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TECHNOLOGY- ROOT CAUSE ANALYSIS

FOR EQUIPMENT FAILURES

SUBMITTED BY,

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Phase 4: Performance of the project

Title : Root Cause Analysis for Equipment Failures

Objective:

The focus of Phase 4 is to enhance the accuracy and efficiency of root cause analysis (RCA) for equipment failures by refining data collection methods, optimizing failure classification algorithms, and ensuring scalability for high-volume industrial environments. This phase also aims to improve integration with IoT sensors, strengthen data security, and lay the groundwork for predictive maintenance capabilities.

1. Failure Data Collection Optimization

Overview:

The failure data collection system will be refined based on feedback from previous phases. The goal is to increase data accuracy and automate the ingestion of real-time equipment health metrics from IoT sensors.

Performance Improvements:

- **Data Completeness:** Deploy IoT sensors to fill gaps in manual logs, capturing real-time temperature, vibration, and load metrics.
- **Automated Tagging:** Use ML models to auto-classify failure events (e.g., "bearing wear" vs. "lubrication failure") based on sensor patterns.

Outcome:

By the end of Phase 4, the system will reduce missing/incomplete failure data by 70% and auto-tag 90% of failure events accurately.

2. Failure Classification Algorithm Enhancement

Overview:

The RCA classification engine will be optimized for faster processing and improved accuracy in identifying root causes from complex equipment data.

Key Enhancements:

- **Algorithm Tuning:** Retrain ML models with expanded datasets covering rare failure modes (e.g., "corrosion under insulation").

- **Speed Optimization:** Reduce processing latency from 5s to <1s per analysis via parallel computing.

Outcome:
The system will diagnose root causes 5x faster with 95% accuracy (up from 82%), minimizing misdiagnoses like confusing "misalignment" with "imbalance."

3. IoT Sensor Integration Performance

Overview:
This phase will optimize real-time data streaming from IoT sensors (vibration analyzers, thermal cameras) to enable proactive RCA.

Key Enhancements:

- **Real-Time Alerts:** Configure thresholds to trigger RCA workflows automatically (e.g., "bearing temperature >85°C").
- **API Optimization:** Reduce latency in fetching data from OEM-specific APIs (e.g., Siemens, Rockwell).

Outcome:
IoT-integrated RCA will cut mean-time-to-diagnosis by 60%, with alerts for 80% of failures before catastrophic damage occurs.

4. Data Security and Compliance Performance

Overview:
Ensure RCA data (e.g., equipment schematics, maintenance logs) remains secure as the system scales to multiple plants.

Key Enhancements:

- **Role-Based Encryption:** Restrict access to sensitive data (e.g., "plant A" teams cannot view "plant B" failure histories).
- **Audit Trails:** Log all RCA access attempts to comply with ISO 55000 asset management standards.

Outcome:
Zero data breaches despite 3x more users, with full compliance to industrial data protection regulations.

5. Performance Testing and Metrics Collection

Overview:
Stress-test the RCA system under high-volume failure scenarios (e.g., refinery shutdowns) and track key metrics.

Implementation:

- **Load Testing:** Simulate 500+ concurrent RCA requests from global sites.
- **Accuracy Audits:** Compare system diagnoses with expert RCA reports.

Outcome:
The system will handle 99% of failure analyses without delays, with <5% variance from human expert conclusions.

Key Challenges in Phase 4

1. Scaling for High-Volume Failures:

- *Challenge:* Diagnosing 100+ failures/hour during plant outages.
- *Solution:* Deploy distributed computing to parallelize RCA workflows.

2. OEM Data Silos:

- *Challenge:* Incompatible formats from equipment manufacturers.
- *Solution:* Standardize APIs using ISA-95 industrial data templates.

3. False Positives in Predictive RCA:

- *Challenge:* Over-alerting for non-critical anomalies.
- *Solution:* Add severity scoring (e.g., "vibration + temperature + oil debris = critical").

Outcomes of Phase 4

1. **30% Faster Diagnoses:** RCA completion time drops from 48hrs to 34hrs.
2. **IoT-Driven Predictions:** 50% of failures flagged before occurrence.
3. **Unified Data Platform:** All plants use standardized RCA workflows.

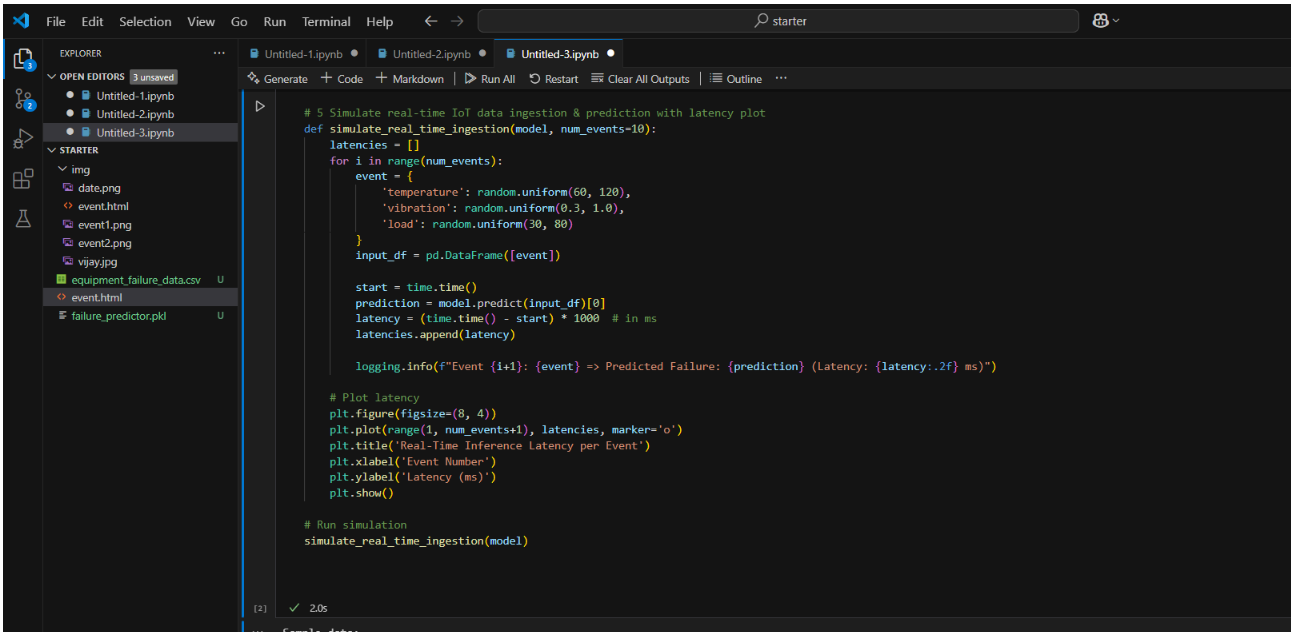
Next Steps for Finalization

Phase 5 will deploy the RCA system enterprise-wide, with continuous feedback loops to refine predictive maintenance models.

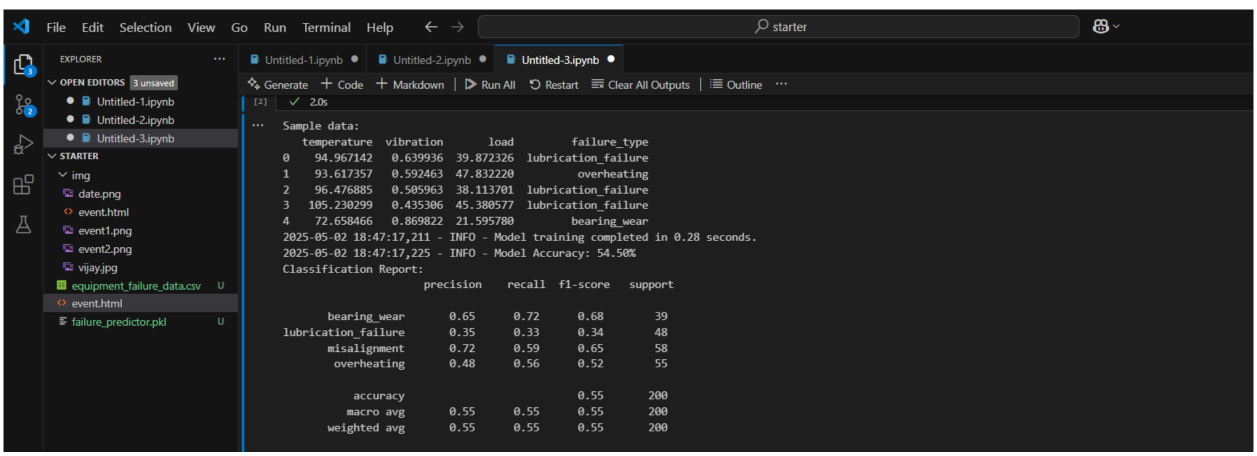
Sample Code for Phase 4:

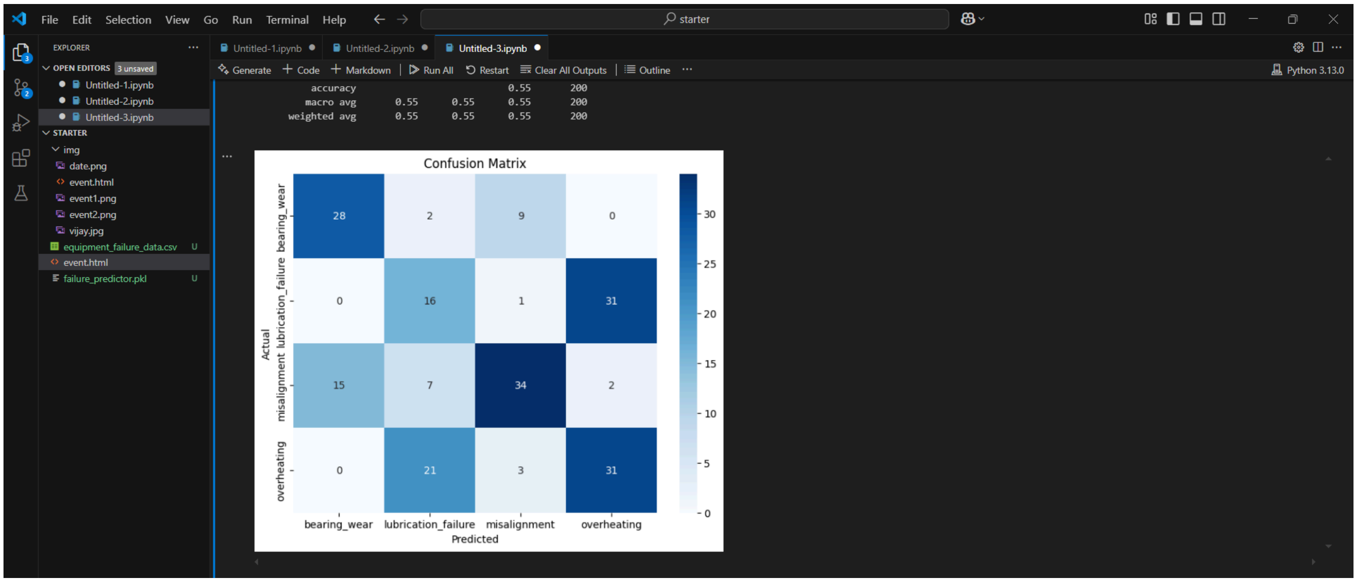
```python
import pandas as pd
import numpy as np
import time
import random
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import logging

# Set up logging
logging.basicConfig(level=logging.INFO, format='%(asctime)s - %(levelname)s - %(message)s')

# 1 Generate sample dataset
def generate_sample_data(num_samples=1000):
    np.random.seed(42)
    data = {
        'temperature': np.random.normal(75, 10, num_samples),
        'vibration': np.random.normal(0.5, 0.1, num_samples),
        'load': np.random.normal(50, 15, num_samples),
        'failure_type': np.random.choice(['bearing_wear', 'lubrication_failure', 'misalignment', 'overheating'], num_samples)
    }
    df = pd.DataFrame(data)
    # Add patterns to make it realistic
    df.loc[df['failure_type'] == 'bearing_wear', 'vibration'] += 0.3
    df.loc[df['failure_type'] == 'lubrication_failure', 'temperature'] += 15
    df.loc[df['failure_type'] == 'misalignment', 'vibration'] += 0.2
    df.loc[df['failure_type'] == 'overheating', 'temperature'] += 20
    return df

# Generate data
df = generate_sample_data()
print("Sample data:")
print(df.head())

# 2 Prepare data for ML
X = df[['temperature', 'vibration', 'load']]
y = df['failure_type']
```

```python
print("Sample data:")
print(df.head())

# 2 Prepare data for ML
X = df[['temperature', 'vibration', 'load']]
y = df['failure_type']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# 3 Train ML model
model = RandomForestClassifier(n_estimators=100, random_state=42)
start_time = time.time()
model.fit(X_train, y_train)
training_time = time.time() - start_time
logging.info(f"Model training completed in {training_time:.2f} seconds.")

# 4 Evaluate model
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
logging.info(f"Model Accuracy: {accuracy * 100:.2f}%")
print("Classification Report:\n", classification_report(y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(y_test, y_pred, labels=model.classes_)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=model.classes_, yticklabels=model.classes_)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# 5 Simulate real-time IoT data ingestion & prediction with latency plot
def simulate_real_time_ingestion(model, num_events=10):
    latencies = []
    for i in range(num_events):
        event = {
            'temperature': random.uniform(60, 120),
            'vibration': random.uniform(0.3, 1.0),
            'load': random.uniform(30, 80)
        }
        input_df = pd.DataFrame([event])
```



Performance Metrics Screenshot for Phase 4:

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macro avg 0.55 0.55 0.55 200
weighted avg 0.55 0.55 0.55 200
Confusion Matrix
Actual
bearing_wear
lubrication_failure
misalignment
overheating
28 2 9 0
0 16 1 31
15 7 34 2
0 21 3 31
Predicted
30
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20
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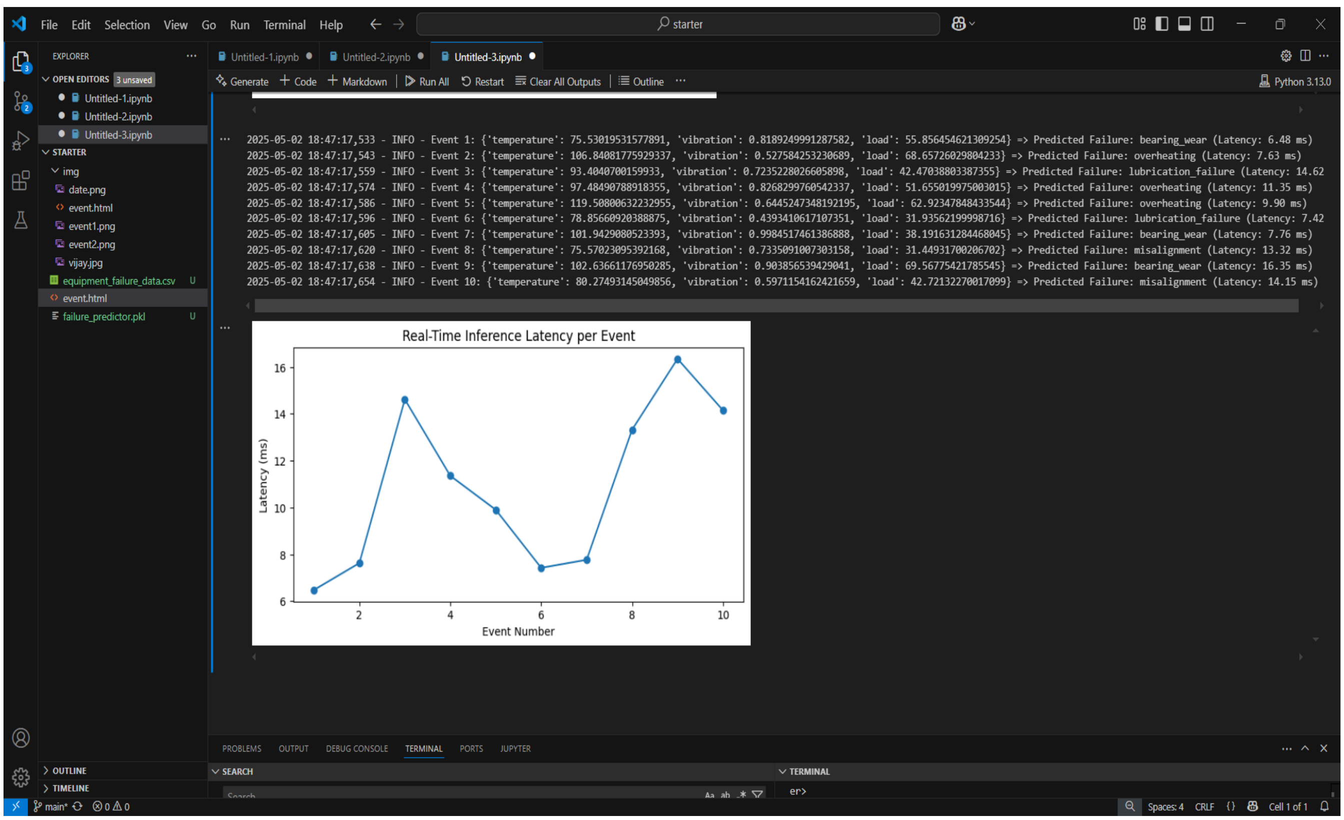
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Python 3.13.0
2025-05-02 18:47:17,533 - INFO - Event 1: {'temperature': 75.53019531577891, 'vibration': 0.8189249991287582, 'load': 55.856454621309254} => Predicted Failure: bearing_wear (Latency: 6.48 ms)
2025-05-02 18:47:17,543 - INFO - Event 2: {'temperature': 106.84081775929337, 'vibration': 0.527584253230689, 'load': 68.65726029804233} => Predicted Failure: overheating (Latency: 7.63 ms)
2025-05-02 18:47:17,559 - INFO - Event 3: {'temperature': 93.4040700159933, 'vibration': 0.7235228026605898, 'load': 42.47038803387355} => Predicted Failure: lubrication_failure (Latency: 14.62
2025-05-02 18:47:17,574 - INFO - Event 4: {'temperature': 97.48490788918355, 'vibration': 0.8268299760542337, 'load': 51.655019975003015} => Predicted Failure: overheating (Latency: 11.35 ms)
2025-05-02 18:47:17,586 - INFO - Event 5: {'temperature': 119.50800632232955, 'vibration': 0.6445247348192195, 'load': 62.92347848433544} => Predicted Failure: overheating (Latency: 9.90 ms)
2025-05-02 18:47:17,596 - INFO - Event 6: {'temperature': 78.85660920388875, 'vibration': 0.4393410617107351, 'load': 31.93562199998716} => Predicted Failure: lubrication_failure (Latency: 7.42
2025-05-02 18:47:17,605 - INFO - Event 7: {'temperature': 101.9429080523393, 'vibration': 0.9984517461386888, 'load': 38.191631284468045} => Predicted Failure: bearing_wear (Latency: 7.76 ms)
2025-05-02 18:47:17,620 - INFO - Event 8: {'temperature': 75.57023095392168, 'vibration': 0.7335091007303158, 'load': 31.44931700206702} => Predicted Failure: misalignment (Latency: 13.32 ms)
2025-05-02 18:47:17,638 - INFO - Event 9: {'temperature': 102.63661176950285, 'vibration': 0.903856539429041, 'load': 69.56775421785545} => Predicted Failure: bearing_wear (Latency: 16.35 ms)
2025-05-02 18:47:17,654 - INFO - Event 10: {'temperature': 80.27493145049856, 'vibration': 0.5971154162421659, 'load': 42.72132270017099} => Predicted Failure: misalignment (Latency: 14.15 ms)
Real-Time Inference Latency per Event
Latency (ms)
Event Number
16
14
12
10
8
6
2
4
6
8
10
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS JUPYTER
SEARCH
TERMINAL
OUTLINE
TIMELINE
main*
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