Cats vs Dogs Classification

End-to-End Production-Grade MLOps Pipeline

Team Details

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1. Project Overview

This project implements a **complete production-ready MLOps pipeline** for binary image classification (Cats vs Dogs).

The pipeline demonstrates:

- Reproducible data versioning (DVC)
- Experiment tracking (MLflow)
- Model training and artifact logging
- Containerized inference (FastAPI + Docker)
- CI/CD automation (GitHub Actions)
- Deployment validation
- Monitoring & post-deployment evaluation

Dataset:

Kaggle Cats vs Dogs Dataset

Images are:

- Converted to RGB
- Resized to 224×224
- Split into train/val/test (80/10/10)
- Augmented for generalization

2. System Architecture

```
Raw Dataset
      ↓
DVC Data Pipeline
      ↓
Training (MLflow Tracking)
      ↓
Model Artifact
      ↓
Docker Build (CI)
      ↓
Docker Hub
      ↓
CD Deployment (Docker Compose)
      ↓
FastAPI Service
      ↓
Monitoring & Evaluation
```

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3. Setup Instructions

3.1 Requirements

- Python 3.10+
- Git
- Docker
- DVC
- MLflow

3.2 Clone Repository

```
git clone https://github.com/Krithika-Madhavan-5421/MLOPS-ASSIGNMENT2-GROUP44.git
cd MLOPS-ASSIGNMENT2-GROUP44
```

3.3 Create Virtual Environment

```
conda create -n cats-dogs-mlops python=3.10 -y
conda activate cats-dogs-mlops
```

or

```
python -m venv venv
source venv/bin/activate
```

3.4 Install Dependencies

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

---

4. Data Versioning & Reproducibility (DVC)

4.1 DVC Pipeline Structure

The project defines reproducible stages in `dvc.yaml`:

```
stages:
  data_preparation:
    cmd: python src/data_preparation.py
    deps:
      - src/data_preparation.py
      - data/raw
    outs:
      - data/processed

  train:
    cmd: python src/train.py
    deps:
      - src/train.py
      - data/processed
    outs:
      - models/model.pth
```

4.2 Running Full Pipeline

To reproduce the entire pipeline:

```
dvc repro
```

This will:

- Run data preprocessing

- Train model
- Regenerate artifacts if dependencies changed

4.3 Pulling Artifacts from Remote

If DVC remote is configured:

```
dvc pull
```

Restores:

- Processed dataset
- Model weights

Why DVC?

- Large data not stored in Git
- Reproducible training
- Controlled dataset versioning
- Automatic dependency tracking

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5. Model Development & Experiment Tracking

5.1 Baseline CNN Model

Architecture:

- 3 Conv blocks
- Batch Normalization
- ReLU
- MaxPooling
- Global Average Pooling
- Fully connected output

Loss Function:

```
BCEWithLogitsLoss
```

5.2 Training

```
python src/train.py
```

Includes:

- Data augmentation
- Learning rate scheduler
- Weight decay
- MLflow experiment logging

5.3 MLflow Tracking

MLflow logs:

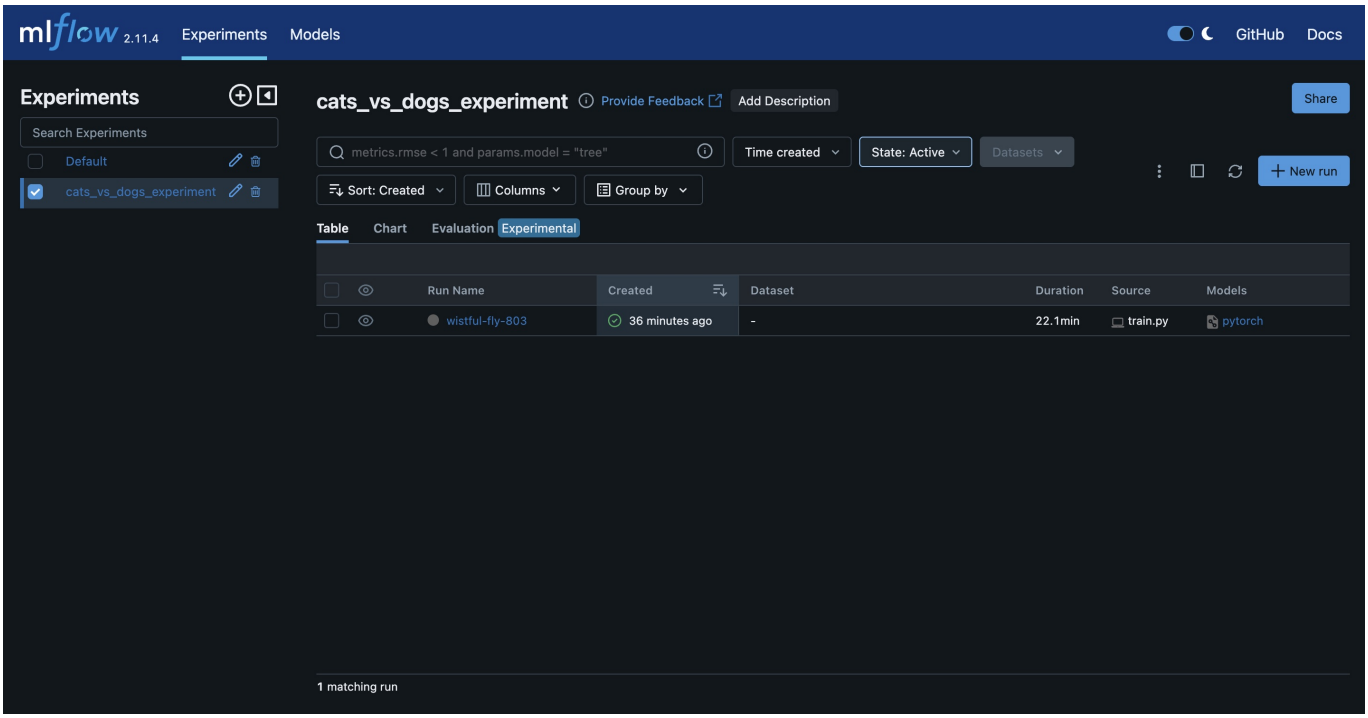
- Hyperparameters
- Loss curves
- Validation accuracy
- Confusion matrix
- Model artifacts

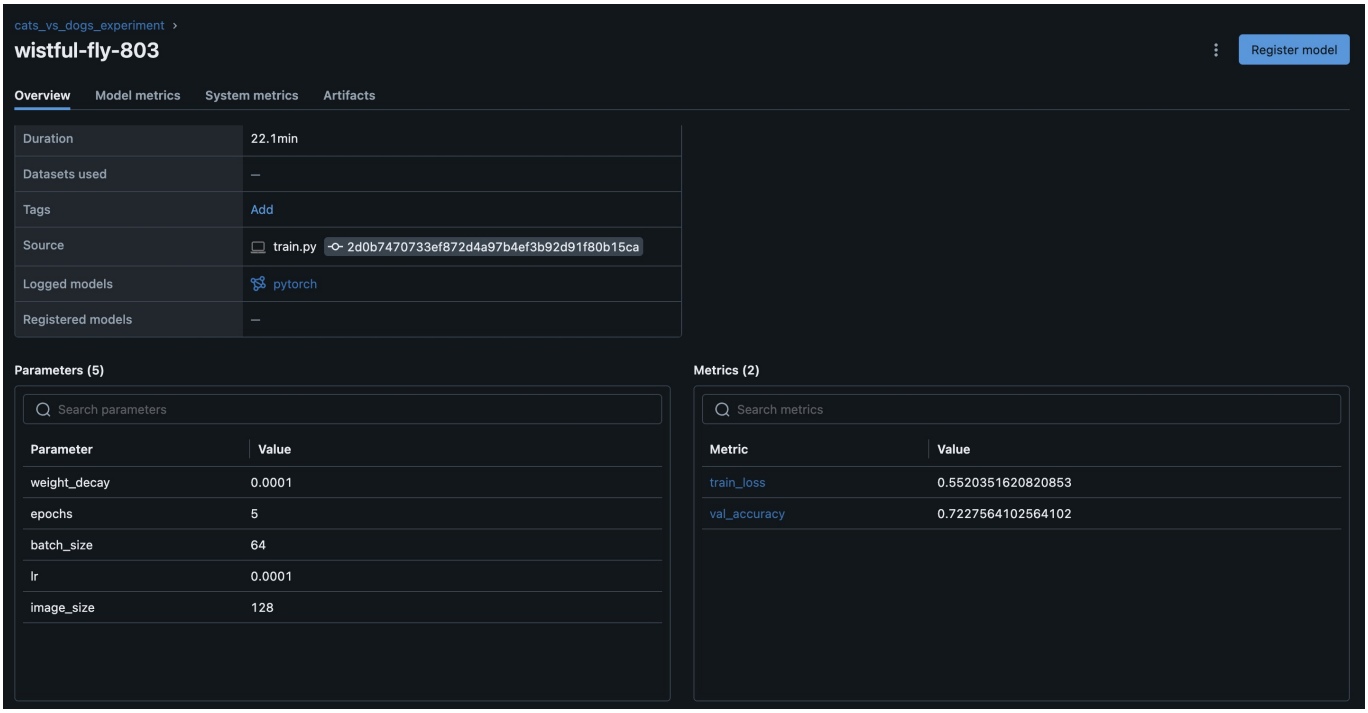
Launch UI:

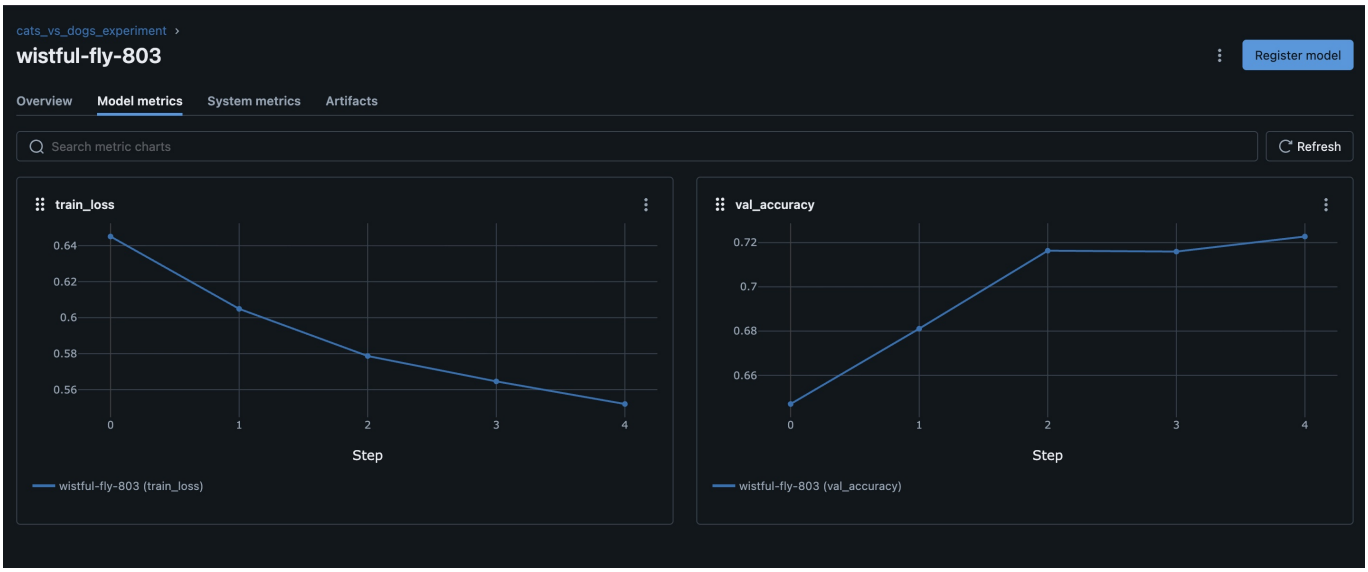
```
mlflow ui
```

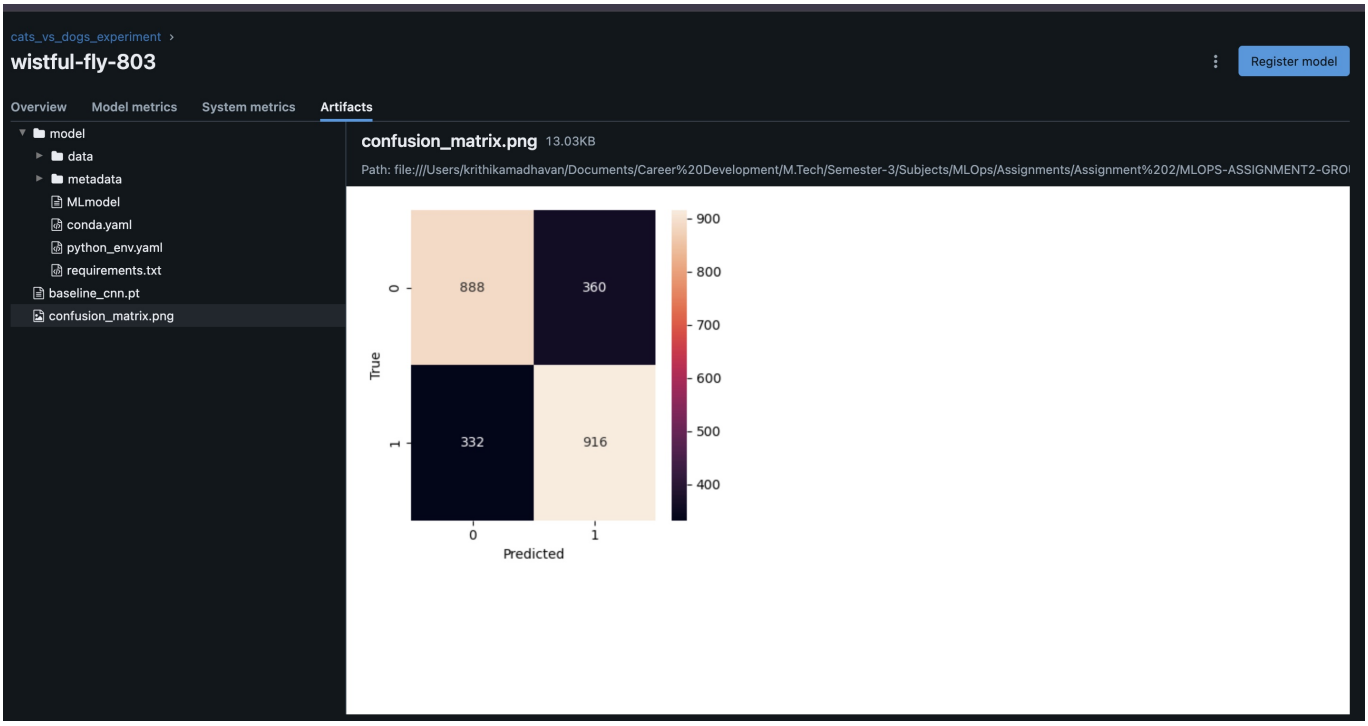
Access:

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


mlflow 2.11.4
Experiments
Models
GitHub
Docs
Experiments
Search Experiments
Default
cats_vs_dogs_experiment
cats_vs_dogs_experiment
Provide Feedback
Add Description
Share
metrics.rmse < 1 and params.model = "tree"
Time created
State: Active
Datasets
Sort: Created
Columns
Group by
New run
Table
Chart
Evaluation
Experimental
Run Name
Created
Dataset
Duration
Source
Models
wistful-fly-803
36 minutes ago
-
22.1min
train.py
pytorch
1 matching run


cats_vs_dogs_experiment ›
wistful-fly-803
Register model
Overview
Model metrics
System metrics
Artifacts
Duration
22.1min
Datasets used
–
Tags
Add
Source
train.py
2d0b7470733ef872d4a97b4ef3b92d91f80b15ca
Logged models
pytorch
Registered models
–
Parameters (5)
Search parameters
Parameter
Value
weight_decay
0.0001
epochs
5
batch_size
64
lr
0.0001
image_size
128
Metrics (2)
Search metrics
Metric
Value
train_loss
0.5520351620820853
val_accuracy
0.7227564102564102





6. Model Serving & Dockerization

6.1 FastAPI Inference Service

Endpoints:

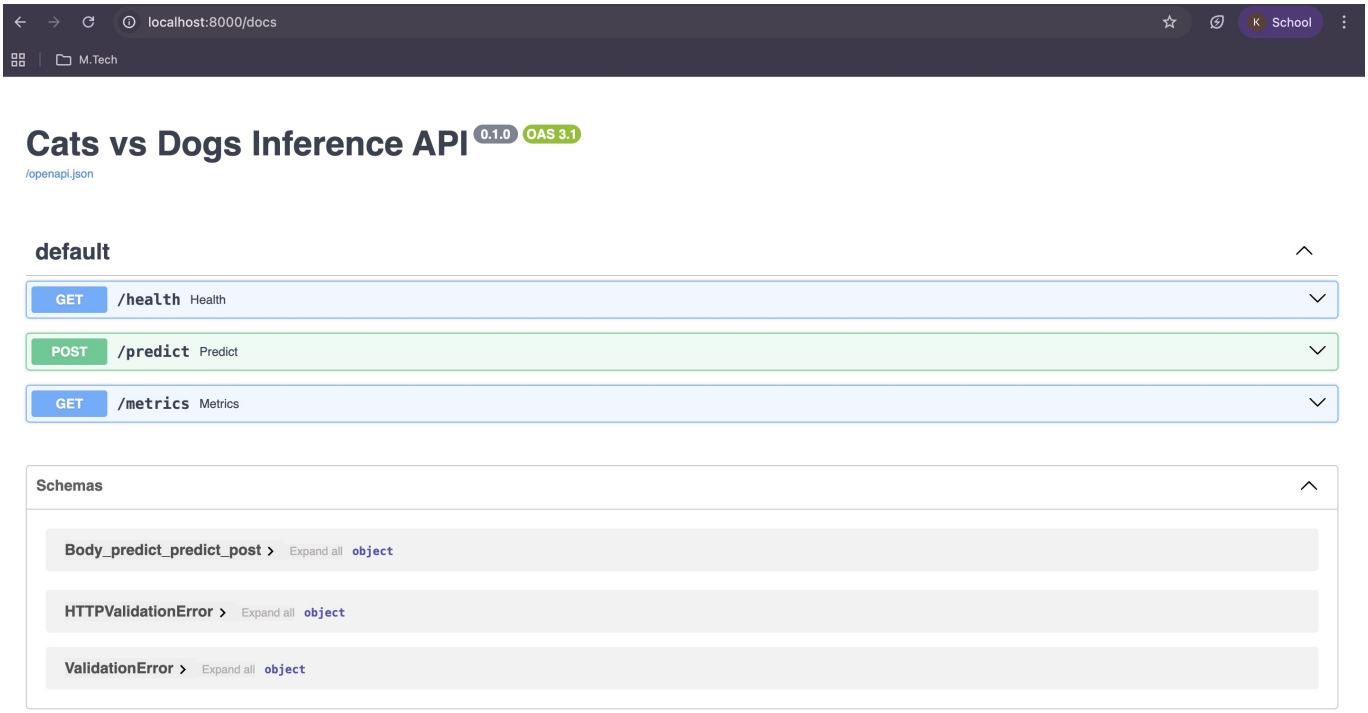
Endpoint	Purpose
`/health`	Health check
`/predict`	Image classification
`/metrics`	Runtime metrics

Run locally:

```
uvicorn src.inference_app:app --host 0.0.0.0 --port 8000
```

Swagger:

```
http://localhost:8000/docs
```



6.2 Docker Build

```
docker build -t <dockerhub-username>/cats-dogs-inference:latest .
```

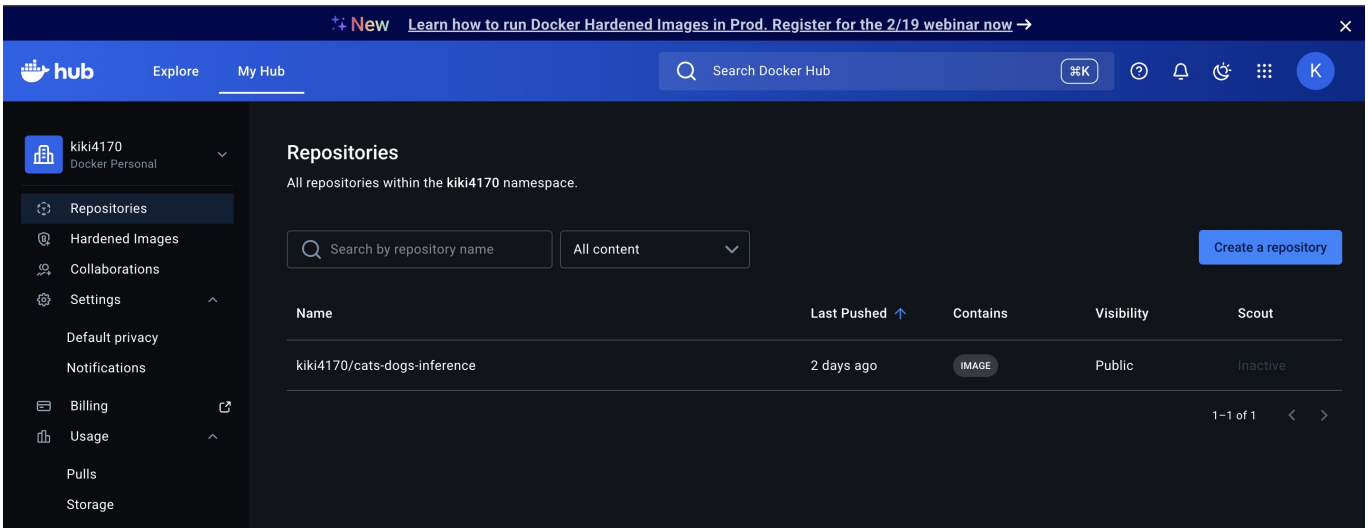
Run:

```
docker run -p 8000:8000 <dockerhub-username>/cats-dogs-inference:latest
```

7. Docker Hub Integration

Manual Push

```
docker login
docker push <dockerhub-username>/cats-dogs-inference:latest
```



GitHub Secrets Required

Add in repository settings:

- `DOCKER_USERNAME`
- `DOCKER_PASSWORD`

CI Docker Push Workflow

```
- name: Login to Docker Hub
  run: echo "${{ secrets.DOCKER_PASSWORD }}" | docker login -u "${{
secrets.DOCKER_USERNAME }}" --password-stdin

- name: Build Image
  run: docker build -t ${{ secrets.DOCKER_USERNAME }}/cats-dogs-
inference:latest .

- name: Push Image
  run: docker push ${{ secrets.DOCKER_USERNAME }}/cats-dogs-
inference:latest
```

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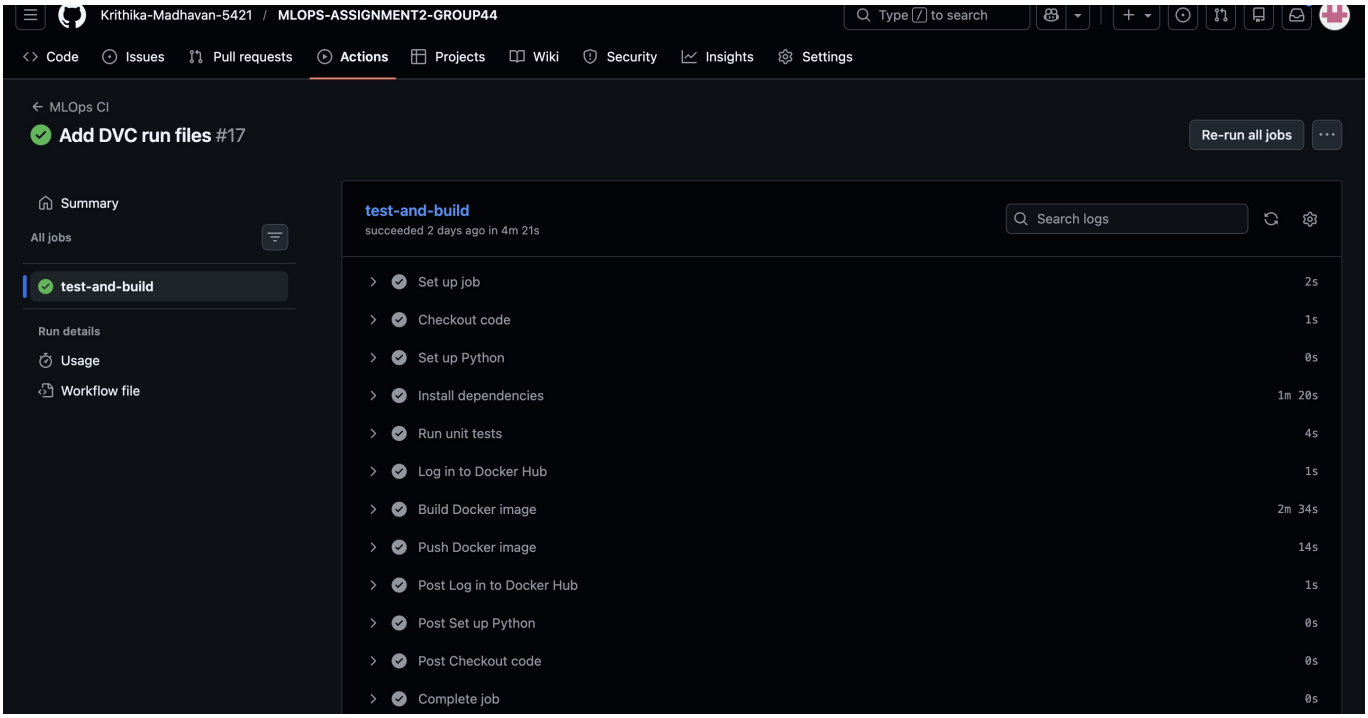
8. Continuous Integration (CI)

Triggered on push.

Pipeline:

1. Install dependencies
2. Run pytest unit tests
3. Build Docker image
4. Push image to Docker Hub



9. Continuous Deployment (CD)

Deployment via Docker Compose.

Example:

```
version: "3.8"
services:
  inference:
    image: <dockerhub-username>/cats-dogs-inference:latest
    ports:
      - "8000:8000"
    restart: always
```

Deploy:

```
docker compose pull
docker compose up -d
```

Smoke tests:

- `/health`
- `/predict`

Fail deployment if tests fail.

cd1.jpg

10. Monitoring & Post-Deployment Evaluation

Runtime Metrics

`GET /metrics` returns:

- Total requests
- Average latency
- Prediction count

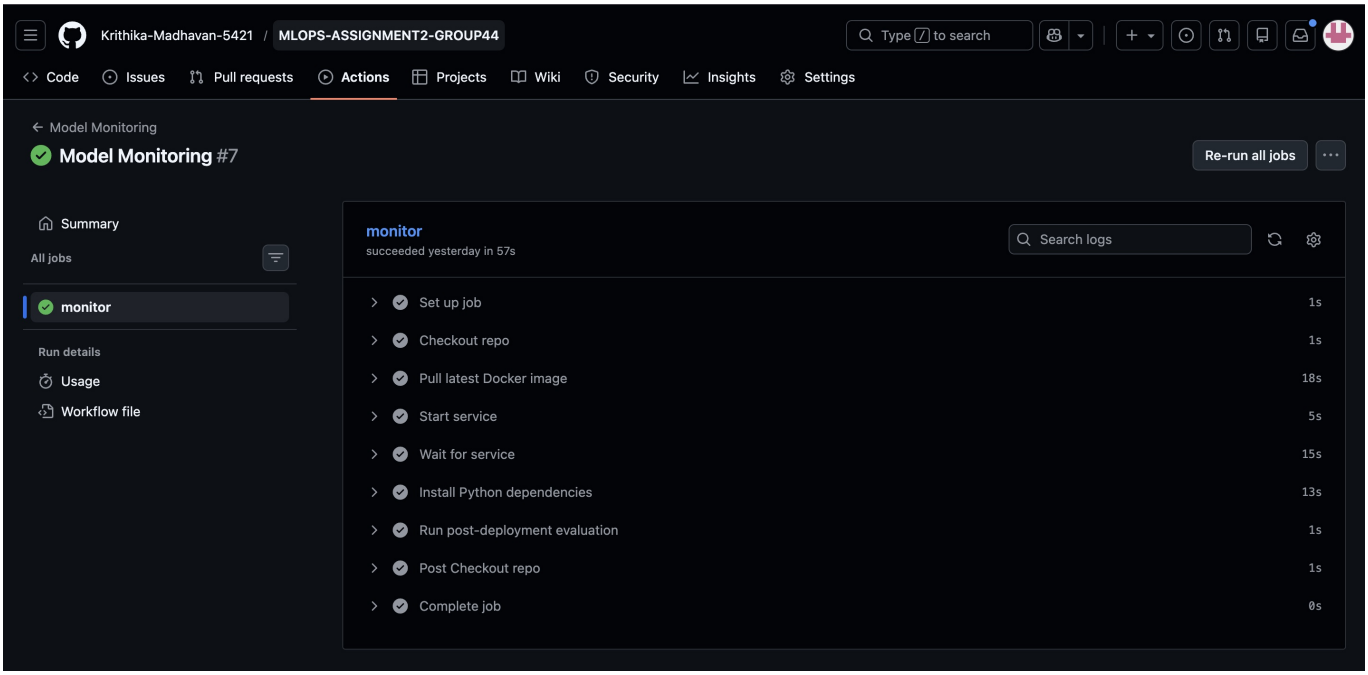
Post-Deployment Accuracy Validation

Separate workflow:

- Sends labeled test data
- Computes accuracy
- Enforces threshold
- Fails if below threshold

Example output:

```
Post-deployment accuracy: 1.0
```



11. Engineering Decisions

- Global Average Pooling reduces parameters
- DVC ensures reproducibility
- MLflow enables experiment tracking

- Docker ensures portability
- CI/CD ensures automation
- Lazy model loading for performance
- Separate monitoring workflow

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12. Repository

🔗 https://github.com/Krithika-Madhavan-5421/MLOPS-ASSIGNMENT2-GROUP44

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13. Conclusion

This project demonstrates a complete industrial-grade ML lifecycle including:

- Reproducible training
- Experiment management
- Containerized inference
- Automated CI/CD
- Monitoring & validation

It reflects production MLOps best practices and ensures:

- Scalability
- Automation
- Reliability
- Deployment readiness
- Performance validation
