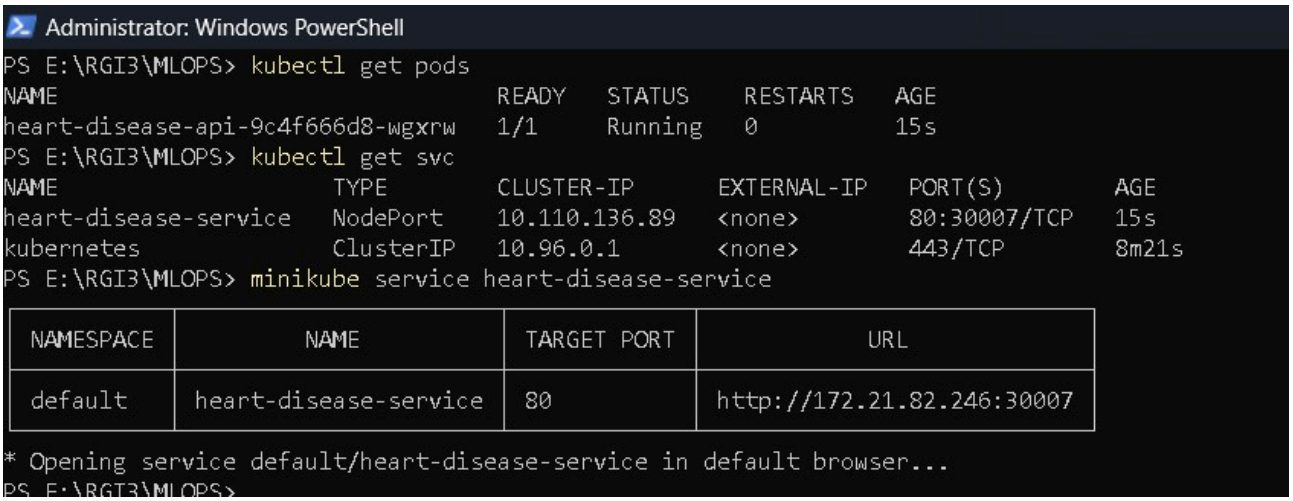
- Docker build logs confirming successful image creation
- Container startup logs indicating the FastAPI service is running
- Successful HTTP response from the `/predict` endpoint returning a prediction and confidence score

Screenshot of successfull Docker run event

1.3 Kubernetes (Local Deployment with Minikube)

Start Minikube

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



Build Docker Image Inside Minikube

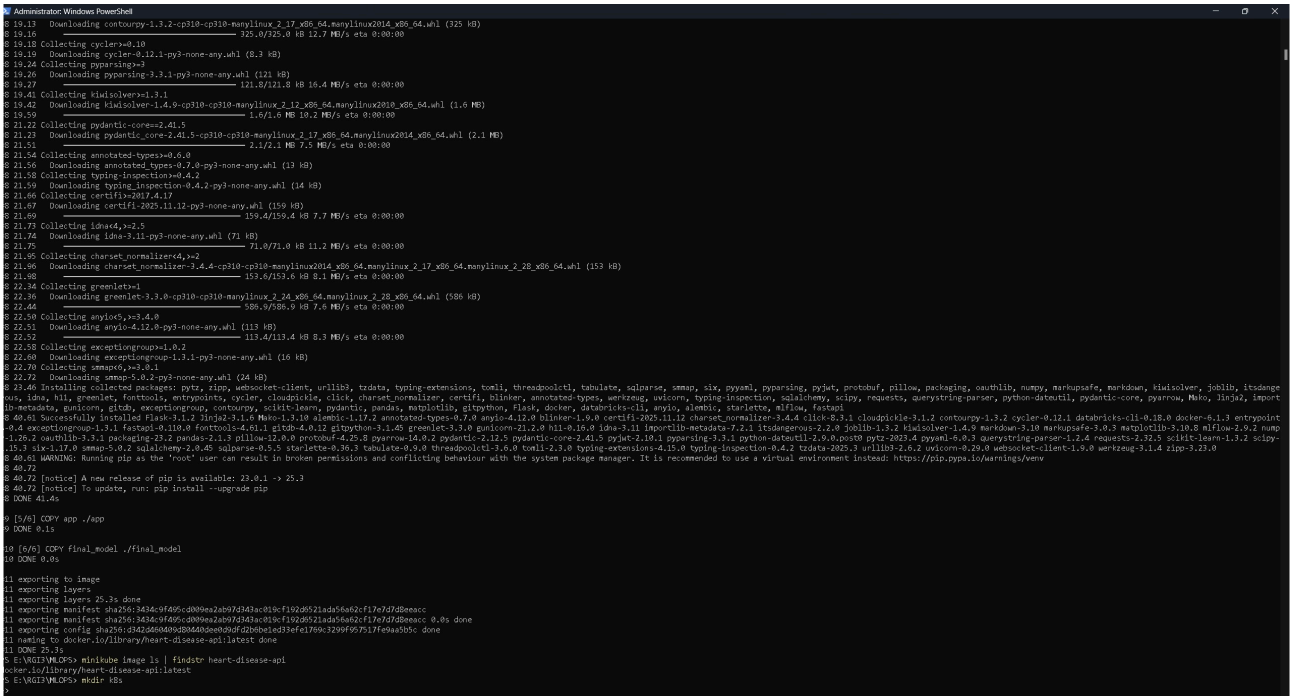
```
minikube image build -t heart-disease-api .
```

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

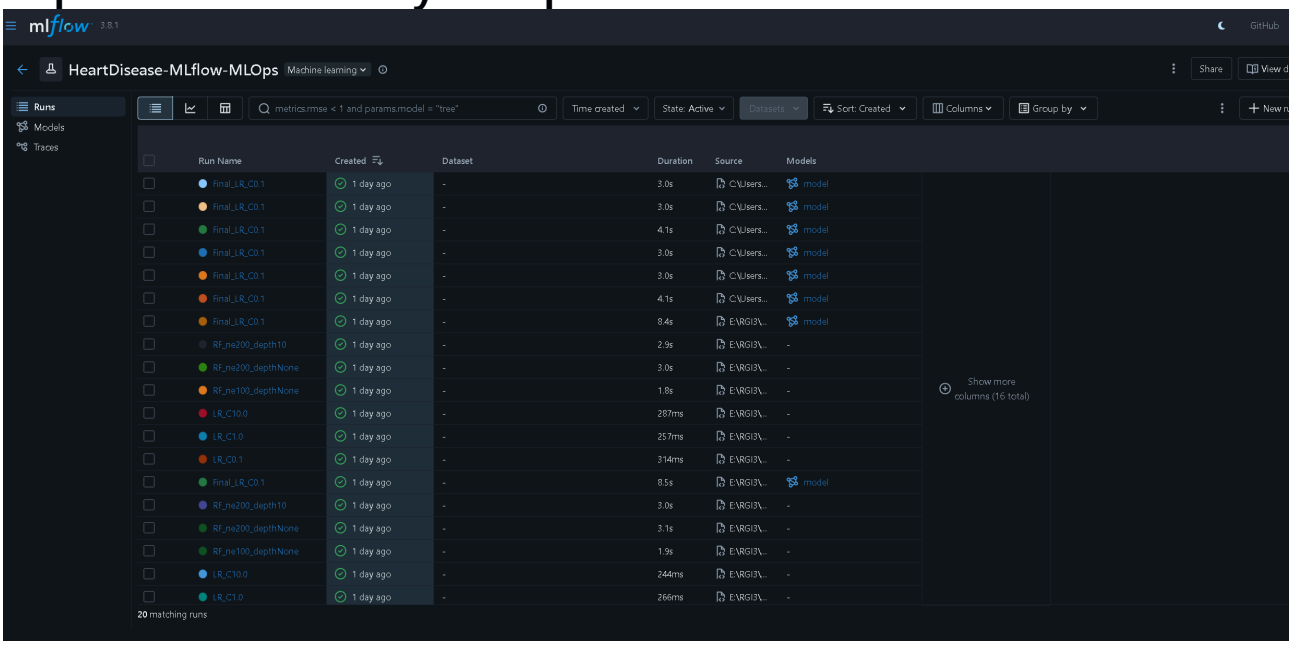
Its stability and ease of monitoring make it well-suited for a production-oriented MLOps pipeline.

3. Experiment Tracking

MLflow was integrated to track:

- Model parameters
- Cross-validation metrics
- Model artifacts

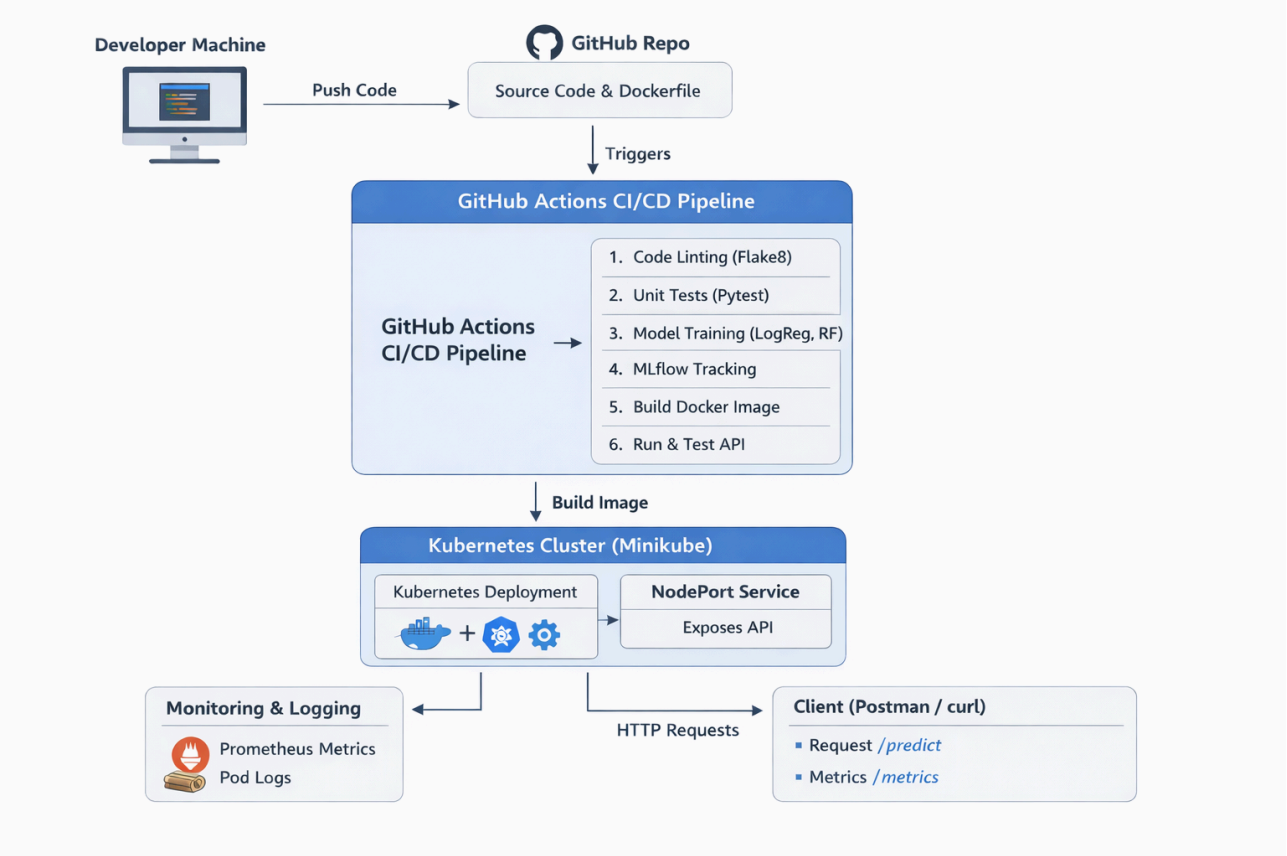
All experiments are logged under a dedicated MLflow experiment for easy comparison.



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



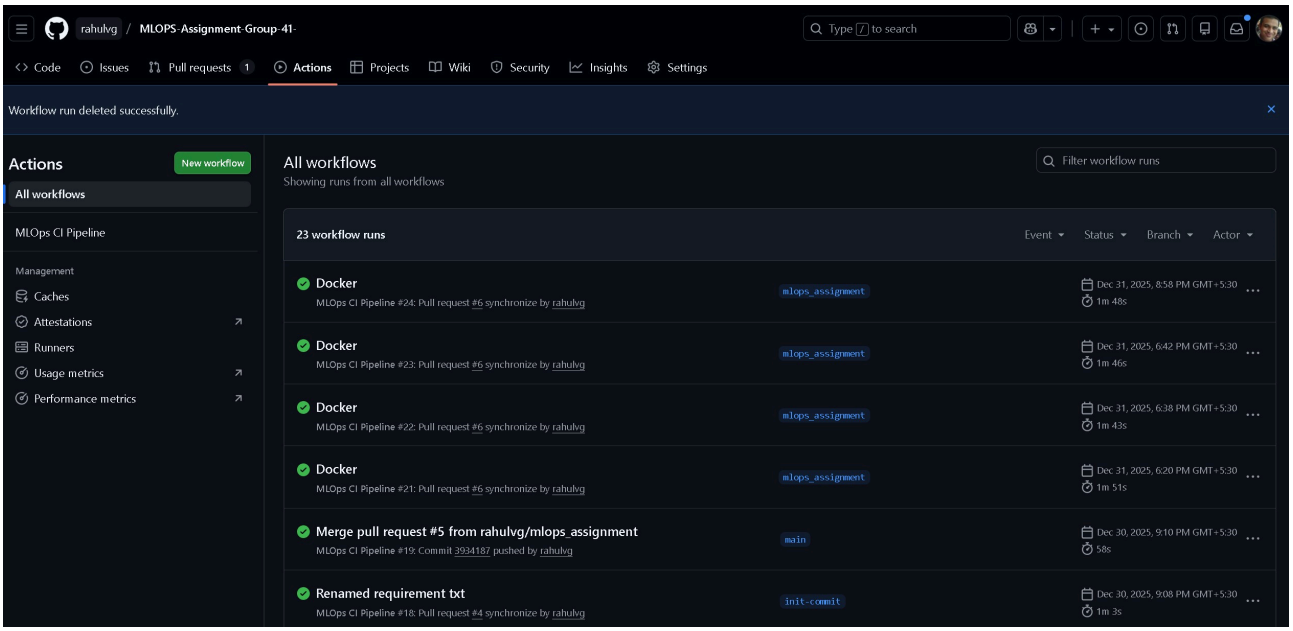
5. CI/CD Pipeline

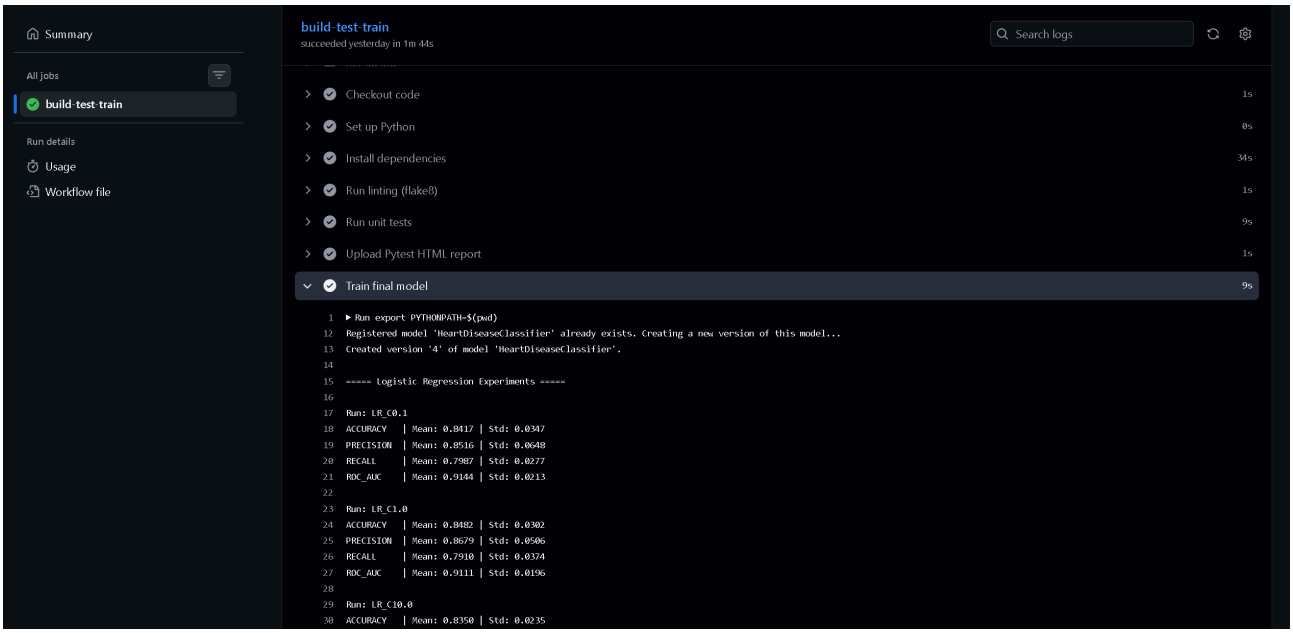
Tools Used

- GitHub Actions
- Pytest
- Flake8
- Docker

Pipeline Stages

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





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

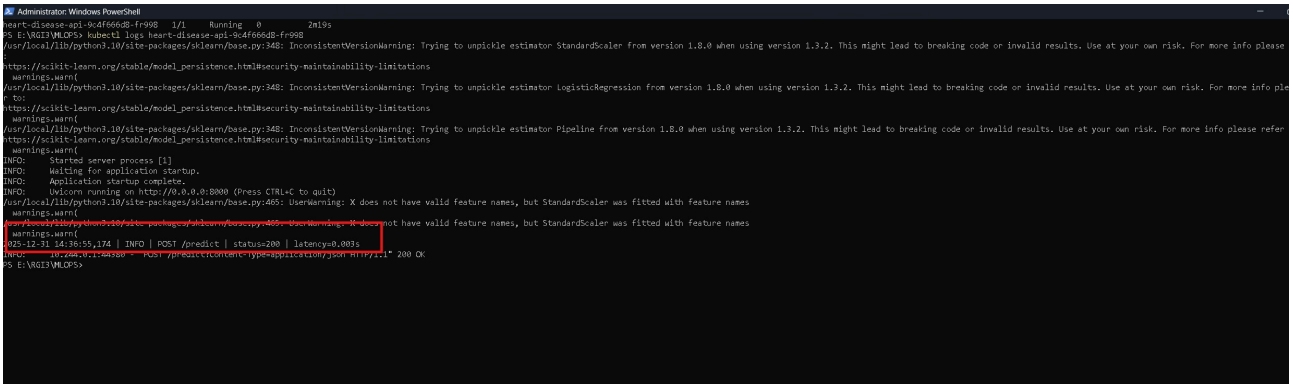
7. Monitoring and Logging

7.1 Logging

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

7.2 Monitoring

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



8. Architecture Overview

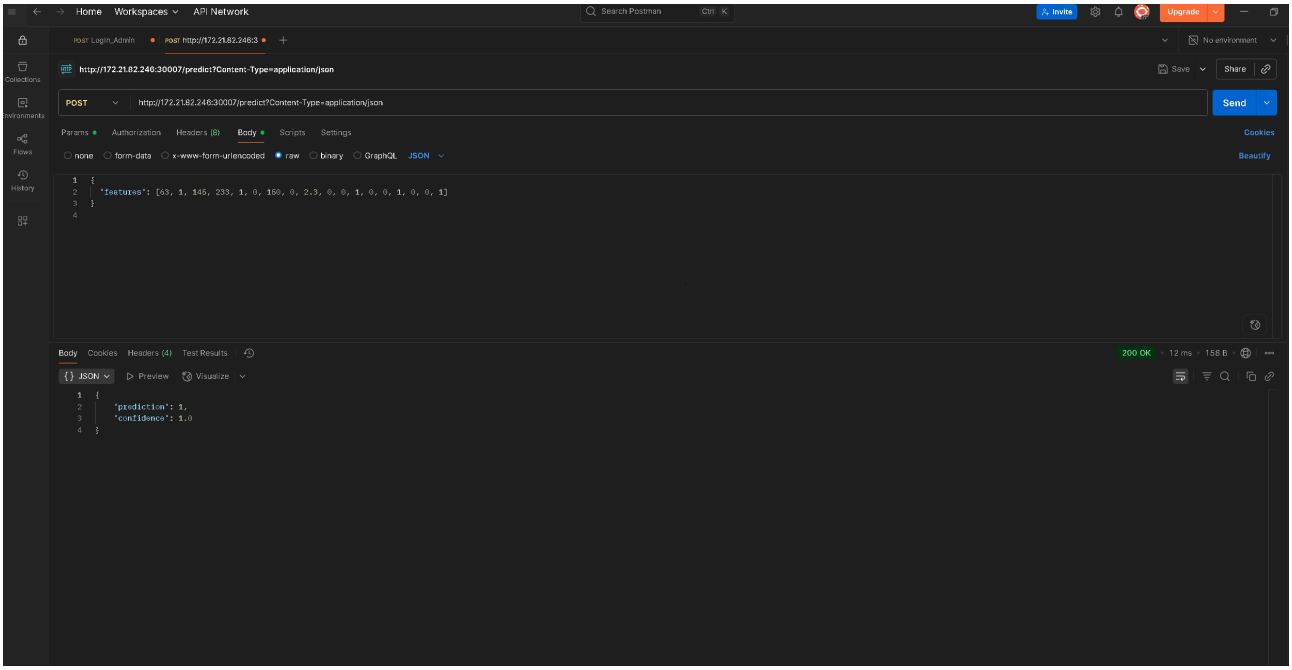
Client (Postman / curl)
→ FastAPI API (/predict, /metrics)
→ Scikit-learn Pipeline
→ Kubernetes Pod
→ NodePort Service

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

9 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]}'"
```



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

https://github.com/rahulvg/MLOPS-Assignment-Group-41-/blob/main/Demo%20Video.mp4

https://drive.google.com/drive/folders/1hGcu4oyM3TusMy8vnackoOLpug7LhJdP?usp=sharing

Appendix: Useful Commands

Launch MLflow with Custom Local DB

```
mlflow ui --backend-store-uri sqlite:///E:/RGI3/MLOPS/mlflow.db
```

Rebuild and Redeploy on Minikube

```
minikube image build -t heart-disease-api .
kubectl delete deployment heart-disease-api
kubectl apply -f k8s/deployment.yaml
```