IIT Madras BS in Data Science
and Applications

MS4001 INDUSTRY 4.0

Predictive Maintenance for
Smart Manufacturing Equipment

Presented By : Optimizers 4.0

Rajarshi Roy - 21f3000348

Samagya Rathi - 21f3002675

Soumyadeep Dhali - 22f1001762

PROBLEM STATEMENT AND RESEARCH QUESTIONS

Problem

Unplanned machine failures in manufacturing lead to high downtime and maintenance costs

Key Challenge

Need to predict failures in advance to optimize maintenance scheduling

Research Questions

- Can we use sensor data to predict failures before they happen?
- Which features are the strongest indicators of machine failure?
- How can predictive maintenance reduce costs and improve machine efficiency?

OBJECTIVE AND CONSTRAINTS

Objective

- Develop a predictive maintenance model that forecasts machine failures in advance.
- Improve equipment uptime and optimize maintenance schedules.

Constraints

- Limited availability of labeled failure data.
- Real-world sensor readings can be noisy or missing.
- Maintenance must be scheduled within operational constraints

OVERVIEW OF THE RELEVANT DATA

Key Data Points

- Engine ID: Identifies different machines.
- Cycle Number: Tracks engine usage over time.
- Sensor Readings: Temperature, pressure, vibration, fuel flow, etc.
- Remaining Useful Life (RUL): Number of cycles left before failure.

Dataset Used

NASA CMAPSS Dataset (Aircraft Engine Sensor Data).

Data Challenge

Need to extract trends from time-series sensor data to make accurate predictions

METHODOLOGY

Data Preprocessing

Handle missing values, scale data, and create rolling-window features.

Feature Engineering

Compute trend-based features (e.g., average temperature in last 10 cycles)

Model Selection

Compare Random Forest and XGBoost for failure prediction.

Model Training and Evaluation

Use early engine cycles for training, later cycles for testing. Metrics used RMSE, MAE, R^2 Score

RESULTS AND IMPLICATIONS

Results

- XGBoost Model: Best performance (Lowest RMSE: 18.5, Highest R^2: 0.85).
- Feature Importance:Temperature & Vibration were the strongest failure predictors.
- Operational Time showed a strong correlation with RUL.
- Prediction Accuracy: Model successfully identified engines nearing failure with high confidence.

Business Implications

- Reduces unplanned downtime, saving maintenance costs.
- Allows proactive scheduling, improving factory efficiency.
- Can be extended to real-time failure monitoring.

THANK YOU

Presented By : Optimizers 4.0