MLOps Assignment Report: Heart Disease Prediction

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1. Introduction

This report details the implementation of an end-to-end MLOps pipeline for heart disease risk prediction using the UCI Heart Disease dataset. The project demonstrates modern MLOps practices including data processing, model development, experiment tracking, CI/CD, containerization, and deployment.

2. Dataset and Data Acquisition

Dataset: UCI Heart Disease Dataset

- **Source**: UCI Machine Learning Repository
- **Features**: 13 clinical features + target
- **Samples**: ~300 instances
- **Target**: Binary (0: no disease, 1: disease)

Data Acquisition:

- Script: `src/data_prep.py` downloads from UCI URL
- Cleaning: Handle missing values (marked as '?'), convert to binary target
- Storage: `data/raw/heart.csv`

3. Exploratory Data Analysis (EDA)

Key Findings (see `notebooks/eda.ipynb`):

- **Class Balance**: Slight imbalance (54% positive cases)
- **Correlations**: Strong correlations between thalach (heart rate) and target, cp (chest pain) and target
- **Distributions**: Age follows normal distribution, cholesterol shows outliers
- **Categorical Analysis**: Higher chest pain types associated with disease

Visualizations:

- Histograms for numerical features
- Correlation heatmap
- Class balance bar plot
- Age distribution by target

4. Feature Engineering and Model Development

Preprocessing Pipeline:

- Numerical: StandardScaler
- Categorical: OneHotEncoder (handle_unknown='ignore')
- Pipeline: ColumnTransformer + Model

Models Evaluated:

1. Logistic Regression (tuned C, penalty)
2. Random Forest (tuned n_estimators, max_depth)

Hyperparameter Tuning: GridSearchCV with 5-fold CV, ROC-AUC scoring

Evaluation Metrics:

- ROC-AUC (primary)
- Accuracy, Precision, Recall

Best Model: Logistic Regression (ROC-AUC: 0.9113)

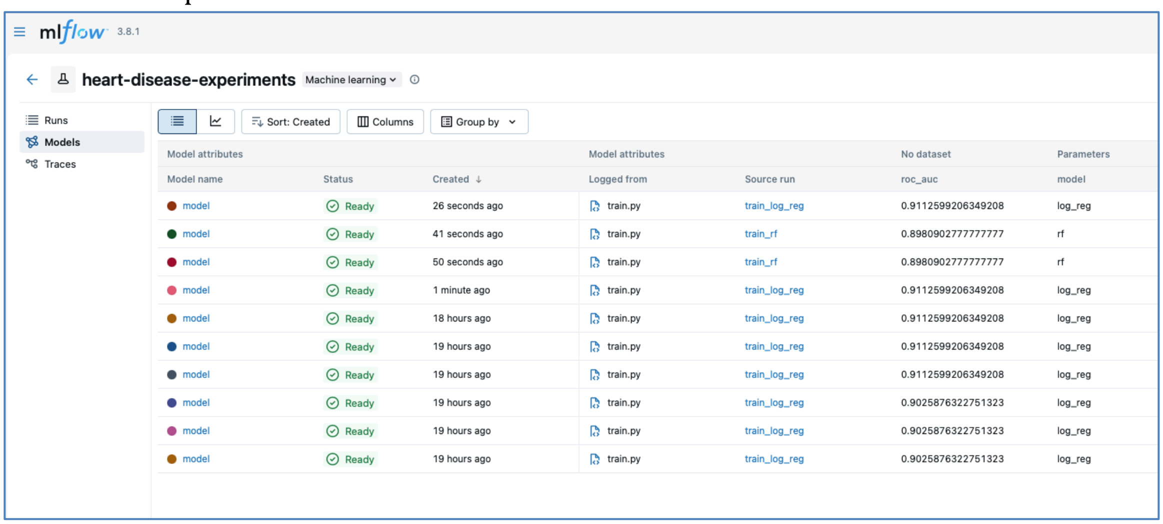
5. Experiment Tracking

Tool: MLflow

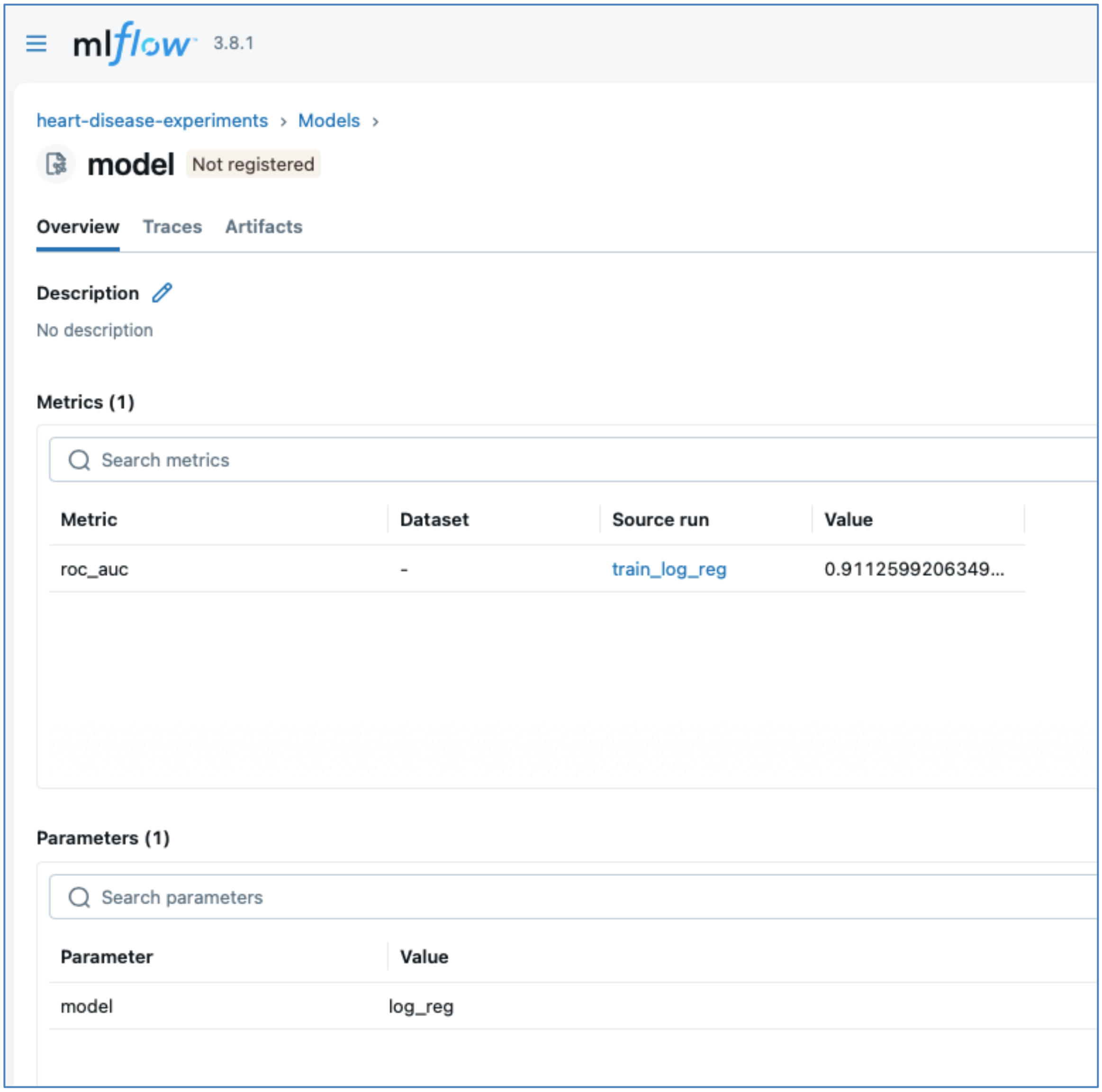
- **Experiments**: Logged parameters, metrics, model artifacts
- **Runs**: Separate runs for each model with best params
- **UI**: `mlflow ui` for visualization

MLflow experiment runs and metrics

- MLflow UI - experiment list



- MLflow UI - best run details



6. Model Packaging and Reproducibility

Format: Joblib pickle with sklearn Pipeline

Dependencies: `requirements.txt` with pinned versions

Reproducibility: Pipeline ensures consistent preprocessing

7. CI/CD Pipeline and Testing

Tool: GitHub Actions

Jobs:

- Ubuntu: Lint (flake8), test (pytest), data prep, train, upload artifact
- Windows: Test only

Tests:

- Data loading: `tests/test_data.py`
- Data prep: `tests/test_prep.py`

Artifacts: Trained model uploaded per run

8. Model Containerization

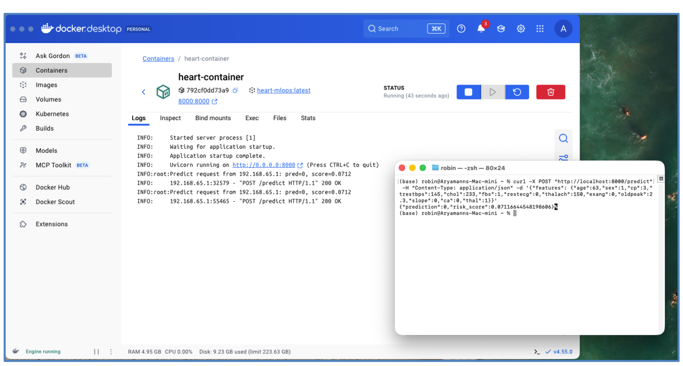
Tool: Docker

Image: Python 3.10 slim + dependencies

API: FastAPI with /predict endpoint

Testing: Local build/run with sample input

Docker build and local container test



9. Production Deployment

Platform: Railway (public cloud)

URL: https://heart-mlops-production.up.railway.app

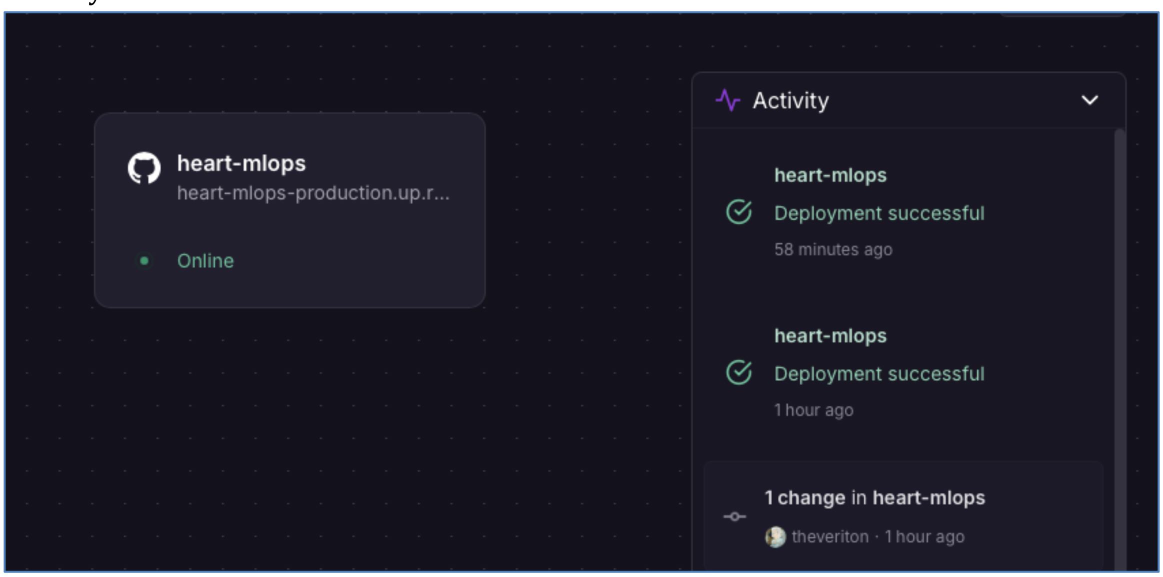
Manifests: Docker-based deployment

Service: Web service with automatic scaling

Verification: Endpoint testing with curl, deployed API functional

Railway deployment

- Railway service dashboard



- Deployed `/predict` response

10. Monitoring and Logging

Logging: Request logging with client IP, prediction, score

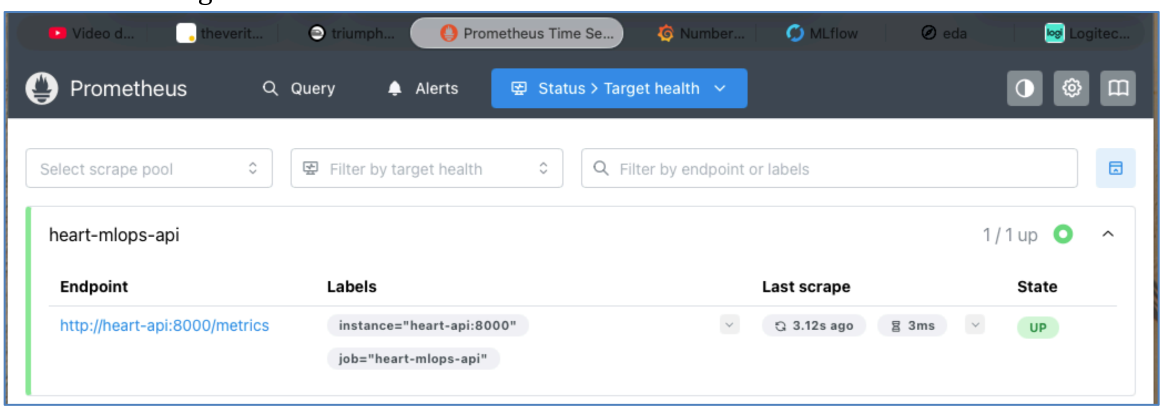
Metrics: `/metrics` endpoint exposes Prometheus-formatted metrics (including `predict_requests_total`)

Monitoring Stack (Local):

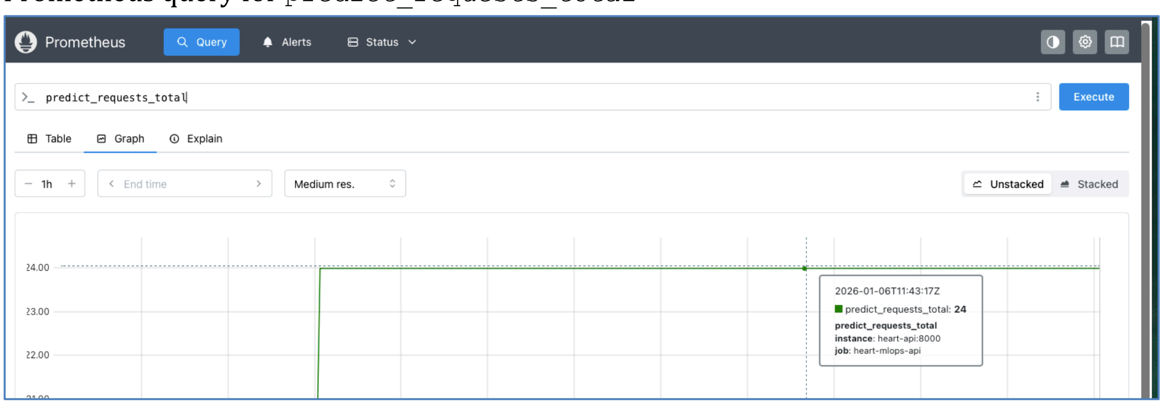
- Prometheus scrapes the API metrics endpoint
- Grafana visualizes metrics from Prometheus

Monitoring Screenshots

- Prometheus targets UP

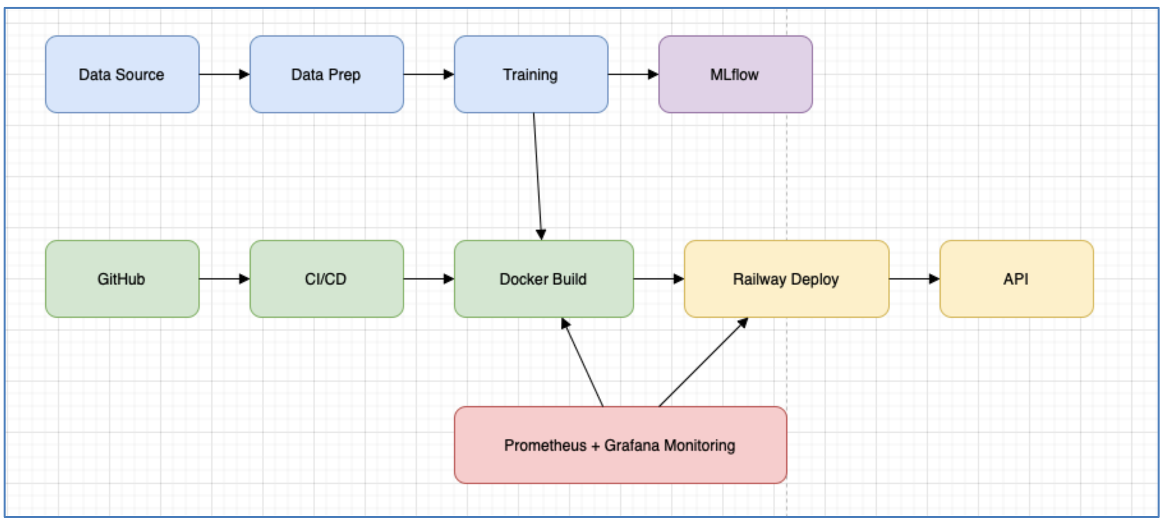


- Prometheus query for `predict_requests_total`



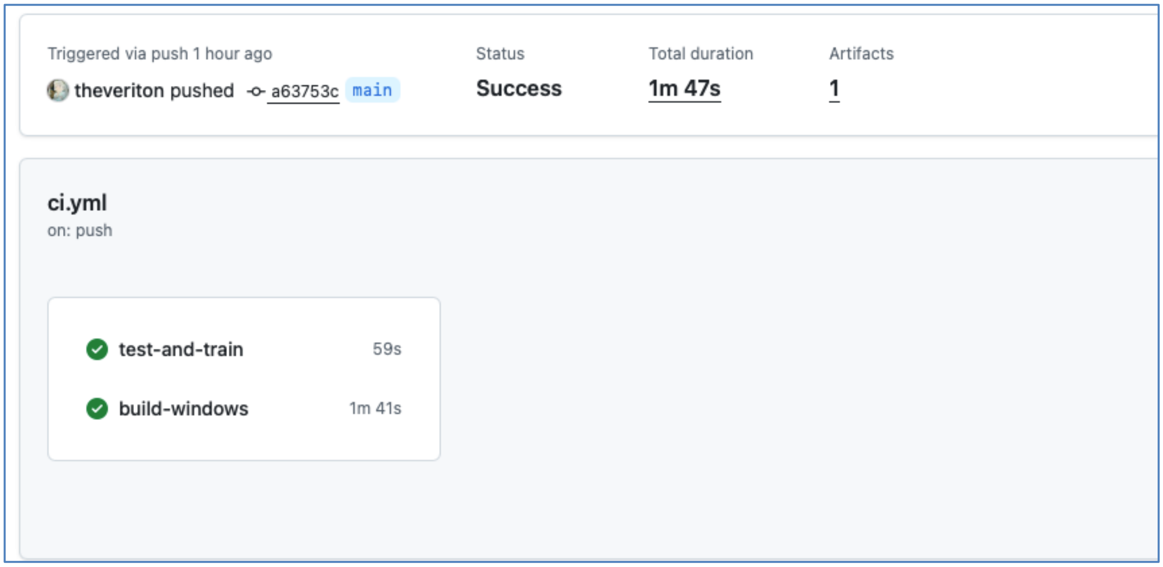
- Grafana dashboard panel showing `predict_requests_total`

11. Architecture Diagram

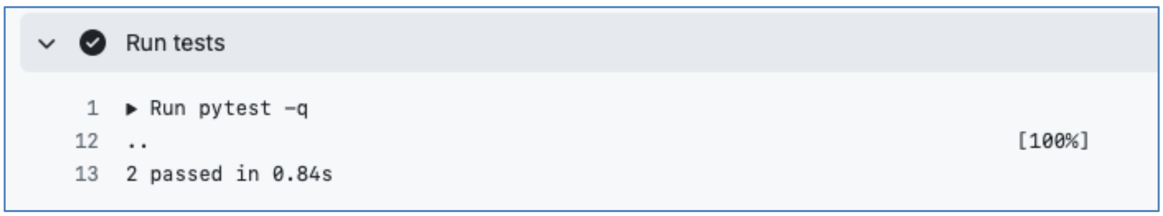


12. CI/CD Workflow Screenshots

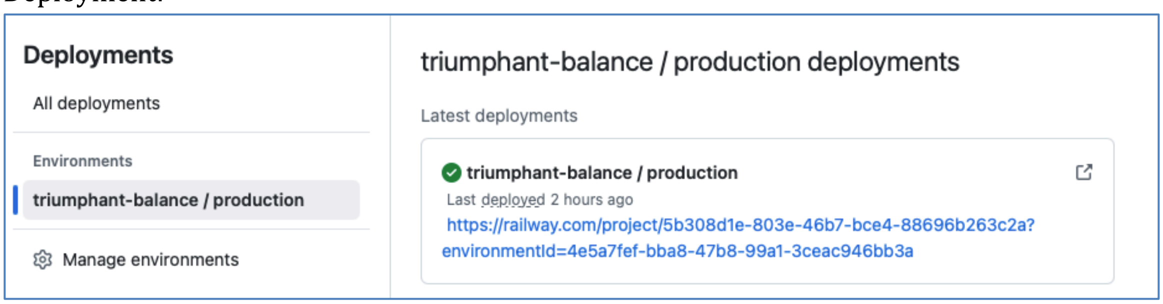
- Build success:



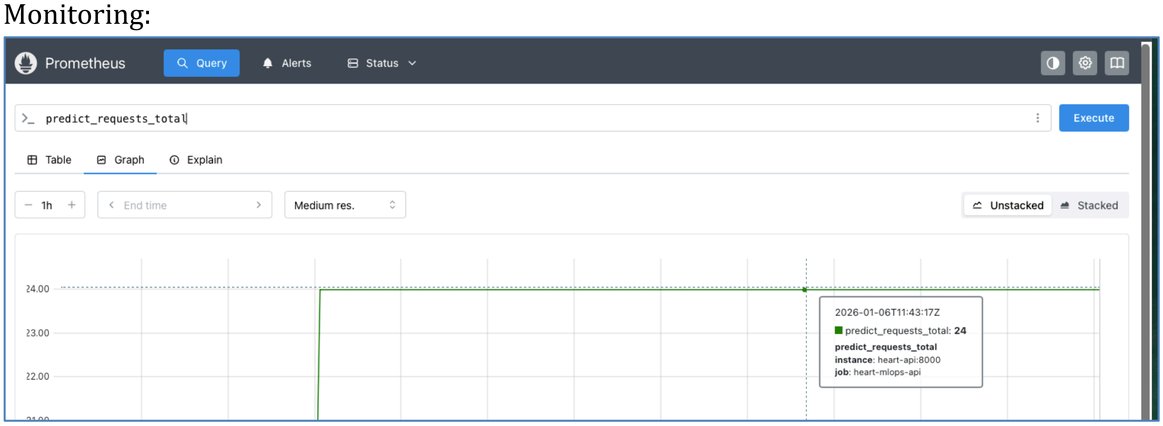
- Test results:



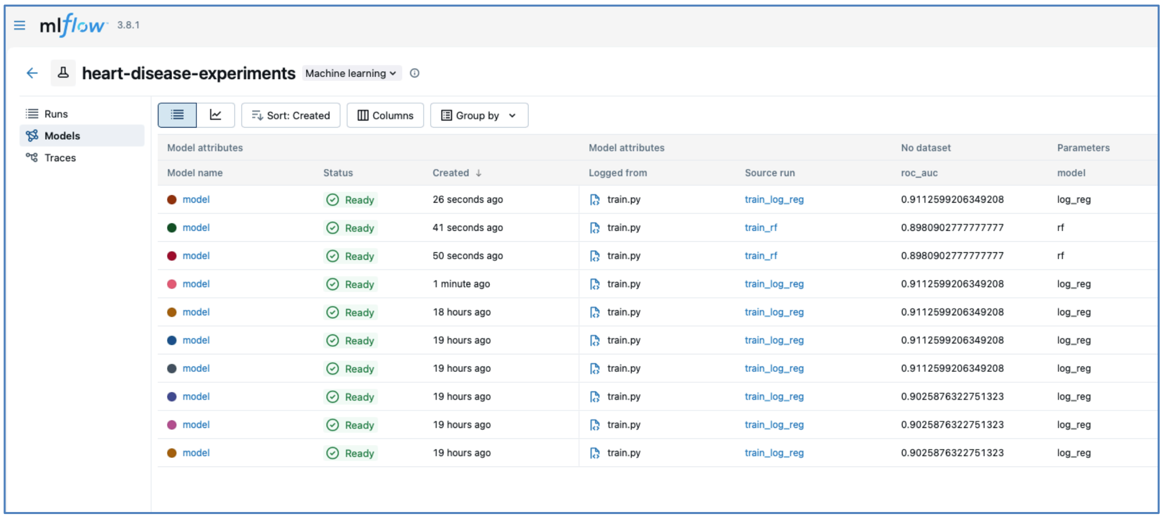
- Deployment:



- Monitoring:



- MLflow:



13. Demo Video

YouTube URL

14. Repository Link

GitHub Repository

15. Conclusion

The project successfully implements all MLOps requirements with automated pipelines, reproducible models, and production-ready deployment on Railway. Key achievements include hyperparameter tuning, experiment tracking, containerization, and public cloud deployment.