Equipment Health Monitoring System

Problem Statement:

Manufacturing companies often face significant costs and operational disruptions due to unexpected equipment failures. Reactive maintenance approaches, where repairs are only performed after a breakdown occurs, can lead to extended downtimes, increased costs, and potential safety risks. To address this challenge, we aim to develop a predictive maintenance solution that can accurately classify different types of equipment failures based on sensor data.

The dataset comprises 10,000 data points with 14 features each. These features include unique identifiers (UIDs), product IDs denoted by letters L, M, or H representing low, medium, and high-quality variants, air temperature, process temperature, rotational speed, torque, tool wear, and a 'machine failure' label indicating whether a failure occurred during the process.

The 'machine failure' label is determined by five independent failure modes: tool wear failure (TWF), heat dissipation failure (HDF), power failure (PWF), overstrain failure (OSF), and random failures (RNF). Each failure mode has specific conditions that lead to process failure, such as tool wear reaching a certain threshold, heat dissipation causing temperature differences, power requirements exceeding limits, or random failure events.

The dataset presents a scenario where the 'machine failure' label indicates whether any of the defined failure modes occurred during the process. This information is crucial for predictive maintenance strategies and understanding equipment performance under different conditions.

Goal:

The goal of this project is to develop a machine learning model capable of accurately classifying different types of equipment failures based on sensor data. By effectively categorizing failures, maintenance teams can better understand the underlying causes and take appropriate actions to address the specific issues. This proactive approach aims to reduce unexpected breakdowns, minimize production disruptions, and optimize maintenance schedules, ultimately leading to improved operational efficiency, cost savings, and enhanced equipment reliability.

Background:

The manufacturing industry relies heavily on complex machinery and equipment to carry out its operations. Unplanned equipment failures can result in costly production stoppages, increased maintenance expenses, and potential safety hazards for workers. Traditional maintenance strategies, such as preventive maintenance based on fixed schedules or reactive maintenance after a breakdown occurs, are often inefficient and fail to address the root causes of equipment failures.

Predictive maintenance, an approach that leverages data analytics and machine learning techniques, offers a proactive solution to identify potential failures before they occur. By analyzing sensor data from equipment, such as temperature, pressure, vibration, and electrical signals, we can detect patterns and anomalies that may indicate impending failures. Early detection of these issues allows for timely interventions, minimizing downtime and maximizing the lifespan of the equipment.

Data set:

https://www.kaggle.com/datasets/stephanmatzka/predictive-maintenance-dataset-ai4i-2020
Predictive Maintenance Dataset (AI4I 2020) (kaggle.com)

About Dataset:(from Kaggle copied)

This synthetic dataset is modeled after an existing milling machine and consists of 10 000 data points from a stored as rows with 14 features in columns.

1. UID: unique identifier ranging from 1 to 10000.
2. product ID: consisting of a letter L, M, or H for low (50% of all products), medium (30%) and high (20%) as product quality variants and a variant-specific serial number.
3. type: just the product type L, M or H from column 2
4. air temperature [K]: generated using a random walk process later normalized to a standard deviation of 2 K around 300 K.
5. process temperature [K]: generated using a random walk process normalized to a standard deviation of 1 K, added to the air temperature plus 10 K.
6. rotational speed [rpm]: calculated from a power of 2860 W, overlaid with a normally distributed noise.
7. torque [Nm]: torque values are normally distributed around 40 Nm with a SD = 10 Nm and no negative values.
8. tool wear [min]: The quality variants H/M/L add 5/3/2 minutes of tool wear to the used tool in the process.
9. a 'machine failure' label that indicates, whether the machine has failed in this particular datapoint for any of the following failure modes are true.

The machine failure consists of five independent failure modes.

1. tool wear failure (TWF): the tool will be replaced of fail at a randomly selected tool wear time between 200 - 240 mins (120 times in our dataset). At this point in time, the tool is replaced 69 times, and fails 51 times (randomly assigned).
2. heat dissipation failure (HDF): heat dissipation causes a process failure, if the difference between air- and process temperature is below 8.6 K and the tools rotational speed is below 1380 rpm. This is the case for 115 data points.
3. power failure (PWF): the product of torque and rotational speed (in rad/s) equals the power required for the process. If this power is below 3500 W or above 9000 W, the process fails, which is the case 95 times in our dataset.
4. overstrain failure (OSF): if the product of tool wear and torque exceeds 11,000 minNm for the L product variant (12,000 M, 13,000 H), the process fails due to overstrain. This is true for 98 datapoints.

5. random failures (RNF): each process has a chance of 0,1 % to fail regardless of its process parameters. This is the case for only 5 datapoints, less than could be expected for 10,000 datapoints in our dataset.
   If at least one of the above failure modes is true, the process fails, and the 'machine failure' label is set to 1. It is therefore not transparent to the machine learning method, which of the failure modes has caused the process to fail.

Use and Value:

Early Failure Detection: The machine learning model trained on historical sensor data can identify subtle patterns and deviations that may signify potential equipment failures. By providing early warning signs, maintenance teams can take proactive measures to address issues before they escalate into more severe breakdowns, minimizing unplanned downtime and associated costs.
Failure Type Classification: Beyond simply detecting potential failures, the solution can accurately classify the specific type of failure based on the sensor data patterns. This capability enables maintenance teams to understand the underlying causes and take targeted actions to address the root issues, rather than employing generic maintenance procedures.
Optimized Maintenance Scheduling: With accurate failure type classification, maintenance teams can prioritize and schedule maintenance activities more effectively. Resources can be allocated strategically, ensuring that critical equipment receives prompt attention, while less urgent issues can be addressed during scheduled maintenance windows, optimizing operational efficiency.
Extended Equipment Lifespan: By addressing potential failures proactively and performing targeted maintenance, the solution can help extend the lifespan of manufacturing equipment. Prolonged equipment operation reduces the need for frequent replacements, contributing to cost savings and improved return on investment.
Increased Operational Reliability: By minimizing unplanned downtime and ensuring timely maintenance, the predictive maintenance solution enhances overall operational reliability. This reliability translates into consistent production outputs, improved product quality, and increased customer satisfaction.

Constraints:

Data Availability: Ensure access to comprehensive and high-quality sensor data from manufacturing equipment, as this data serves as the foundation for training and validating the machine learning model.
Domain Expertise: Collaborate closely with subject matter experts, such as maintenance engineers and equipment manufacturers, to integrate domain knowledge and translate the model's outputs into actionable insights.
Integration with Existing Systems: Design the solution to seamlessly integrate with the company's existing maintenance management systems, ensuring smooth adoption and efficient workflow integration.
Computational Resources: Depending on the complexity of the machine learning model and the volume of data involved, allocate sufficient computational resources for training, validation, and deployment of the solution.

Regulatory Compliance: Ensure that the solution adheres to relevant industry regulations, safety standards, and data privacy requirements, particularly if handling sensitive equipment or personnel data.

By addressing these goals and constraints, the predictive maintenance solution will empower manufacturing companies to optimize their operations, reduce costs associated with unplanned downtime, enhance equipment reliability, and ultimately achieve a competitive advantage in their respective industries.