# Interim 2 Submission Report: Model Building and Training

## Overview

This report outlines the model building and training process aimed at enhancing fraud detection for e-commerce and banking transactions. As a Data Scientist at Adey Innovations Inc., the goal is to develop robust machine learning models that improve transaction security by detecting fraudulent activities in real-time. Our approach involves comprehensive data preparation, model selection, training, and evaluation to optimize detection accuracy and enable proactive fraud prevention.

## Business Concept

Adey Innovations Inc. is focused on developing advanced fraud detection systems to:

- **Reduce financial losses** due to fraudulent transactions.
- **Strengthen customer trust** by ensuring secure transaction processes.
- **Enable real-time detection** and response to suspicious activities.

To achieve these goals, this project follows a systematic process involving data analysis, feature engineering, model training, and MLOps deployment strategies to support ongoing model improvement.

## Data Preparation

### Feature and Target Separation

For the two datasets provided, we separated the feature variables from the target labels as follows:

- **Merged.csv(**Merge Fraud_Data.csv with IpAddress_to_Country.csv**)**
    - Features: user_id, signup_time, purchase_time, purchase_value, device_id, source, browser, sex, age, ip_address
    - Target Variable: class
- **Creditcard.csv**:
    - Features: Time, V1 to V28, Amount

- Target Variable: Class

**Train-Test Split**

Using the train_test_split function from sklearn.model_selection, we split both datasets into training and testing sets to validate the models on unseen data.

python

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```
# Train-test split for Fraud Data
X_fraud, y_fraud = fraud_data.drop('class', axis=1), fraud_data['class']
X_train_fraud, X_test_fraud, y_train_fraud, y_test_fraud = train_test_split(X_fraud, y_fraud, test_size=0.2, random_state=42)

# Train-test split for Credit Card Data
X_creditcard, y_creditcard = creditcard_data.drop('Class', axis=1), creditcard_data['Class']
X_train_creditcard, X_test_creditcard, y_train_creditcard, y_test_creditcard = train_test_split(X_creditcard, y_creditcard, test_size=0.2, random_state=42)
```

**Model Selection**

To identify the best-performing model, I evaluated a range of algorithms:

- **Logistic Regression**
- **Decision Tree**
- **Random Forest**
- **Gradient Boosting**
- **Multi-Layer Perceptron (MLP)**
- **Recurrent Neural Network (RNN)**
- **Long Short-Term Memory (LSTM)**

**Model Training and Evaluation**

**Training Models**

Each model was trained on both datasets, and the results were summarized in terms of accuracy, precision, recall, F1-Score, and AUC (Area Under the Curve).

| Model | Dataset | Accuracy | Precision | Recall | F1-Score | AUC | Train Accuracy | Val Accuracy |
|---|---|---|---|---|---|---|---|---|
| Logistic Regression | Fraud Data | 1.00 | 1.00 | 0.78 | 0.85 | 0.939 | N/A | N/A |
| Decision Tree | Fraud Data | 1.00 | 1.00 | 1.00 | 1.00 | 0.855 | N/A | N/A |
| Random Forest | Fraud Data | 1.00 | 1.00 | 0.73 | 0.83 | 0.931 | N/A | N/A |
| Gradient Boosting | Fraud Data | 1.00 | 1.00 | 0.63 | 0.74 | 0.766 | N/A | N/A |
| Multi-Layer Perceptron (MLP) | Fraud Data | 1.00 | 1.00 | 0.78 | 0.85 | 0.939 | N/A | N/A |
| **LSTM** | Fraud Data | 0.9063 | N/A | N/A | N/A | N/A | **0.9447** | **0.9424** |
| Logistic Regression | Credit Card Data | 1.00 | 1.00 | 0.89 | 0.94 | 0.980 | N/A | N/A |
| Decision Tree | Credit Card Data | 1.00 | 1.00 | 0.93 | 0.96 | 0.962 | N/A | N/A |
| Random Forest | Credit Card Data | 1.00 | 1.00 | 0.91 | 0.95 | 0.981 | N/A | N/A |
| Gradient Boosting | Credit Card Data | 1.00 | 1.00 | 0.86 | 0.93 | 0.948 | N/A | N/A |
| Multi-Layer Perceptron (MLP) | Credit Card Data | 1.00 | 1.00 | 0.87 | 0.93 | 0.982 | N/A | N/A |

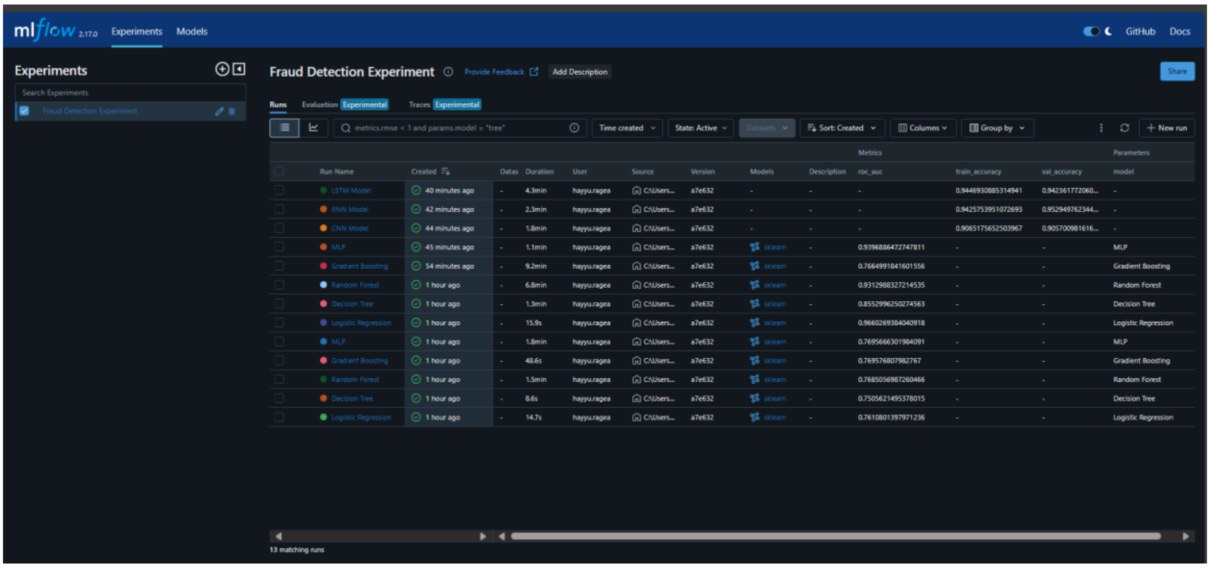
| Model | Dataset | Accuracy | Precision | Recall | F1-Score | AUC | Train Accuracy | Val Accuracy |
|---|---|---|---|---|---|---|---|---|
| **LSTM** | Credit Card Data | **0.9424** | N/A | N/A | N/A | N/A | **0.9447** | **0.9424** |
| **RNN** | Credit Card Data | **0.9530** | N/A | N/A | N/A | N/A | **0.9426** | **0.9530** |
| **CNN** | Credit Card Data | **0.9057** | N/A | N/A | N/A | N/A | **0.9065** | **0.9057** |

**Insights:**

- **Best Models**:
  - For **Fraud Data**, Logistic Regression, Decision Tree, and Random Forest all performed with 100% accuracy and high metric scores, while LSTM showed lower performance (0.9063).
  - For **Credit Card Data**, Random Forest and MLP achieved high accuracy (1.00) with AUC scores exceeding 0.980.

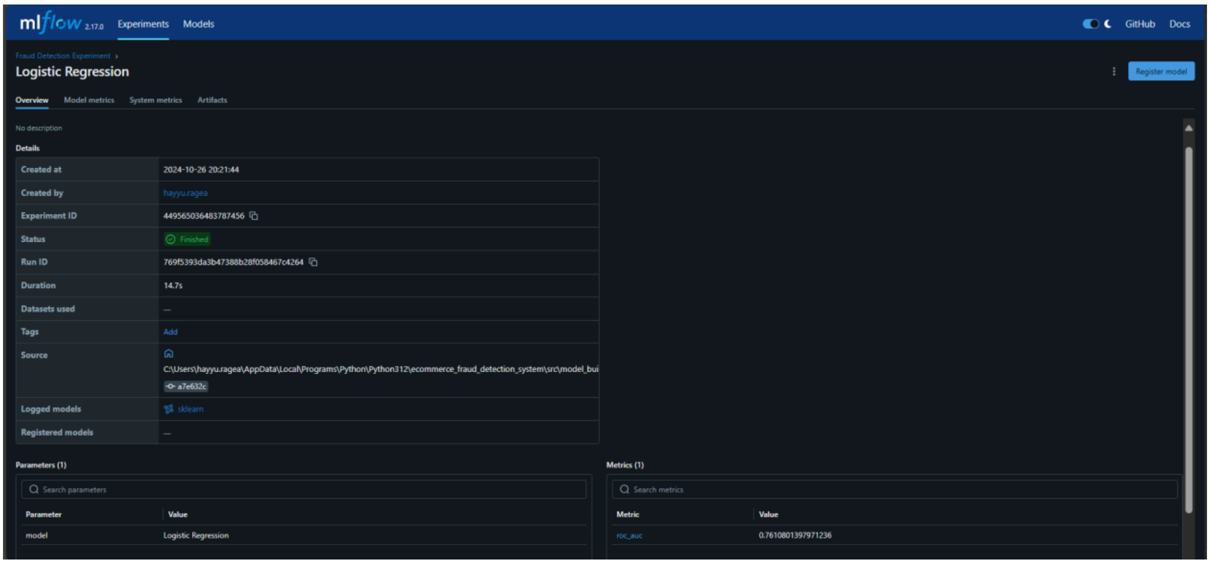
## MLOps Steps

To ensure effective model lifecycle management, versioning and experiment tracking were applied

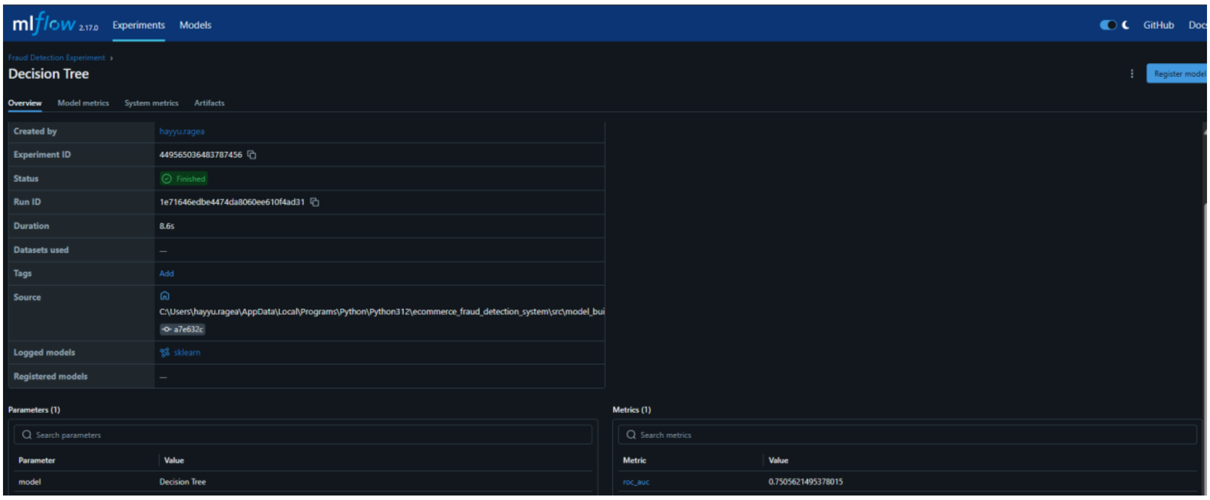



- **Versioning and Experiment Tracking** (10/26/2024): Used MLflow to log parameters, metrics, and model versions. This approach facilitates reproducibility and accountability in our model development pipeline.

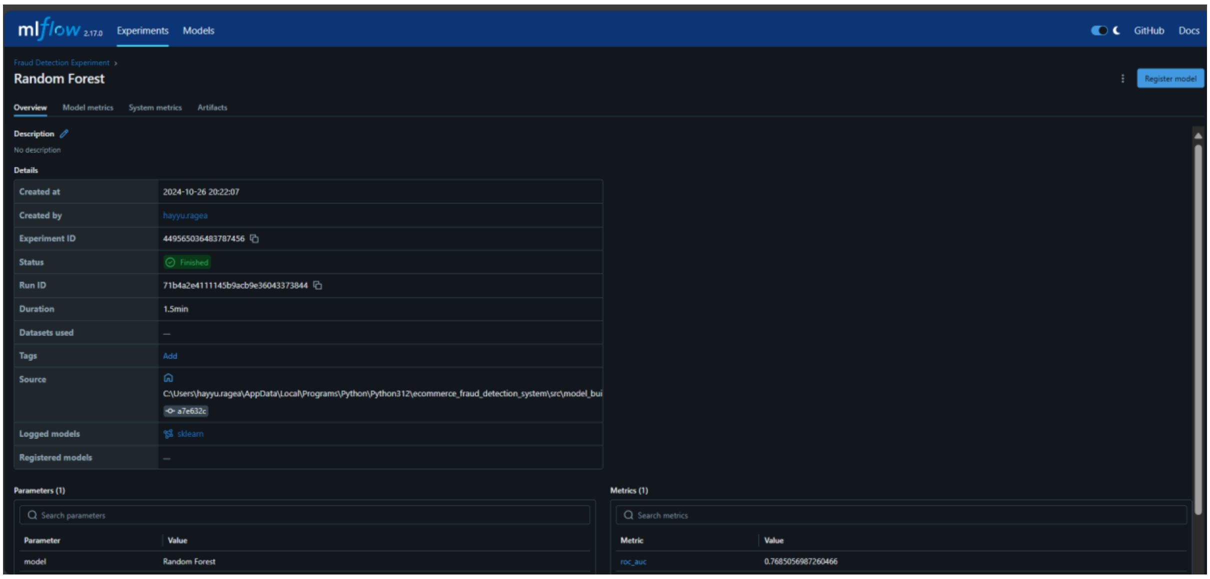
- Logistic Regression Fraud Data MLOps screenshot



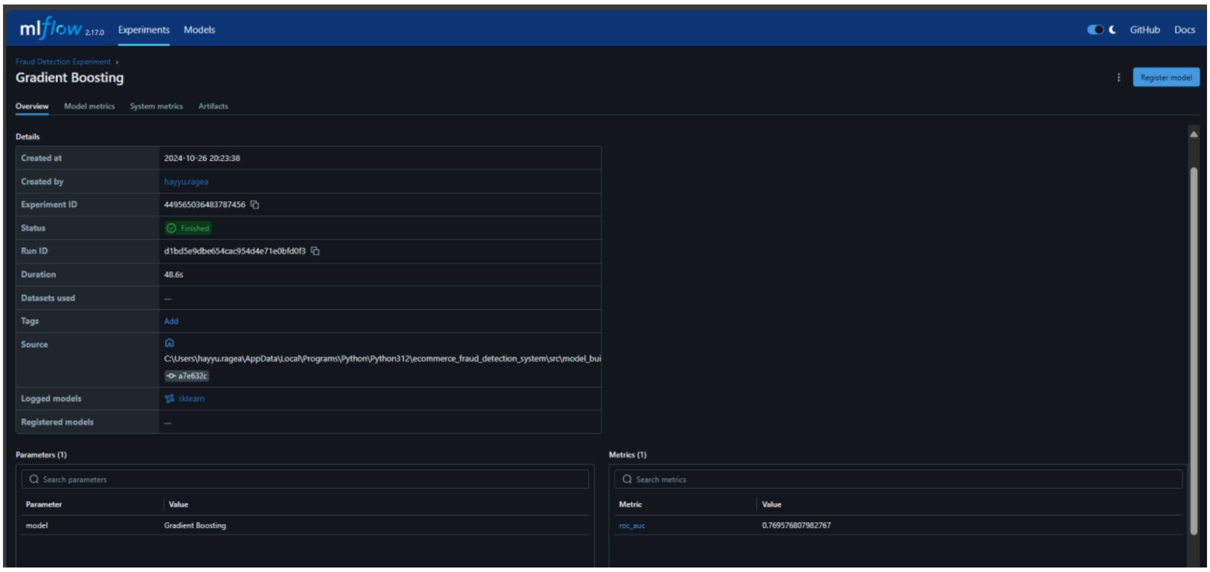

- Decision Tree Fraud Data MLOps screenshot



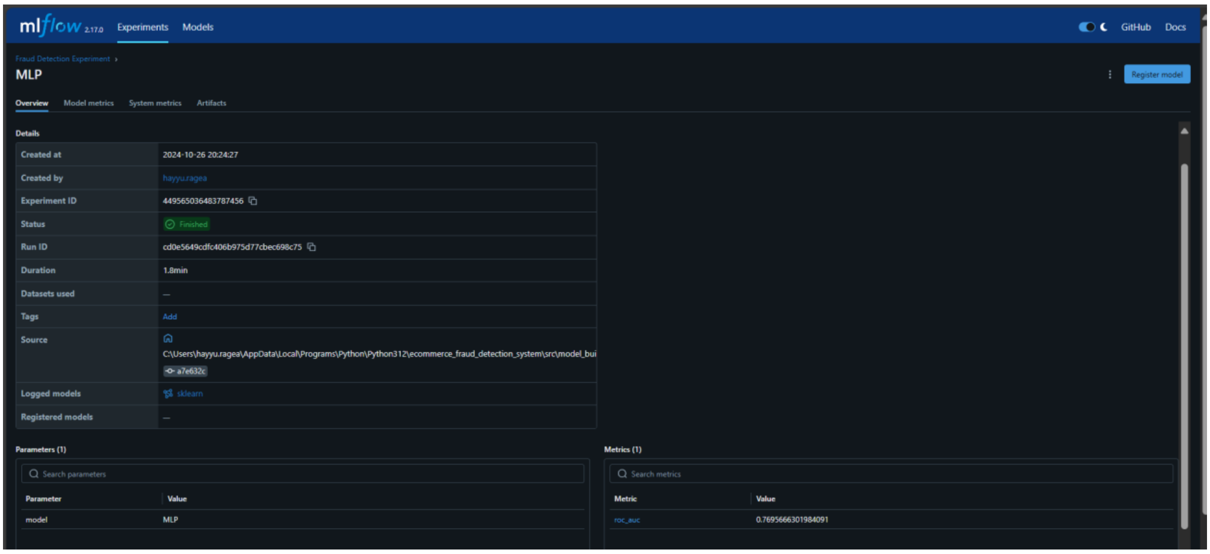
- Random Forest Fraud Data MLOps screenshot



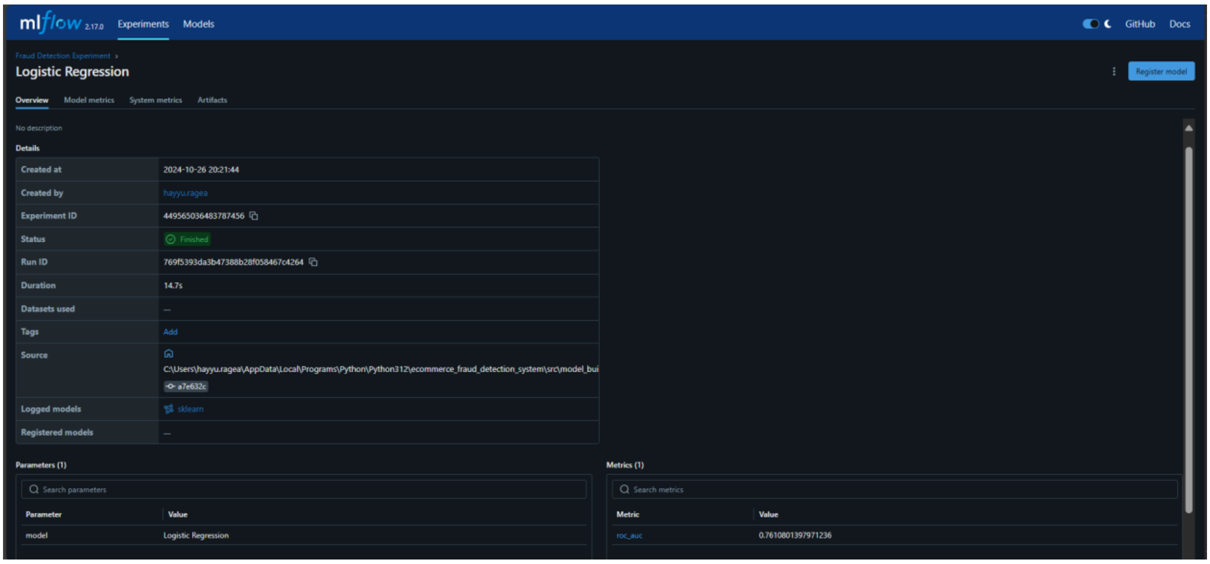

- Gradient Fraud Data MLOps screenshot



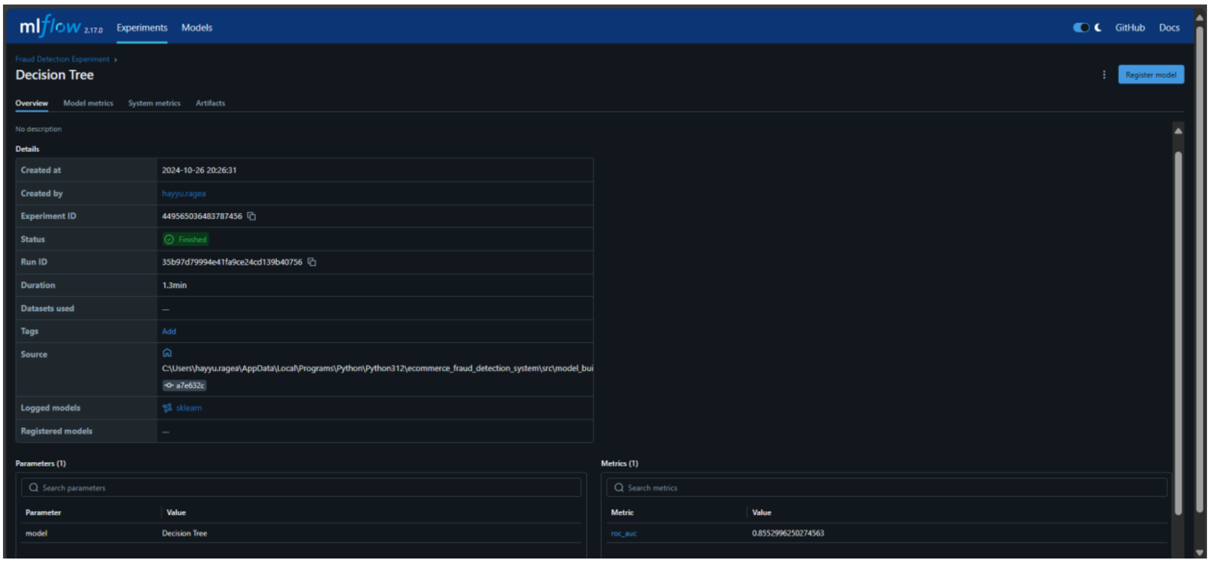
- Multi-Layer Perceptron (MLP) Fraud Data MLOps screenshot



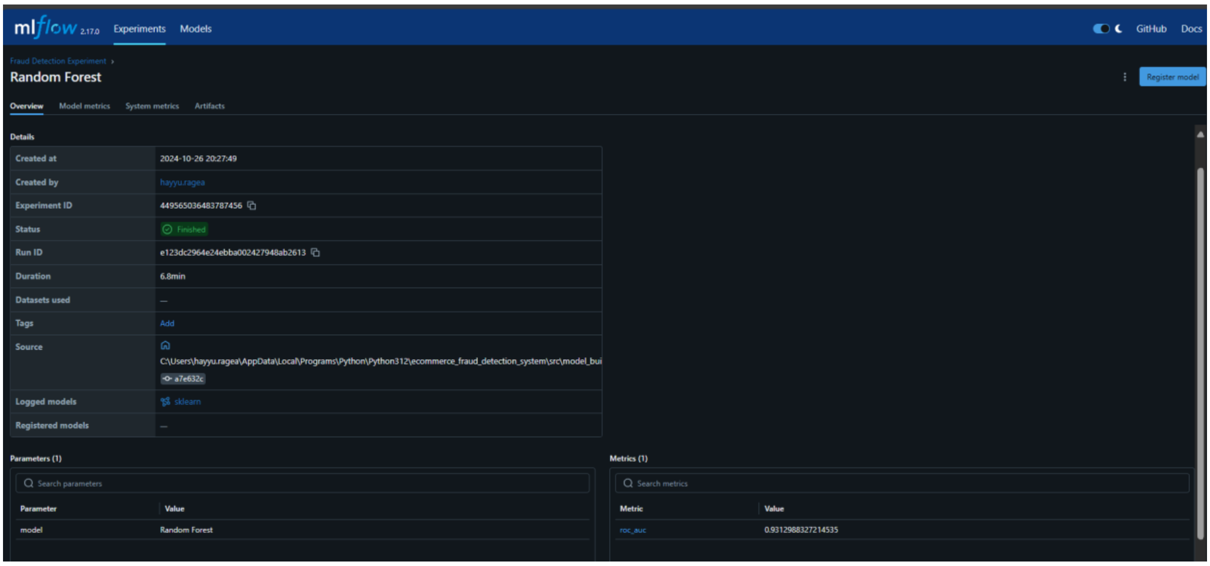

- Logistic Regression Credit Card Data  Data MLOps screenshot



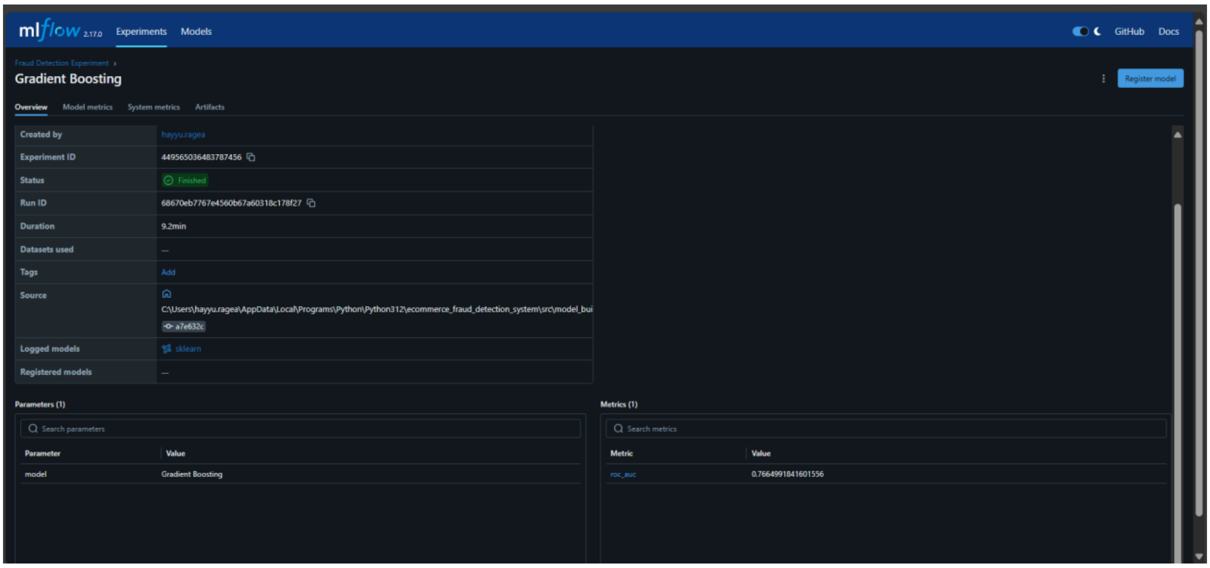
- Decision Tree Credit Card Data  Data MLOps screenshot



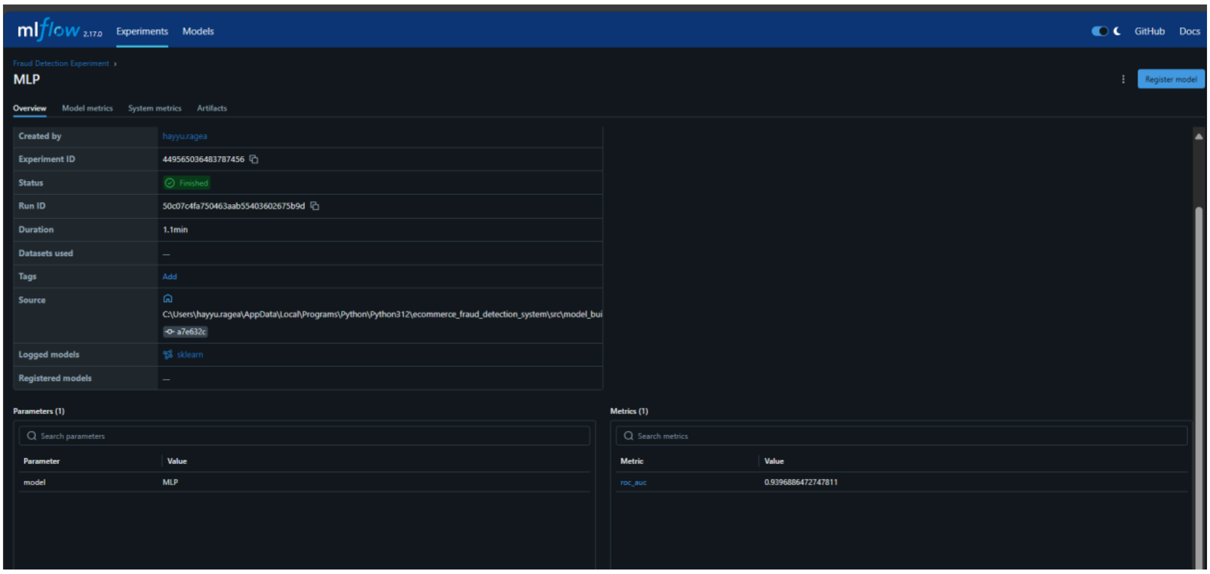

- Logistic Regression Credit Card Data  Data MLOps screenshot



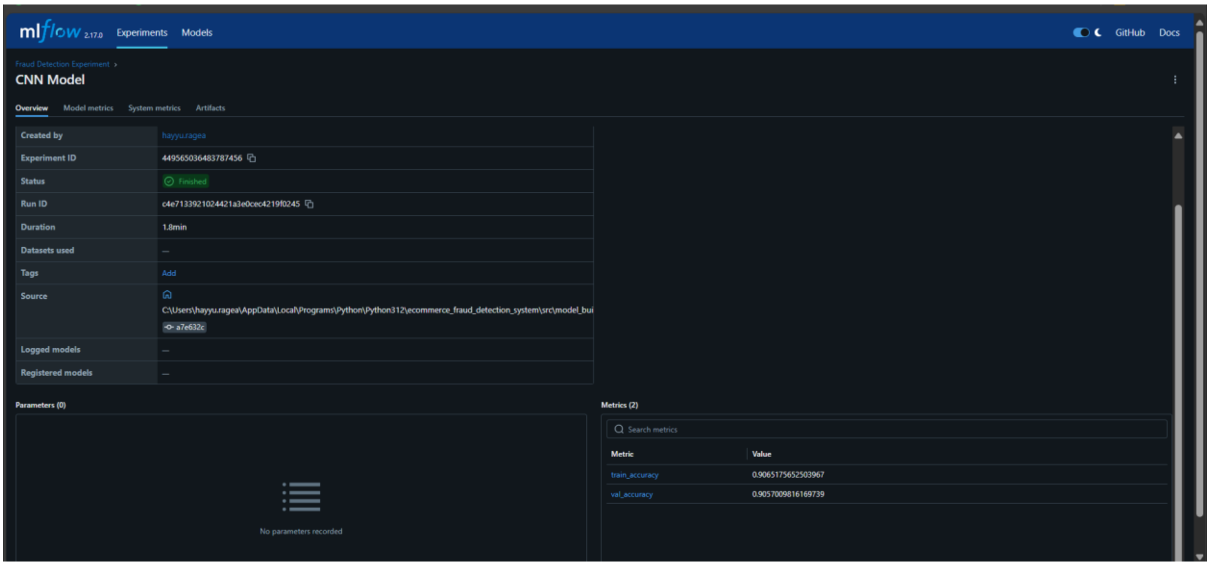
- Gradient Credit Card Data  Data MLOps screenshot



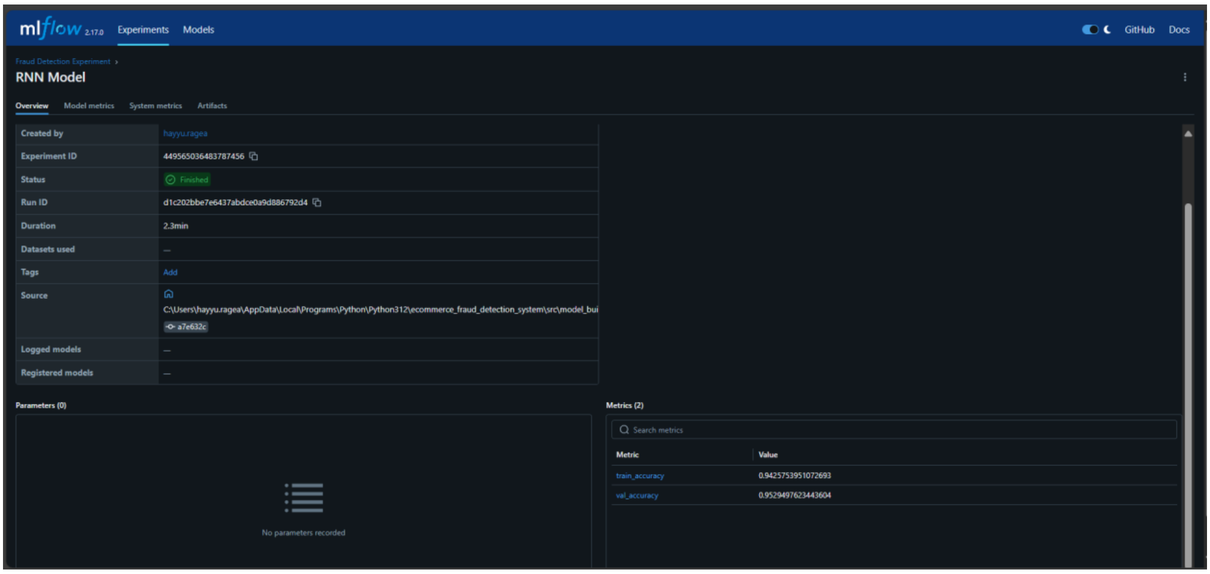

- Multi-Layer Perceptron (MLP) Credit Card Data  Data MLOps screenshot



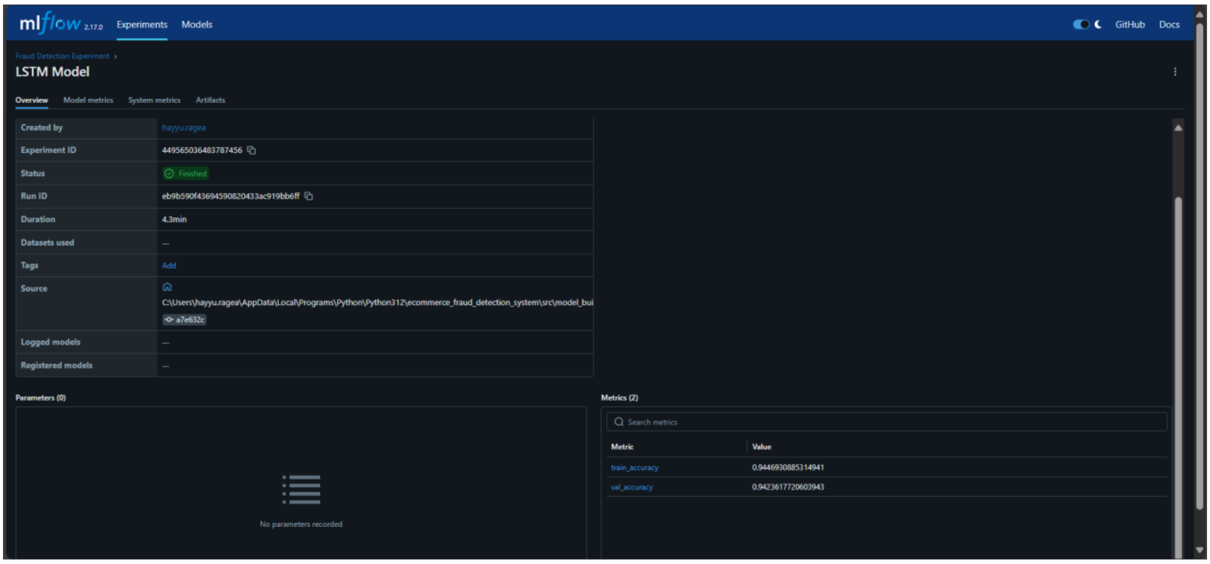
- Convolutional Neural Network (CNN) Credit Card Data  Data MLOps screenshot




- Recurrent Neural Network (RNN) Credit Card Data  Data MLOps screenshot



- Long Short-Term Memory (LSTM) Credit Card Data  Data MLOps screenshot




**Project Impact**

The model building and training process have positioned Adey Innovations Inc. to proactively secure transactions and foster customer trust by implementing reliable, real-time fraud detection solutions.

**GitHub Link**:**https://github.com/HaYyu-Ra/ecommerce_fraud_detection_analysis/blob/master/notebooks/model_biulding.ipynb**

**Conclusion**:

The Random Forest model demonstrated consistent accuracy and robustness across both datasets, making it a suitable choice for deployment. Future steps include optimizing model parameters, managing any convergence warnings, and fine-tuning to improve overall performance.