

MLOps Iris Classification – End to End Pipeline

Group No: 70

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Assignment Tasks

This project implements a comprehensive MLOps implementation for Iris flower classification with automated training, monitoring, and deployment capabilities addressing the following assignment requirements:

Part 1: Repository and Data Versioning

- **GitHub Repository:** Complete project hosted on GitHub with clean structure
https://github.com/SaritGhoshBits25/MLOps_Assignment_Group70
- **Docker Hub Repository:**
<https://hub.docker.com/r/wp1412011989/iris-api>
- **Data Loading & Preprocessing:** Automated data preprocessing pipeline
(src/data_preprocessing.py)

Directory Structure: Well-organized project structure with separate directories for source code, data, models, tests, and monitoring

```
├── src/                                # Source code
│   ├── api.py                         # FastAPI application with monitoring
│   ├── train.py                       # Model training with MLflow
│   ├── data_preprocessing.py          # Data preprocessing pipeline
│   ├── database.py                   # Database operations and logging
│   └── retrain_pipeline.py            # Automated retraining pipeline
├── data/                              # Dataset files
│   ├── iris_raw.csv                  # Raw iris dataset
│   ├── iris_train.csv                # Training data
│   └── iris_test.csv                 # Test data
```

```

├── models/           # Trained model artifacts
├── tests/            # Test suite
├── monitoring/       # Monitoring configuration
│   └── prometheus.yml # Prometheus configuration
├── .github/workflows/ # CI/CD pipeline
│   └── ci-cd.yml      # GitHub Actions workflow
├── Dockerfile        # Container configuration
├── docker-compose.yml # Multi-service orchestration
└── requirements.txt   # Python dependencies

```

Data Version Control (DVC):

This project uses DVC for data versioning and pipeline management. DVC tracks data files and ensures reproducible data processing workflows.

- **Data tracking:** Raw iris dataset (`data/iris_raw.csv`)
- **Pipeline:** Automated data preprocessing pipeline
- **Remote storage:** Local remote for data versioning

DVC Files Structure

```

├── .dvc/
│   └── config      # DVC configuration
├── data/
│   ├── .gitignore  # Git ignores data files
│   ├── iris_raw.csv.dvc # DVC tracks raw data
│   ├── iris_train.csv # Generated by pipeline
│   └── iris_test.csv  # Generated by pipeline
└── dvc.yaml        # Pipeline definition

```

Part 2: Model Development & Experiment Tracking

Multiple Models: Implementation of classification models:

- Logistic Regression
- Random Forest
- Support Vector Machine (SVM)

Model Information:

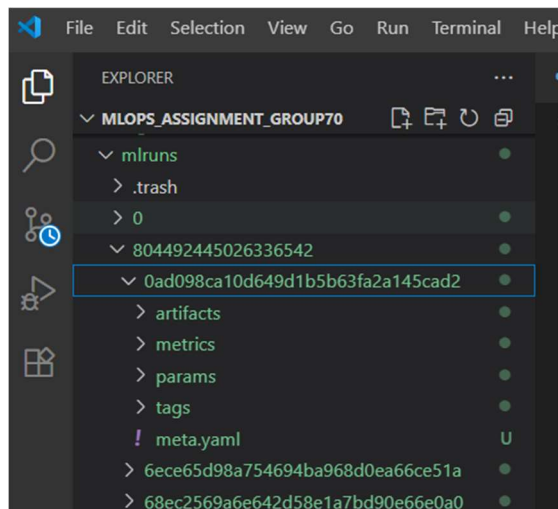
- **Dataset:** Iris flower classification
- **Features:** Sepal length/width, Petal length/width
- **Classes:** Setosa, Versicolor, Virginica
- **Models:** Logistic Regression, Random Forest, SVM
- **Evaluation:** Accuracy, Precision, Recall, F1-score

MLflow Integration:

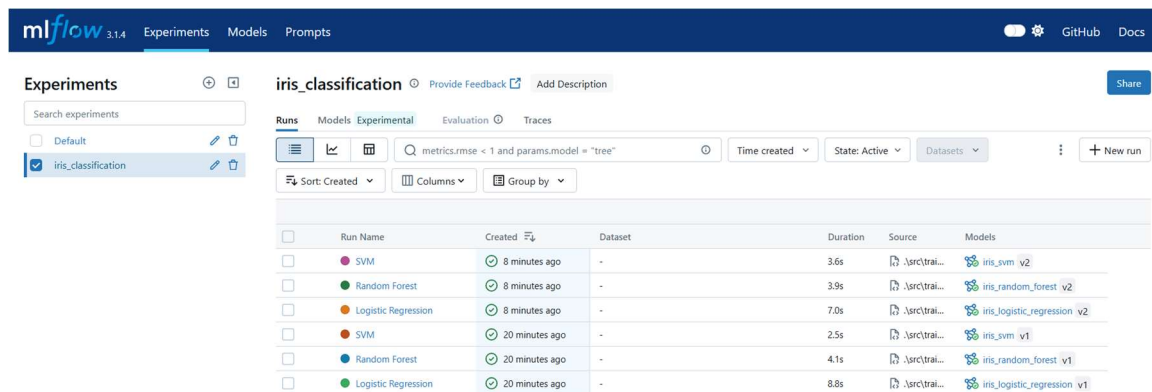
- Experiment tracking with parameters and metrics (`src/train.py`)
- Model versioning and artifact storage
- Model registry for best model selection

Following directories are created by MLflow under `mlruns/<experiment-id>/<run-id>/`:

- `params/`: model hyperparameters
- `metrics/`: performance metrics
- `artifacts/`: saved models
- `tags/`: metadata like model name or author



- MLflow UI accessible at `http://localhost:5000`

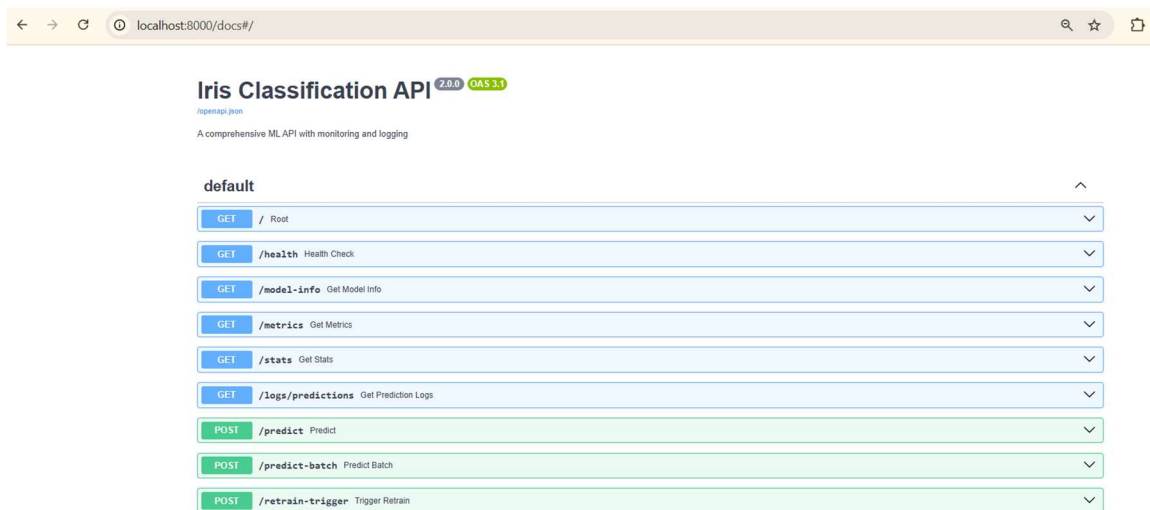


- **Model Selection:** Automated best model selection based on performance metrics

Part 3: API & Docker Packaging

FastAPI Implementation: High-performance REST API (`src/api.py`) with:

- Automatic API documentation with Swagger UI
- GET / - API information and status
- GET /health - Health check endpoint
- POST /predict - Make predictions single predictions
- POST /predict/batch - Batch predictions for batch predictions
- GET /model/info - Current model information
- GET /metrics - Prometheus metrics
- POST /retrain-trigger - Retrain Model

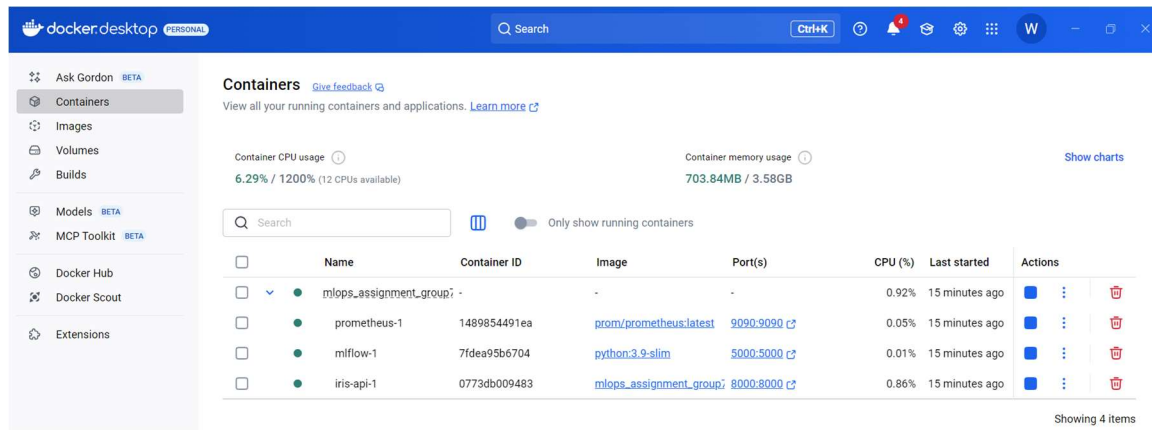


Pydantic schemas are used for request validation.

Docker Containerization: This is fully containerized using Docker.

- Multi-stage Dockerfile for optimized images
- Docker Compose orchestration (`docker-compose.yml`)
- Health checks and restart policies
- Build and run with Docker Compose

```
docker-compose up --build
```

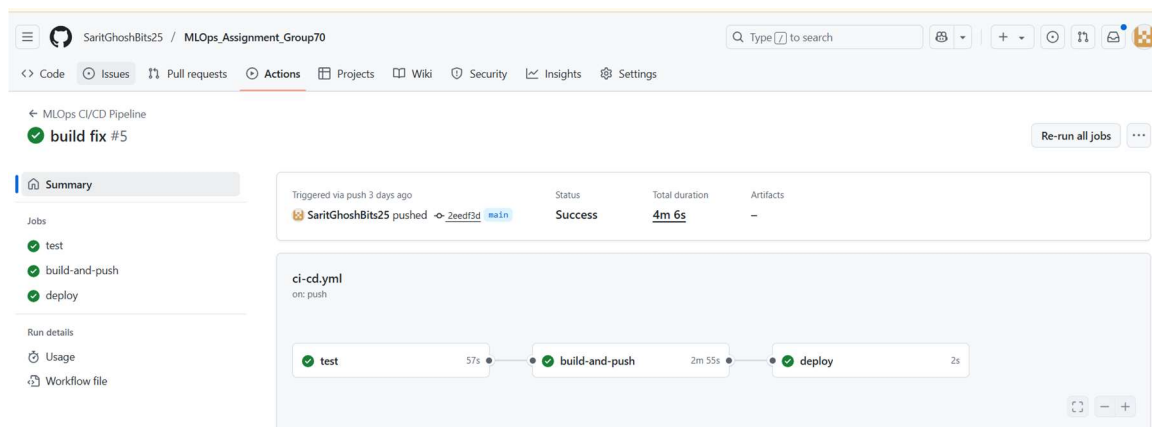


This will start:

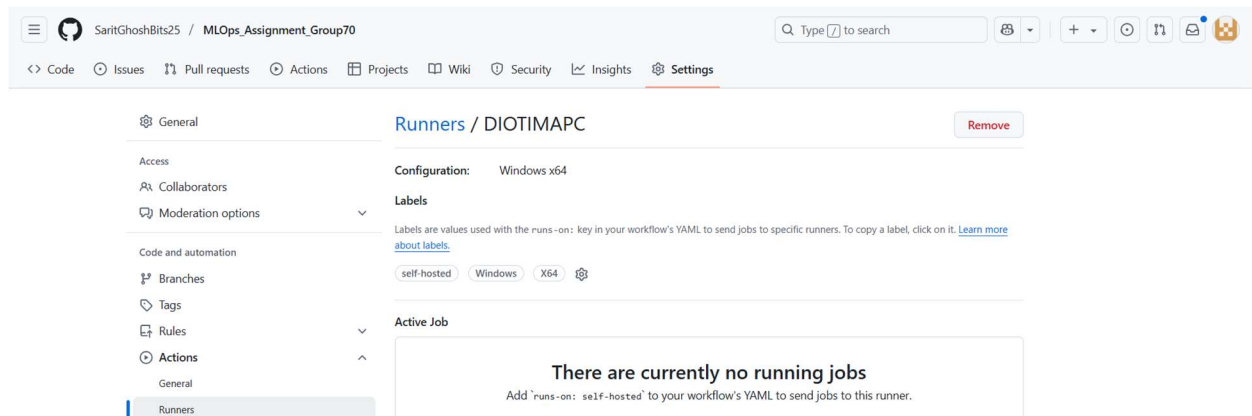
- **Iris API:** http://localhost:8000
- **Prometheus:** http://localhost:9090
- **MLflow:** http://localhost:5000
- **JSON Input/Output:** Structured JSON request/response format with validation

Part 4: CI/CD with GitHub Actions

- **Automated Pipeline** (.github/workflows/ci-cd.yml):
- **Testing Stage:** Code linting, unit tests, and API health verification
- **Build Stage:** Docker image building and container testing
- **Deploy Stage:** Automated deployment with health monitoring
- **Code Quality:** Automated linting and testing on every push
- **Docker Hub Integration:** Automated image building and registry push



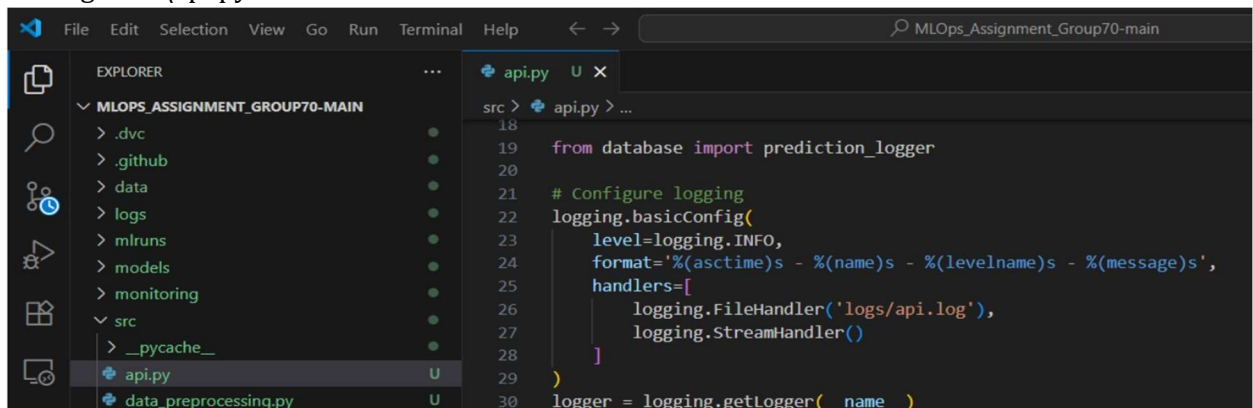
- **Deployment:** Local deployment with self-hosted runner



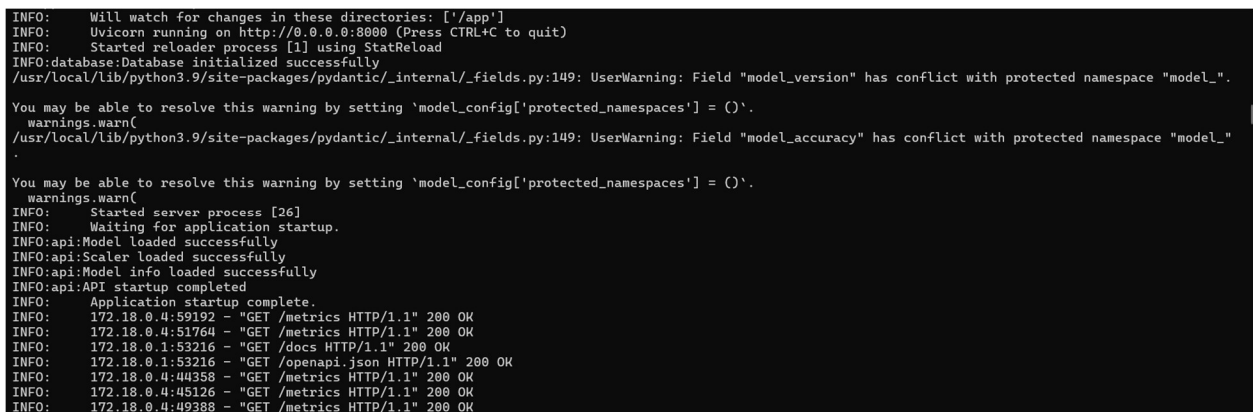
Part 5: Logging and Monitoring

Comprehensive Logging:

- API logs: src\api.py



API Logging:



- **Container logs:** docker-compose logs <service-name>
- **MLflow logs:** Available in MLflow UI

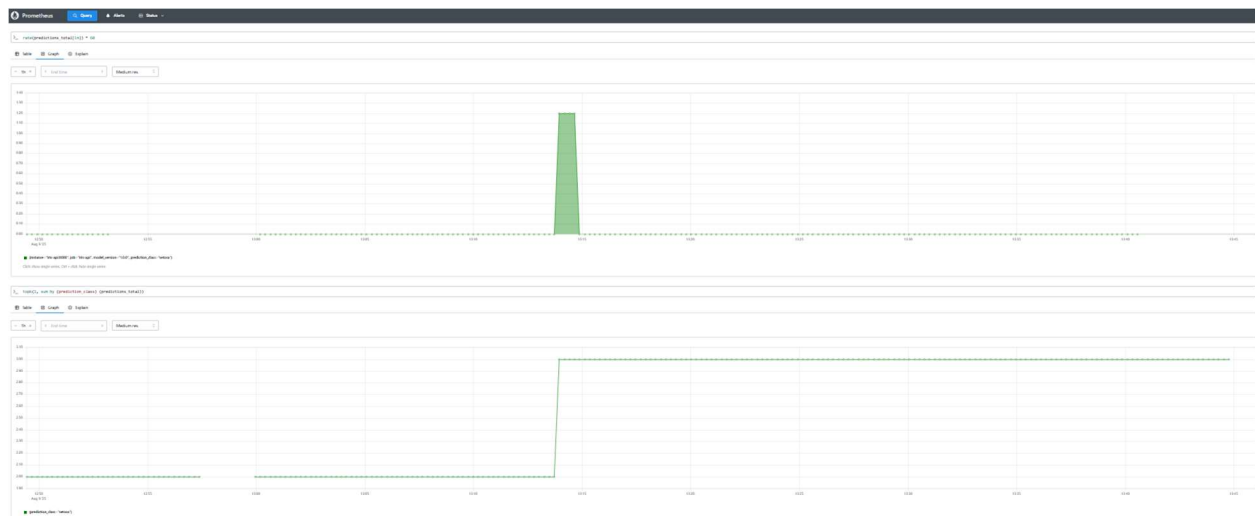
All predictions are logged to SQLite database for persistence storage with (`src/database.py`):

- Prediction ID and timestamp
- Input features and predictions
- Model version and confidence scores
- Request metadata

id	timestamp	endpoint	method	status_code	response_time_ms	client_ip	error_message
1	2025-08-08T16:57:40.916654	/metrics	GET	200	81.2022686004639	172.18.0.3	NULL
2	2025-08-08T16:57:49.845136	/metrics	GET	200	1.16205215454102	172.18.0.3	NULL
3	2025-08-08T16:57:59.840455	/metrics	GET	200	0.974655151367188	172.18.0.3	NULL
4	2025-08-08T16:58:09.838267	/metrics	GET	200	1.07765197753906	172.18.0.3	NULL
5	2025-08-08T16:58:19.839541	/metrics	GET	200	0.864267349243164	172.18.0.3	NULL
6	2025-08-08T16:58:29.840958	/metrics	GET	200	1.51228904724121	172.18.0.3	NULL
7	2025-08-08T16:58:39.839539	/metrics	GET	200	1.23429298400879	172.18.0.3	NULL
8	2025-08-08T16:58:49.839601	/metrics	GET	200	0.972509384155273	172.18.0.3	NULL
9	2025-08-08T16:58:59.825437	/metrics	GET	200	1.5556812286377	172.18.0.3	NULL
10	2025-08-08T16:59:09.834313	/metrics	GET	200	2.77590751647949	172.18.0.3	NULL

Monitoring Integration:

- Prometheus metrics endpoint (`/metrics`)
- Custom metrics for predictions, latency, and model performance
- Prometheus configuration (`monitoring/prometheus.yml`)



Health Monitoring: Dedicated health check endpoints for system status

Part 6: Summary + Demo

- **Architecture Documentation:** Comprehensive summary with system architecture
- **Demo Preparation:** Complete setup instructions and API usage examples
- **Video Walkthrough:** Ready-to-demonstrate solution with all components integrated

Bonus Features

Input Validation:

- Pydantic models for request/response validation
- Schema-based input validation with error handling

Prometheus Integration:

- Full Prometheus monitoring setup
- Custom metrics dashboard ready
- Real-time performance monitoring

Model Retraining via API:

The `/retrain` endpoint supports:

- Automated retraining pipeline (`src/retrain_pipeline.py`)
- Performance-based retraining triggers
- Continuous model improvement workflow
- Retraining the best model
- Logging it to MLflow
- Saving the new model to registry