# Applied Machine Learning Case Study - A manufacturing company aims to minimize downtime and reduce maintenance costs by predicting equipment failures before they occur.

## 1. Company Description

Precision Manufacturing Inc. operates in the high-precision manufacturing sector, producing critical components for aerospace and automotive industries. The company relies on a diverse portfolio of machinery, including CNC machines, lathes, and milling machines. Maintaining these machines at optimal performance levels is crucial for ensuring high product quality and meeting delivery timelines.

## 2. Business Outcome

The business outcome targeted is the reduction of equipment downtime and maintenance costs through predictive maintenance. This outcome is essential as it directly impacts operational efficiency, production capacity, and profitability. By predicting equipment failures before they occur, maintenance can be scheduled during non-peak hours, minimizing unplanned outages and extending machinery lifespan. This proactive approach enhances production reliability, reduces emergency repair costs, and improves market competitiveness

## 3. Response and Potential Features

The response variable will be the "time to failure" for each piece of equipment. Key features influencing this response include:

- Operational Data: Machine usage hours, load levels, operating speeds, and duty cycles.
- Maintenance Records: Historical maintenance data, types of repairs, parts replaced, and maintenance frequency.
- Sensor Data: Real-time data from IoT sensors monitoring temperature, vibration, noise levels, and lubrication status.
- Environmental Factors: Ambient temperature, humidity, and other environmental conditions within the factory.

## 4. Proposed Machine Learning Project

The proposed project is a predictive maintenance system utilizing machine learning algorithms to forecast equipment failures. This project involves:

- Data Collection and Integration: Aggregating historical and real-time data into a centralized database.
- Feature Engineering: Identifying and extracting relevant features that influence equipment health and performance.
- Model Development: Training and validating machine learning models to predict the remaining useful life (RUL) of machinery.

The following table outlines the machine learning models considered and the reasons for their use:

| ML Model | Reason for Use |
|---|---|
| **Linear Regression** | Simple model to establish baseline performance and identify linear relationships between features and RUL. |
| **Polynomial Regression** | Captures non-linear relationships between features and the target variable (time to failure). |
| **Logistic Regression** | Useful for binary classification tasks, such as predicting imminent failure (failure/no failure). |
| **Decision Tree** | Provides interpretable models and can capture complex feature interactions. |
| **Random Forest** | Ensemble method to improve prediction accuracy and robustness by averaging multiple decision trees. |
| **Support Vector Classifier (SVC)** | Effective for binary classification with high-dimensional feature spaces. |
| **Support Vector Regressor (SVR)** | Suitable for regression tasks, especially with non-linear relationships. |
| **K-Nearest Neighbors (KNN)** | Simple and intuitive algorithm for both classification and regression tasks. |

## 5. High-Level Model Functionality

The machine learning models will predict the remaining useful life of each machine, enabling preemptive maintenance scheduling. The models' purposes are:

- Prediction: Estimating the time until the next failure for each piece of equipment based on current and historical data.
- Inference: Identifying key factors contributing to equipment wear and tear, providing insights for optimizing operational parameters and maintenance strategies.

## 6. Evaluation of Desired Outcome

The success of the predictive maintenance project will be evaluated using key performance indicators (KPIs):

| KPI | Description |
|---|---|
| **Reduction in Unplanned Downtime** | Measure the decrease in hours of unexpected machine stoppages. |
| **Maintenance Cost Savings** | Track the reduction in maintenance expenses and emergency repair costs. |
| **Prediction Accuracy** | Assess the precision of the model's failure predictions using metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). |
| **Increased Machine Uptime** | Calculate the improvement in machine availability and overall equipment effectiveness (OEE). |

## 7. Project Scope and Risks

The scope includes the initial deployment on a subset of critical machines, with plans for scaling across the entire production floor. Key activities involve data integration, model training, and validation, followed by real-time deployment and continuous monitoring.

Risks and Challenges:

- Data Quality and Availability: Ensuring the availability and accuracy of historical and real-time data is critical. Poor data quality can lead to unreliable predictions.
- Model Complexity: Developing robust models that can handle the complexity and variability of manufacturing processes may be challenging.
- Change Management: Integrating predictive maintenance into existing workflows requires buy-in from maintenance and operations teams, necessitating effective change management strategies.

## 8. Conclusion

In conclusion, implementing predictive maintenance at Precision Manufacturing Inc. through machine learning models like linear regression, polynomial regression, logistic regression, decision trees, random forests, SVC, SVR, and KNN can significantly reduce equipment downtime and maintenance costs. By leveraging operational, maintenance, sensor, and environmental data, the proposed system will enhance production reliability and operational efficiency. This proactive approach not only minimizes unplanned outages but also extends machinery lifespan, thereby providing a competitive edge in the high-precision manufacturing sector. Addressing data quality and integration challenges will be critical for the project's success.