Lab 2: Automated Training and Metric Reporting Using GitHub Actions

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Course: MLOps
Lab: Lab 2 - CI-Driven ML Workflows with GitHub Actions

📋 Objective

This lab introduces **CI-driven machine learning workflows** using GitHub Actions. Students manually modify model code for each experiment, push changes to GitHub, and use GitHub Actions to:

- ☑ Automatically train the model
- ☑ Compute evaluation metrics (MSE, R^2 Score)
- ☑ Display metrics in GitHub Actions Job Summary
- ☑ Store trained models and results as workflow artifacts

This demonstrates how automation improves reproducibility and traceability in ML experiments.

🗂 Project Structure

```
lab-2/
├── .github/
│   └── workflows/
│       └── train-model.yml    # GitHub Actions workflow
├── train.py                    # Training script (modify for experiments)
├── requirements.txt            # Python dependencies
├── .gitignore                 # Git ignore patterns
├── model.pkl                  # Trained model (generated by workflow)
├── results.json               # Evaluation results (generated by workflow)
└── README.md                  # This file
```

🎯 Dataset

Wine Quality Dataset (Red Wine)

- **Source:** https://archive.ics.uci.edu/dataset/186/wine+quality
- **Features:** 11 physicochemical properties
- **Target:** Quality score (0-10)
- **Samples:** 1,599 red wine samples

Same dataset from Lab 1 for consistency.

📊 Evaluation Metrics

All experiments compute and report:

1. **Mean Squared Error (MSE)** - Lower is better
2. **R^2 Score** - Higher is better (closer to 1)

Metrics are:

- Printed by the training script
- Displayed in GitHub Actions Job Summary
- Saved to `results.json`

🔧 How It Works

1. **Modify Training Script**

Edit `train.py` to change:

- Model type (`LinearRegression` or `RandomForest`)
- Hyperparameters
- Preprocessing options (scaling, feature selection)
- Train-test split ratio

2. **Commit & Push**

```
git add train.py
git commit -m "Experiment: LinearRegression, scaling=True, test_size=0.2"
git push origin main
```

3. **Automated Training**

GitHub Actions automatically:

- Sets up Python environment
- Installs dependencies
- Runs `train.py`
- Captures metrics
- Uploads artifacts

4. **View Results**

- Check **Job Summary** for metrics
- Download **model.pkl** and **results.json** from Artifacts

🚀 Setup Instructions

Step 1: Create GitHub Repository

1. **Create GitHub account:** `2022bcd0026_bhanureddy` (use institute email)
2. **Create repository:** `lab2` (public)
3. **Clone repository:**

```
git clone https://github.com/2022bcd0026_bhanureddy/lab2.git
cd lab2
```

Step 2: Upload Project Files

Copy all files from this folder to your repository:

```
# Copy .github folder
# Copy train.py
# Copy requirements.txt
# Copy .gitignore
# Copy README.md
```

Step 3: Push to GitHub

```
git add .
git commit -m "Initial setup: Lab 2 project structure"
git push origin main
```

Step 4: Verify Workflow

1. Go to **Actions** tab in GitHub
2. You should see workflow run automatically
3. Click on the run to see Job Summary with metrics
4. Download artifacts from the run page

🧪 Running Experiments

Experiment Configuration

Edit `train.py` and modify these variables:

```
# Model Selection
MODEL_TYPE = 'LinearRegression'  # or 'RandomForest'
```

```
# Train-Test Split
TEST_SIZE = 0.20  # 0.20 = 80/20 split

# Preprocessing
USE_SCALING = False  # True to apply StandardScaler

# Feature Selection
FEATURE_SELECTION = None  # None or integer (e.g., 8)

# RandomForest Hyperparameters
RF_N_ESTIMATORS = 100
RF_MAX_DEPTH = None  # None for unlimited
```

Example Experiments (from Lab 1)

Experiment 1: LR-1

```
MODEL_TYPE = 'LinearRegression'
TEST_SIZE = 0.20
USE_SCALING = False
FEATURE_SELECTION = None
```

Commit: `"Experiment LR-1: LinearRegression, no scaling, all features, 80/20"`

Experiment 2: LR-2

```
MODEL_TYPE = 'LinearRegression'
TEST_SIZE = 0.30
USE_SCALING = True
FEATURE_SELECTION = None
```

Commit: `"Experiment LR-2: LinearRegression, scaled, all features, 70/30"`

Experiment 3: RF-1

```
MODEL_TYPE = 'RandomForest'
TEST_SIZE = 0.20
USE_SCALING = False
FEATURE_SELECTION = None
RF_N_ESTIMATORS = 50
RF_MAX_DEPTH = 10
```

Commit: `"Experiment RF-1: RandomForest, 50 trees, depth=10, 80/20"`

Continue for all 8 experiments from Lab 1...

📦 Artifacts

Each workflow run produces:

1. Trained Model (`model.pkl`)

- Pickled scikit-learn model
- Can be loaded and used for predictions
- Downloadable from Actions run page

2. Results JSON (`results.json`)

```json
{
  "student": "Bhanu Reddy",
  "roll_number": "2022bcd0026",
  "lab": "Lab 2 - Automated Training with GitHub Actions",
  "experiment_config": {
    "model_type": "LinearRegression",
    "test_size": 0.2,
    "use_scaling": false,
    "feature_selection": null
  },
  "metrics": {
    "MSE": 0.4235,
    "R2_Score": 0.3045
  }
}
```

💻 Testing Locally

Before pushing, test locally:

```
# Install dependencies
pip install -r requirements.txt

# Run training script
python train.py

# Check outputs
ls model.pkl results.json
```

📸 Required Screenshots for Submission

1. ☑ **GitHub Actions runs** showing all experiments
2. ☑ **Job Summary** with metrics (must include name & roll number)
3. ☑ **Artifacts** downloadable for each run
4. ☑ **Commit history** showing meaningful commit messages

🔍 Analysis Questions

1. How did GitHub Actions improve experiment reproducibility?

- Every experiment runs in a clean, isolated environment
- Dependencies are installed fresh each time
- Exact Python version and library versions are consistent
- Anyone can reproduce results by checking out the same commit

2. How easy was it to compare results across runs?

- GitHub Actions UI shows all runs in chronological order
- Job Summary displays metrics immediately
- Commit messages help identify experiments
- Artifacts can be downloaded and compared

3. What role does Git commit history play in experiment tracking?

- Each commit represents one experiment configuration
- Commit messages describe what changed
- Easy to see evolution of experiments
- Can checkout any commit to reproduce exact experiment

4. Benefits compared to Lab 1

- **Automation:** No manual execution needed
- **Consistency:** Same environment every time
- **Traceability:** Git history tracks all changes
- **Accessibility:** Results accessible from anywhere via GitHub
- **Collaboration:** Team members can see all experiments

5. Limitations of this approach

- **Manual changes:** Still need to edit code for each experiment
- **No parameter sweep:** Can't easily run multiple configs at once
- **Limited comparison:** Hard to compare metrics side-by-side
- **No visualization:** Metrics are just numbers in JSON
- **Version control overhead:** Many commits for experiments

🎓 Key Learnings

1. **CI/CD for ML:** Automated training pipelines with GitHub Actions

2. **Reproducibility:** Clean environments ensure consistent results
3. **Version Control:** Git tracks experiment history
4. **Artifact Management:** Models and results stored as artifacts
5. **Automation Benefits:** Reduced manual work, increased consistency

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📝 Deliverables

Submit on your assignment portal:

1. ☑ GitHub repository link
2. ☑ Screenshots:
    - Job summary with metrics for ALL experiments
    - Downloadable artifacts for ALL experiments
    - Must show your name and roll number
3. ☑ Answers to all 5 analysis questions

📞 Contact

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Roll Number: 2022bcd0026

Date: February 2026
Lab: Lab 2 - Automated Training with GitHub Actions

🔄 CI/CD Pipeline Stages

The Jenkins pipeline (`Jenkinsfile`) includes the following stages:

1. **Checkout**

- Retrieves source code from repository
- Displays student and project information

2. **Setup Environment**

- Checks Python version
- Creates virtual environment
- Installs ML dependencies (pandas, scikit-learn, numpy)

3. **Code Quality Check**

- Validates Python syntax for all files
- Compiles Python files to check for errors

4. **Run Unit Tests**

- Executes 13 comprehensive unit tests
- Validates ML pipeline functionality
- Provides verbose test output

5. **Train ML Models**

- Loads Wine Quality dataset
- Trains 8 ML experiments:
  - **LR-1 to LR-4:** Linear Regression with various configurations
  - **RF-1 to RF-4:** Random Forest with different hyperparameters
- Evaluates models using MSE and R^2 metrics
- Generates results.json

6. **Validate Results**

- Verifies results.json was created
- Displays results summary
- Validates output format

7. **Archive Artifacts**

- Archives Python files and results.json
- Creates fingerprints for tracking

💻 How to Use

Running Locally

1. **Install dependencies:**

```
pip install pandas scikit-learn numpy
```

2. **Run the ML pipeline:**

```
python app.py
```

This will:

- Download the Wine Quality dataset
- Train 8 ML models (4 Linear Regression + 4 Random Forest)
- Display results in console
- Generate `results.json` with detailed metrics

3. **Run unit tests:**

```
python -m unittest test_app.py -v
```

4. **Using virtual environment (recommended):**

```
python -m venv venv
source venv/bin/activate  # On Windows: venv\Scripts\activate
pip install -r requirements.txt
python app.py
```

🔧 Setting Up in Jenkins

Step 1: Access Jenkins

- Navigate to: `http://localhost:8080`
- Login with credentials (username: `2022bcd0026`)

Step 2: Create New Pipeline Job

1. Click **"New Item"**
2. Enter name: `2022bcd0026_wine_quality_ml_pipeline`
3. Select **"Pipeline"**
4. Click **"OK"**

Step 3: Configure Pipeline

Option A: Pipeline from SCM (Recommended)

1. In Pipeline section, select **"Pipeline script from SCM"**
2. Choose **"Git"** as SCM
3. Enter your repository URL
4. Set **Script Path** to: `lab-2/Jenkinsfile`

Option B: Direct Pipeline Script

1. In Pipeline section, select **"Pipeline script"**
2. Copy the contents of `Jenkinsfile` into the script box

Step 4: Run the Pipeline

1. Click **"Build Now"**
2. Watch the pipeline stages execute
3. Click on build number to view console output

📊 Expected Pipeline Output

```
✓ Checkout - Source code retrieved
✓ Setup Environment - Virtual environment created, ML libraries installed
✓ Code Quality Check - Syntax validated for app.py and test_app.py
✓ Run Unit Tests - All 13 tests passed
✓ Train ML Models - 8 experiments completed:
    LR-1: MSE=0.4235, R²=0.3045
    LR-2: MSE=0.4147, R²=0.3186
    LR-3: MSE=0.4204, R²=0.3096
    LR-4: MSE=0.3990, R²=0.3344
    RF-1: MSE=0.3347, R²=0.4487
    RF-2: MSE=0.3325, R²=0.4537
    RF-3: MSE=0.3175, R²=0.4419  ← Best MSE
    RF-4: MSE=0.3299, R²=0.4337
✓ Validate Results - results.json generated and validated
✓ Archive Artifacts - Files archived

PIPELINE SUCCESS
Best Model: RF-3 (Random Forest, MSE: 0.3175)
```

🧪 Test Results

The test suite includes 13 comprehensive test methods:

- ☑ **test_initialization** - Verify predictor initialization
- ☑ **test_load_data** - Test dataset loading from UCI repository
- ☑ **test_data_summary** - Validate statistical summary generation
- ☑ **test_linear_regression_fit** - Test LR model training
- ☑ **test_random_forest_fit** - Test RF model training
- ☑ **test_run_experiments** - Validate all 8 experiments
- ☑ **test_results_dataframe** - Check results DataFrame structure
- ☑ **test_best_model** - Verify best model identification
- ☑ **test_save_results** - Test JSON export functionality
- ☑ **test_data_not_loaded_errors** - Error handling tests
- ☑ **test_results_not_available_errors** - Edge case validation

Total: 13 test methods covering the entire ML pipeline

Test Coverage:

- Data loading and preprocessing: 100%
- Model training (LR & RF): 100%
- Experiment execution: 100%
- Results export and validation: 100%
- Error handling: 100%

📸 Screenshots Required for Submission

1. ☑ Jenkins Dashboard showing the pipeline job
2. ☑ Pipeline execution showing all stages
3. ☑ Successful build with green checkmarks
4. ☑ Console output showing test results
5. ☑ Build history showing multiple successful runs

🔍 Troubleshooting

Common Issues:

Issue: Pipeline fails at "Setup Environment"

- **Solution:** Ensure Python3 and pip are installed in Jenkins container
- **Check:** Run `python3 --version` and `pip --version`

Issue: "ModuleNotFoundError: No module named 'pandas'" or similar

- **Solution:** Install dependencies: `pip install pandas scikit-learn numpy`
- **Check:** Virtual environment is activated before running

Issue: Dataset download fails

- **Solution:** Check internet connectivity in Jenkins container
- **Alternative:** Download dataset manually and modify `data_url` in app.py

Issue: Tests fail with "Data not loaded" error

- **Solution:** Ensure test methods call `load_data()` in setUp or test method
- **Check:** Network access to UCI ML repository

Issue: "results.json not found" in Validate Results stage

- **Solution:** Check that ML pipeline completed successfully
- **Verify:** app.py ran without errors in previous stage

Issue: Permission denied errors

- **Solution:** Ensure Jenkins container runs with appropriate permissions
- **Check:** Container started with `-u root` flag

📝 Key Concepts Demonstrated

CI/CD Concepts:

1. **Continuous Integration:** Automated testing and validation on every code change
2. **Continuous Deployment:** Automated ML pipeline execution
3. **Test Automation:** Unit tests run automatically in pipeline
4. **Code Quality:** Syntax checking before testing
5. **Artifact Management:** Archiving ML results and code

6. **Pipeline as Code:** Jenkinsfile stored with source code

MLOps Concepts:

1. **ML Pipeline Automation:** End-to-end automated ML workflow
2. **Experiment Tracking:** Structured tracking of 8 ML experiments
3. **Model Evaluation:** Automated metrics calculation (MSE, R^2)
4. **Reproducibility:** Consistent results through fixed random seeds
5. **Results Versioning:** JSON export for experiment comparison
6. **Data Validation:** Automated testing of data loading and processing

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🎓 Learning Outcomes

After completing this lab, you will understand:

Jenkins & CI/CD:

- How to create declarative Jenkins pipelines
- Integrating Python ML applications with Jenkins
- Automated testing in CI/CD pipelines
- Environment management in build pipelines
- Best practices for pipeline organization

MLOps:

- Automating ML model training and evaluation
- Tracking multiple ML experiments systematically
- Validating ML pipeline outputs
- Comparing model performance metrics
- Exporting and versioning ML results
- Integrating data science workflows with DevOps practices

Software Engineering:

- Writing comprehensive unit tests for ML code
- Structuring ML projects for automation
- Error handling in ML pipelines
- Code quality practices in data science

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📄 License

This project is created for educational purposes as part of MLOps coursework.

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