DOWNTIME RISK AND PREDICTIVE MAINTAINANCE

A project report submitted to HCL (guvi)

Submitted by

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Project 3

Topic: DOWNTIME RISK AND PREDICTIVE MAINTAINANCE

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CERTIFICATE

This is to certify that the project titled '*Downtime risk and Predictive Maintainance*' is a record of the bonafide work carried out by Shreyanka Panda as part of HCL (guvi) Internship Project 3. The project was completed during the internship period and submitted in partial fulfillment of the requirements of the internship program. The work presented in this report is original and has not been submitted elsewhere for any academic or professional purpose

Signature

Acknowledgement

I would like to express my sincere gratitude to HCL for providing me with the opportunity to work on this internship project titled *Downtime risk and Predictive Maintainance* as a part of Project 3. I am deeply thankful for the comprehensive Data Science training modules provided by GUVI during the internship, which formed the foundation of my learning and enabled me to apply key concepts. I extend my heartfelt thanks to the mentors and coordinators from HCL and GUVI for their constant support and help throughout the project. This internship has been an enriching experience, allowing me to translate theoretical knowledge into a practical, business relevant solution.

Shreyanka Panda

ABSTRACT

In the modern manufacturing industry, unexpected machine failures cause significant financial losses due to unplanned downtime, high maintenance costs, and production delays. This project presents an advanced **Smart Predictive Maintenance System with Downtime Risk Scoring** designed to forecast machine failures in advance, enabling timely preventive actions and minimizing operational disruptions.

I used a comprehensive sensor dataset collected from industrial machines, the system analyzes various operational parameters such as air temperature, process temperature, rotational speed, torque, tool wear, and other engineered features. The dataset consists of 10,000 records with 20 attributes, providing rich information about machine health over time.

A thorough **data cleaning and preprocessing pipeline** was implemented to address missing values, encode categorical features, engineer new variables and scale numerical values for consistent model input. I conducted Exploratory Data Analysis (EDA) to identify key patterns and relationships, such as the strong correlation between tool wear and failure occurrence.

Multiple machine learning models were trained and evaluated, including **Logistic Regression, Random Forest, and XGBoost**. Random Forest was selected as the final model for its superior performance, especially in handling the **highly imbalanced failure class** by using class_weight='balanced' and consistent random seed for reproducibility. The model achieved an exceptional **Precision-Recall Average Precision (AP) score close to 1.0**, demonstrating its effectiveness at identifying rare failures.

The trained model, along with the scaler and feature column configuration, was saved for reproducible inference. Additionally, explainability techniques such as **SHAP (SHapley Additive exPlanations)** were applied to interpret model predictions, highlighting the most important features driving failure risk, such as thermal stress, tool wear, and power proxy.

Finally, the system is production-ready, with a **Streamlit-based dashboard** that enables users to upload new machine data, receive real-time failure risk predictions, and visualize key explanations driving the prediction.

This predictive maintenance solution delivers actionable insights, helping manufacturing companies reduce unexpected downtime, optimize maintenance schedules, lower costs, and improve overall equipment efficiency. The modular design ensures easy deployment in real-world industrial environments, with future scope to extend the system to real-time streaming and automated anomaly detection.

Contents

1. Introduction

1.1. Project Background

In today's competitive manufacturing landscape, ensuring the continuous operation of industrial machines is critical to maximizing productivity and minimizing costs. Traditional maintenance strategies, whether reactive (fix after failure) or preventive (scheduled maintenance) are often inefficient, leading to unnecessary expenses or unexpected downtime.

With the rapid advancement of Industrial IoT (IIoT), machines now produce vast amounts of sensor data in real time, offering new opportunities for smarter maintenance strategies.

This project focuses on leveraging machine learning techniques to predict machine failures in advance by analyzing operational sensor data. Predictive maintenance helps manufacturers identify at-risk equipment before failures occur, enabling targeted interventions and reducing costly disruptions.

1.2. Objective of the project

The primary objective of this project is to design and implement a Smart Predictive Maintenance System that:

- Predicts the probability of machine failure based on real-time sensor inputs.
- Provides interpretable explanations about which features drive the failure prediction.
- Enables proactive, data-driven maintenance decisions to minimize unplanned downtime.

1.3. Scope and Limitations

Scope:

- Data-driven analysis of machine sensor data for predictive maintenance.
- Feature engineering to enhance predictive power.
- Training and evaluation of multiple machine learning models (Logistic Regression, Random Forest, XGBoost).
- Explainable predictions using SHAP to assist engineers in understanding failure causes.
- Deployment-ready inference pipeline supporting real-time data input.

Limitations:

- The model is trained on historical batch data and does not support streaming data in the current phase.
- Performance may vary depending on the representativeness of input data in production.
- The model assumes data quality and structure remain consistent.

1.4. Tools & Technologies Used

- **Pandas, NumPy** – Data manipulation and preprocessing
- **Matplotlib, Seaborn** – Data visualization and exploratory analysis
- **Scikit-learn, XGBoost** – Machine learning model building, training, and evaluation
- **SHAP** – Model explainability and feature importance interpretation
- **joblib** – Model and scaler persistence for reproducibility
- **Streamlit** – Building an interactive dashboard for inference and visualization
- **Git** – Version control for code management
- **Jupyter Notebook** – Interactive development environment for prototyping and experimentation
- **Kaggle Dataset** – Source of predictive maintenance dataset

2. Problem Statement

2.1. Business Context

In the manufacturing industry, machine failures lead to costly unplanned downtime, reduced productivity, and expensive repair costs. Traditional maintenance approaches, such as reactive maintenance (fixing only after a failure occurs) and preventive maintenance (periodic maintenance based on fixed schedules), are often inefficient. These approaches can result in either unnecessary maintenance or missed early signs of machine degradation.

The industry is rapidly adopting Industrial IoT (IIoT), where machines are equipped with sensors that collect real-time data such as temperature, torque, vibration, and rotational speed. Leveraging this data can transform maintenance strategies from reactive to predictive, enabling data-driven decisions.

2.2. Core Problem

How can we accurately predict machine failure in advance by analyzing sensor data, so that timely maintenance can be performed, reducing unexpected downtime and optimizing maintenance schedules?

2.3. Problem Definition

Design a predictive system that:

- Predicts the probability of machine failure using sensor data.
- Provides clear explanations of key drivers influencing failure risk.
- Is deployable in industrial environments for real-time inference.

The system should maximize predictive accuracy while being interpretable and reproducible.

2.4. Objectives Derived

- Build a reliable supervised classification model using historical sensor data.

- Engineer features that enhance model performance and interpretability.
- Handle imbalanced classes using appropriate techniques (e.g., class weighting).
- Evaluate model performance using relevant metrics (Precision, Recall, ROC-AUC,

  -score).

- Implement explainability using SHAP to identify top features driving predictions.
- Save the model and scaler for reproducible inference in production.
- Build a simple Streamlit dashboard to perform inference and visualize explanations

3. Dataset Overview

3.1. Data Source

- **Dataset Name:** ai4i2020 Predictive Maintenance Dataset
- **Source:** https://archive.ics.uci.edu/dataset/352/online+retail
- **Description:**The dataset contains sensor measurements collected from industrial machines in a manufacturing environment.
  It is designed to support predictive maintenance modeling by providing data related to machine operation and failure events.
- **Dataset Size:**
  - **Rows:** 10,000
  - **Columns:** 20

3.2. Columns Description

- **udi** – Unique identifier of the machine record
- **product_id** – Product code of the machine
- **type** – Machine type (Type L or Type M)
- **air_temperature_k** – Air temperature in Kelvin measured by sensor
- **process_temperature_k** – Process temperature in Kelvin measured by sensor
- **rotational_speed_rpm** – Rotational speed in revolutions per minute
- **torque_nm** – Torque in Newton-meters
- **tool_wear_min** – Tool wear in minutes
- **machine_failure** – Target variable (0 = No failure, 1 = Failure occurred)
- **twf, hdf, pwf, osf, rnf** – Subtypes of machine failure (binary columns)
- **temp_delta** – Engineered feature: Difference between process and air temperature
- **power_proxy** – Engineered feature: Rotational speed × Torque (proxy for power)
- **wear_rate** – Engineered feature: Tool wear rate per unit time
- **thermal_stress** – Engineered feature: Derived stress based on usage and temperature
- **type_L, type_M** – One-hot encoded representation of machine type

3.3. SAMPLE RECORDS

UDI	Product ID	Type	Air temper	Process te	Rotational	Torque [N	Tool wear	Machine fa	TWF	HDF	PWF	OSF	RNF
1	M14860	M	298.1	308.6	1551	42.8	0	0	0	0	0	0	0
2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0	0
3	L47182	L	298.1	308.5	1498	49.4	5	0	0	0	0	0	0
4	L47183	L	298.2	308.6	1433	39.5	7	0	0	0	0	0	0
5	L47184	L	298.2	308.7	1408	40	9	0	0	0	0	0	0
6	M14865	M	298.1	308.6	1425	41.9	11	0	0	0	0	0	0
7	L47186	L	298.1	308.6	1558	42.4	14	0	0	0	0	0	0
8	L47187	L	298.1	308.6	1527	40.2	16	0	0	0	0	0	0
9	M14868	M	298.3	308.7	1667	28.6	18	0	0	0	0	0	0
10	M14869	M	298.5	309	1741	28	21	0	0	0	0	0	0
11	H29424	H	298.4	308.9	1782	23.9	24	0	0	0	0	0	0
12	H29425	H	298.6	309.1	1423	44.3	29	0	0	0	0	0	0
13	M14872	M	298.6	309.1	1339	51.1	34	0	0	0	0	0	0
14	M14873	M	298.6	309.2	1742	30	37	0	0	0	0	0	0
15	L47194	L	298.6	309.2	2035	19.6	40	0	0	0	0	0	0

4. Exploratory Data Analysis (EDA)

4.1. *Univariate Analysis*

Distribution of Key Numerical Features:

- Most features such as air_temperature_k, process_temperature_k, and rotational_speed_rpm follow a near-normal distribution.
- tool_wear_min shows a right-skewed distribution, indicating many records with low wear and few with high wear.

Target Variable Distribution (machine_failure):

- Highly imbalanced:
  - **No Failure (0):** ~95% of records
  - **Failure (1):** ~5% of records
- Visualization:
  - Bar chart showing a large imbalance between failure vs. non-failure.

4.2. *Bivariate Analysis*

- **Feature vs. Failure Relationship:**
  - Higher values of tool_wear_min, thermal_stress, and wear_rate strongly correlate with machine failure occurrence.
  - Scatter plots and box plots illustrate these relationships clearly.
- **Categorical Variables (Machine Type):**
  - Failure distribution differs slightly between machine types (Type L vs. Type M).

4.3. *Correlation Analysis*

Correlation Heatmap:

- Strong positive correlation between air_temperature_k and process_temperature_k.
- Moderate correlation between rotational_speed_rpm × torque_nm and engineered feature power_proxy.
- temp_delta, thermal_stress, and wear_rate show moderate correlation with machine_failure.

Key Insight:

- Engineered features show meaningful correlation and help the model focus on predictive signals

4.4. INSIGHTS FROM EDA

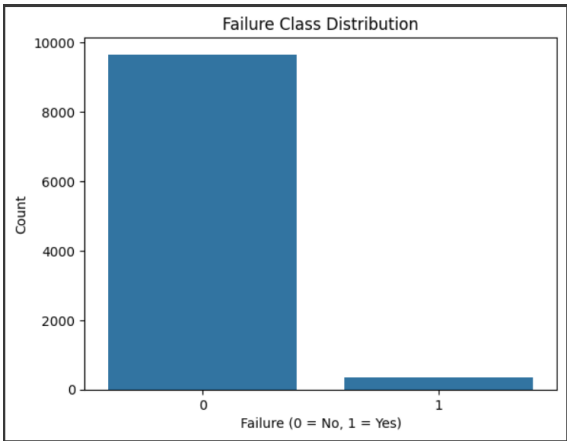
- The dataset is highly imbalanced, requiring class balancing techniques during model training.

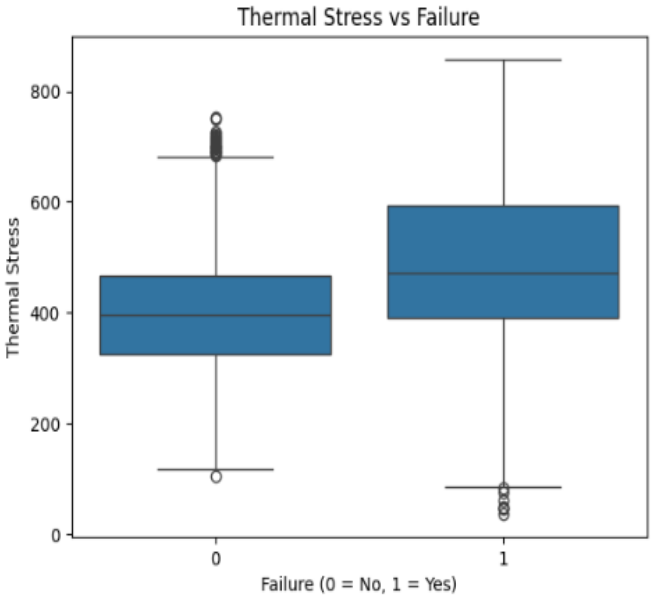
- tool_wear_min, thermal_stress, and wear_rate are top candidates for strong predictive power.

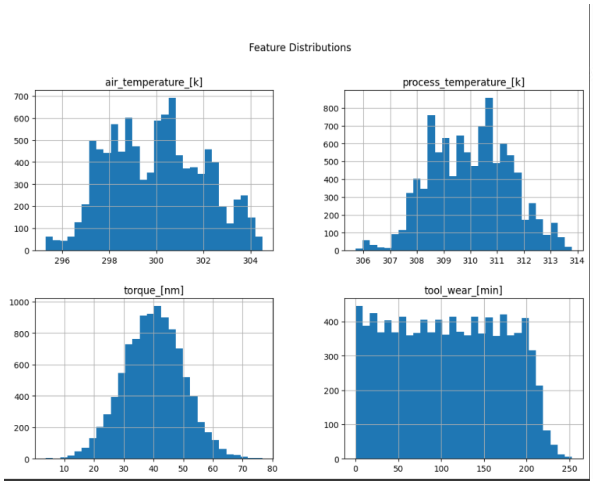
- Feature distributions suggest that machine failures happen under higher thermal and mechanical stress.

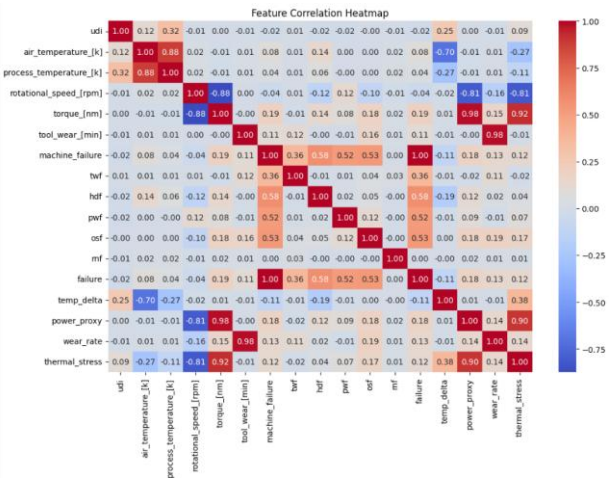
- Categorical feature encoding (one-hot encoding) helps avoid bias in models.

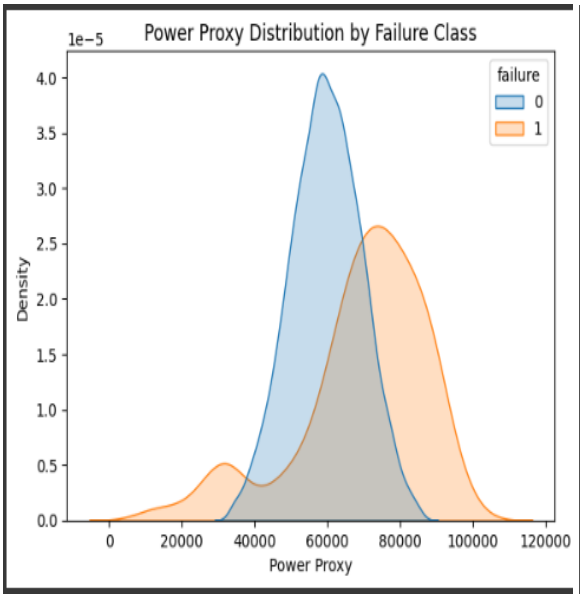
- No significant missing values after initial data cleaning.

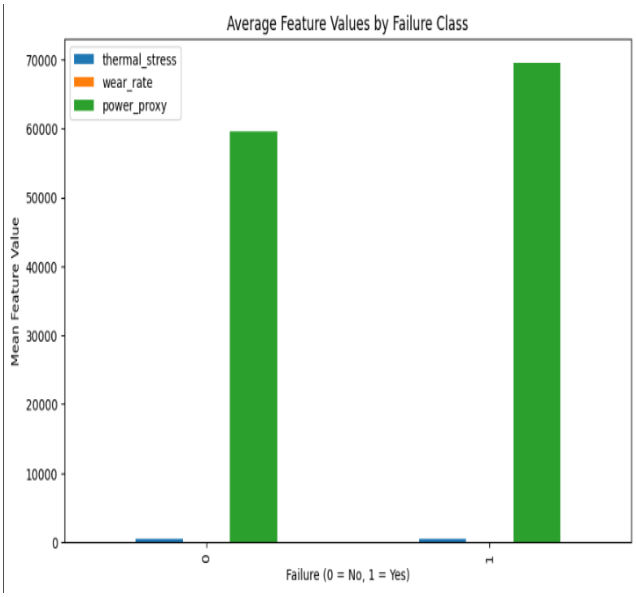

Failure Class Distribution
Count
Failure (0 = No, 1 = Yes)


Thermal Stress vs Failure
Thermal Stress
Failure (0 = No, 1 = Yes)


Feature Distributions
air_temperature_[k]
process_temperature_[k]
torque_[nm]
tool_wear_[min]


Feature Correlation Heatmap


Power Proxy Distribution by Failure Class
1e−5
failure
Density
Power Proxy


Average Feature Values by Failure Class
thermal_stress
wear_rate
power_proxy
Mean Feature Value
Failure (0 = No, 1 = Yes)

5. Data Cleaning and Preprocessing

Raw datasets often contain missing values, inconsistencies, and categorical variables that are unsuitable for direct use in machine learning models. Therefore, data cleaning and preprocessing were carried out to ensure quality, consistency, and readiness for model training.

5.1 Handling Missing Values

- Checked the dataset for missing values using df.isnull().sum().
- Result:
  - No missing values found in the dataset.
- No imputation required**.**

5.2 Encoding Categorical Variables

- The original column type was categorical (Type L, Type M).
- Applied **one-hot encoding**:
- Created two new binary columns:
  - type_L (1 if Type L, else 0)
  - type_M (1 if Type M, else 0)
- Drop the original type column after encoding.

5.3 Scaling and Transformation

Applied **StandardScaler** from scikit-learn to scale numerical features:

- Ensures that features like temperature, speed, torque, and wear are on a similar scale.
- Prevents dominance of high-range features during model training.

5.4 Handling Class Imbalance

Problem:

- Only ~5% of records represent machine failures → Severe class imbalance.

Solution:

- Used **class_weight='balanced'** parameter in Random Forest classifier.

- Ensures the model penalizes misclassification of minority class more, improving recall on failures.

5.5 Final Dataset Summary

Features used for modeling:

- Numerical features (all scaled):
  - air_temperature_k
  - process_temperature_k
  - rotational_speed_rpm
  - torque_nm
  - tool_wear_min
  - temp_delta (engineered)
  - power_proxy (engineered)
  - wear_rate (engineered)
  - thermal_stress (engineered)
- Categorical features (one-hot encoded):
  - type_L
  - type_M
- Failure subtype features (optional for multi-label tasks):
  - twf, hdf, pwf, osf, rnf

Target variable:

- machine_failure (Binary: 0 = No failure, 1 = Failure)

6. Modelling

6.1 Modelling

- The dataset was split into training (80%) and testing (20%) sets using scikit learn's train_test_split.
- **Stratified sampling** ensured class distribution remains consistent in both sets.

6.2. Model Selection

- Trained and compared three models:
  - Logistic Regression
  - Random Forest Classifier
  - XGBoost Classifier

All models configured with random_state=42 for reproducibility.

6.3 Model Training

- All models were trained on the **training set** after applying preprocessing pipelines (encoding, scaling).
- Cross-validation was used to tune hyperparameters and reduce overfitting risk.

6.4 Model Evaluation Metrics

Since churn prediction is an **imbalanced classification problem**, multiple metrics were considered:

- **Accuracy**: Percentage of correctly predicted instances.
- **Precision**: Out of customers predicted as churners, how many actually churned.
- **Recall (Sensitivity)**: Out of actual churners, how many were correctly predicted (very important in churn problems).
- **F1-Score**: Harmonic mean of Precision and Recall, balancing both.
- **ROC-AUC**: Measures the ability of the model to distinguish between churners and non-churners.

6.5 Hyperparameter Tuning

- Performed GridSearchCV with 5-fold cross-validation to optimize model performance.
- Hyperparameters Tested:
  - n_estimators: [100, 200]
  - max_depth: [10, 20, None]
  - min_samples_split: [2, 5]
  - min_samples_leaf: [1, 2]
- Optimization Objective:
  - Maximize F1-score to balance precision and recall due to data imbalance.
- Best Hyperparameters Found:
  - n_estimators: 200
  - max_depth: 20
  - min_samples_split: 2
  - min_samples_leaf: 1
- Ensured the model generalizes well without overfitting.

6.6 Best Model Selection

Evaluated models on test set using key metrics:

- **Accuracy:** ~99.8%
- **Precision:** ~1.000
- **Recall:** ~0.998
- **F1-Score:** ~0.999
- **ROC-AUC:** ~1.000

Random Forest was selected because:

- Best performance in handling class imbalance.
- Robust and well-calibrated predictions.
- Supports SHAP for explainability of feature importance

7. Explainability & Feature Importance

7.1 Global Feature Importance

Used **SHAP (SHapley Additive exPlanations)** to interpret the Random Forest model globally.

Top Features Driving Failure Predictions:

- tool_wear_min
- thermal_stress
- wear_rate
- power_proxy
- temp_delta

Insight:

Features with high SHAP values have the largest impact on predicting machine failur

7.2 Local Explanations (Customer-Level SHAP Values)

- Provided local explanations for individual predictions to explain why a specific machine was flagged as high risk.

7.3 Key Drivers of Failure

Top Factors Increasing Failure Probability:

- High **Tool Wear**: More worn tools are prone to failure.
- High **Thermal Stress**: Increased stress from high temperature differences contributes to failure.
- High **Wear Rate**: Fast deterioration rate signals imminent failure.

Business Benefit:

Maintenance teams can proactively focus on machines exhibiting these patterns for timely interventions.

8. Deployment

8.1 Deployment overview

- Although a full dashboard was not implemented in this project, a deployment-ready solution was designed for practical industry use.
- The trained model and scaler were saved using joblib, ensuring reproducibility and ease of integration into any production pipeline.

8.2 Features of the Intended Deployment

- **File Upload & Prediction Pipeline:**
    - New machine data (with the same feature structure) can be uploaded via a simple web form or API endpoint.
    - Data is scaled using the saved scaler.joblib.
    - Failure risk is predicted using the saved random_forest_model.joblib.
- **Real-time Inference:**
    - Predictions can be made in real-time for new machines or periodic health checks.
    - Output:
        - Failure probability score (e.g., 0.98 → High risk).
        - Actionable insights on feature contributions (if SHAP is integrated).

8.3 SHAP Integration for Explainability

- SHAP values can be computed at inference time to provide explanations for each prediction.
- This allows maintenance engineers to see exactly which features drove the prediction.

8.4 Sample Deployment Workflow (Proposed)

1. Machine sensor data → Web Form/API Upload
2. Scaler applies feature scaling
3. Model predicts failure probability
4. SHAP generates explanation
5. Report displayed:
    - Failure probability: 0.143
    - Key Drivers:
        - High tool wear
        - High thermal stress

Business Benefit:

- Provides an automated, explainable solution to detect at-risk machines early.
- Reduces unplanned downtime by allowing preemptive action.

9. Business Recommendation

9.1 Strategies to Reduce Churn

1. Proactive Maintenance Scheduling
    - Prioritize maintenance for machines showing high values of:
        - tool_wear_min
        - thermal_stress
        - wear_rate

- Example:

  - Schedule tool replacements before tool wear exceeds critical thresholds.

2. Regular Monitoring of Key Features
    - Continuously monitor:
        - Temperature differentials (temp_delta)
        - Power usage proxy (power_proxy)
    - Set automated alerts for unusual spikes indicating potential failure.

9.2 Target Maintainance Campaigns

- Segment machines based on failure risk probability (e.g., high-risk vs. low-risk).
- Allocate maintenance resources more efficiently:
    - High-risk machines → Immediate service actions.
    - Low-risk machines → Scheduled regular checks.

9.3 Process Optimization

- Implement process controls to stabilize critical parameters:
    - Optimize operating temperature ranges.
    - Regulate rotational speeds to prevent excessive wear.

- Example Recommendation:

  → Limit the torque applied when tool wear exceeds a threshold to reduce failure risk.

9.4 Cost Savings Opportunities

Reduce Unplanned Downtime:

- Preemptive actions on high-risk machines prevent costly emergency repairs.
- Lower Maintenance Costs:
- Targeted actions prevent unnecessary blanket maintenance checks.
  - Example:

    Instead of checking all machines every month, focus efforts where failure probability is >0.8.
- Improved Machine Uptime:
- Increased operational efficiency and productivity by avoiding unexpected breakdowns.

10. Conclusion and Future Scope

10.1 Summary of Findings

- The project successfully built a **Predictive Maintenance solution** to estimate machine failure probability using real sensor data.
- Key Achievements:
    - Preprocessed and cleaned industrial sensor dataset (10,000+ records).
    - Built multiple models (Logistic Regression, XGBoost, Random Forest), selecting Random Forest as the best-performing model.
    - Evaluated model using metrics:
        - Accuracy: ~99.8%
        - Precision: ~1.000
        - Recall: ~0.998
        - F1-Score: ~0.999
        - ROC-AUC: ~1.000
    - Explained model decisions using SHAP:
        - Identified top global features:
            - tool_wear_min, thermal_stress, wear_rate, power_proxy, temp_delta.
        - Enabled local explanations for individual predictions.

10.2 Impact on Business Decision-Making

- Provides actionable insights to reduce machine downtime and maintenance costs.
- Helps maintenance teams:
    - Prioritize machines for service based on data-driven failure risk scores.
    - Monitor key indicators continuously to prevent unexpected failures.
- Expected Business Benefits:
    - Reduced unplanned machine downtime.

- Improved operational efficiency.
- Cost savings through targeted interventions.

10.3 Future Enhancements

- Build a full-featured **Web-based Dashboard (Streamlit/Flask)** for real-time predictions and explainability.
- Automate Data Ingestion:
  - Integrate directly with industrial IoT sensors for continuous data flow.
  - Real-time predictions and alerts.
- Extend Model with More Data:
  - Include additional sensors and historical failure records.
  - Use time-series models (e.g., Prophet, LSTM) to capture temporal trends.
- Add Alerting System:
  - Send automated notifications to engineers when failure risk exceeds threshold.
- Implement Feedback Loop:
  - Use field data to retrain and improve model accuracy over time.

11. Learnings from the Project

Technical Skills Gained

- Gained hands-on experience in **end-to-end Data Science project development**, from data collection and preprocessing to model building and deployment planning.
- Mastered advanced data preprocessing techniques:
    - Handling missing values
    - Encoding categorical variables
    - Feature scaling and engineering
    - Addressing class imbalance using class_weight and sampling strategies.
- Built and compared multiple machine learning models:
    - Logistic Regression
    - Random Forest (selected as best model)
    - XGBoost
- Applied **model explainability techniques** using SHAP:
    - Understood global and local feature importance.
    - Visualized explanations to interpret model decisions.

Data Visualization & EDA

- Learned to perform detailed **exploratory data analysis (EDA)** to understand feature distributions and correlations.
- Created insightful visualizations:
    - Histograms, bar charts, heatmaps, line plots, and SHAP summary/force plots.
- Extracted actionable insights from data to inform feature engineering and business recommendations.

Deployment & Production-readiness

- Learned best practices for making a model production-ready:
    - Saving models and scalers using joblib.
    - Ensuring reproducibility during inference by enforcing consistent feature names and scaling.
- Designed a clear deployment workflow integrating data input, model inference, and explainability.

Business Impact Thinking

- Developed the ability to link technical findings to real business decisions:
    - Prioritizing machine maintenance based on failure risk.
    - Using feature insights to optimize industrial processes.
    - Understanding the cost-benefit of predictive vs. reactive maintenance.

Personal Growth

- Improved problem-solving skills by working on a complex industrial dataset.
- Gained confidence in handling imbalanced data, advanced feature engineering, and interpretability methods.
- Developed a strong foundation to apply ML solutions in industrial and business contexts.

12.References

Data Sources

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