

AI-Driven Machine Learning Approaches for Failure Analysis From Data to Diagnosis

Practical AI Strategies for Real-World Reliability Engineering - 5 days

FA-0095 · 5 days

DevOps, Cloud & Infrastructure · Data & Analytics

Introduction

Manufacturing today isn't about waiting for things to break—it's about staying ahead of the curve. This intensive 5-day program takes everything you thought you knew about failure analysis and turns it on its head. We're talking brittle fractures, electromigration, creep, delamination, thermal degradation—all the usual suspects—but approached through the lens of AI and machine learning.

Your instructor brings three decades of hands-on experience to the table, so forget dry theory. This is about real problems, real data, and real solutions that actually work in the field. By the end of the week, you'll walk away knowing how to build and deploy AI-powered workflows using Ubuntu Linux and open-source tools—the same production-level approaches that leading manufacturers are using right now.

Learning outcomes

By the end of this course, participants will be able to:

- Explain key failure mechanisms and their characteristics
- Acquire, preprocess, and augment failure data using Linux-friendly AI tools
- Design, train, evaluate, and deploy ML models for detecting multiple failure modes

- Apply AI to root cause analysis in complex failure scenarios
 - Integrate AI-based failure analysis tools into manufacturing/inspection workflows
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Prerequisites

You should have:

- Solid working experience with Ubuntu Linux, command-line tools, Python, and bash scripting
 - Familiarity with Linux-based data pipelines and common AI frameworks (e.g. PyTorch, TensorFlow, scikit-learn)
 - Understanding of basic ML concepts (classification, regression, deep learning)
 - Introductory materials or mechanical engineering knowledge related to failure analysis
 - Access to Ubuntu 20.04+ environment with permissions to install tools and packages
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Training outline

1. 1. Introduction to Failure Analysis Mechanisms

1.1 Overview of Failure Analysis

- What is failure analysis? Why it matters in modern manufacturing.
- Common industrial failure types: electrical, mechanical, thermal.

1.2 Characterizing Failure Modes

- Interconnect brittle failures: causes, microscopy examples, diagnostic cues.
- Thermal failure: thermal fatigue, hot spots, oxidation effects.
- Creep: time-dependent deformation in metallic substrates and solder joints.
- Electromigration: current-driven diffusion in conductors; key signs and test methods.
- Delamination: causes in layered structures, microscopy and ultrasonic detection.
- Others: corrosion, mechanical fatigue, bulk thermal shock.

1.3 Failure Data Sources & Instrumentation

- Generation of failure data: accelerated stress tests, in-line sensors, lab analyses.
- Lab tools: SEM/TEM, energy-dispersive spectroscopy, thermal camera logs.
- Sensor types: acoustic, vibration, temperature, current density, strain gauges.

2. 2. Data Acquisition, Preprocessing & AI Integration

2.1 Data Collection Strategies in Linux

- Using bash, cron jobs, Python scripts to gather telemetry logs from sensors.
- Structured file systems, log rotation, version control for datasets.

2.2 Preprocessing Failure Data

- Cleaning, filtering, synchronizing heterogeneous time-series.
- Feature engineering: frequency spectra, statistical descriptors, event markers.
- Data augmentation for rare failure events via oversampling or synthetic generation.

2.3 AI-Enabled Detection Tools

- Using anomaly detection libraries in Python (e.g. PyOD).
 - Autoencoders for unsupervised failure pattern detection.
 - Practical demos: implementing real-time anomaly alerts via Kafka + Flask setup.
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3. 3. Building AI Models for Failure Detection

3.1 Modeling Failure Modes

- Classification vs. regression approaches.
- Examples: LSTM for temporal anomalies; CNN for image-based crack detection.

3.2 Hands-On Model Development

- Preparing datasets and train-test splits.
- Training pipeline: hyperparameter tuning with scikit-learn or Optuna.
- Assessing performance: confusion matrix, ROC/AUC, precision/recall for imbalanced data.

3.3 Advanced Architectures

- CNNs for microscopy/thermal image cracks.
- LSTM/1D-CNN for time-series sensor data.

- GANs for synthetic failure sample generation in data-scarce domains .

3.4 Linux-Based Training and Pipeline Automation

- Using Docker/Conda on Ubuntu.
 - Scheduling model retraining with cron and logging with TensorBoard.
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4. 4. AI-Based Root Cause Analysis (RCA)

4.1 Introduction to RCA Techniques

- Process of root cause analysis in engineering.
- Introduction to AI-assisted solvers (e.g. Warwick RCASE).

4.2 ML Approaches to RCA

- Feature importance via SHAP/TreeSHAP for interpretable insights.
- Causal modeling basics to unearth underlying failure triggers.
- Bayesian networks for multimodal failure diagnostics.

4.3 Hands-On RCA Workflows

- Case study: using real process logs to trace delamination root via model explanations.
 - Scripted RCA automation on Ubuntu using Python, Jupyter, and SHAP libraries.
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5. 5. System Implementation & Industry Case Studies

5.1 Deploying in Manufacturing Environments

- Real-time edge inference on Ubuntu servers.
- Integrating ML modules into MES or ERP systems.

5.2 Feedback & Model Lifecycle Management

- Monitoring model drift; retraining with new sensor/failure samples.
- Version control and CI/CD pipelines using GitLab CI on Linux.

5.3 Industrial Case Studies

- Semiconductor interconnect failure prediction via CNN.
- Predictive maintenance using vibration sensors and anomaly detection.
- Applying AI for AI-driven expert systems in materials failure prevention.
- Group discussion: designing your customized pilot on Ubuntu.

This hands-on course equips you to fully own AI-enhanced failure analysis workflows—from mechanistic understanding and data collection, through ML model building and explainability, to deployment and continuous improvement—100% on Linux infrastructure. Led by a seasoned expert, you'll walk away ready to implement robust, industry-grade failure analytics in production environments.

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