Predictive Maintenance with a Milling Machine Use Case

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Predictive Maintenance with a Milling Machine Use Case

Estimated time to read: 5 minutes

The information that follows serves to guide you on how to implement a predictive maintenance workflow using machine learning.

Overview

Predictive maintenance uses machine data to predict when a failure is likely to occur, which enables proactive maintenance to minimize downtime and reduce costs. In this tutorial, we will demonstrate how to implement predictive maintenance for a milling machine, leveraging insights gathered during data collection.

This use case focuses on the following key failure scenarios:

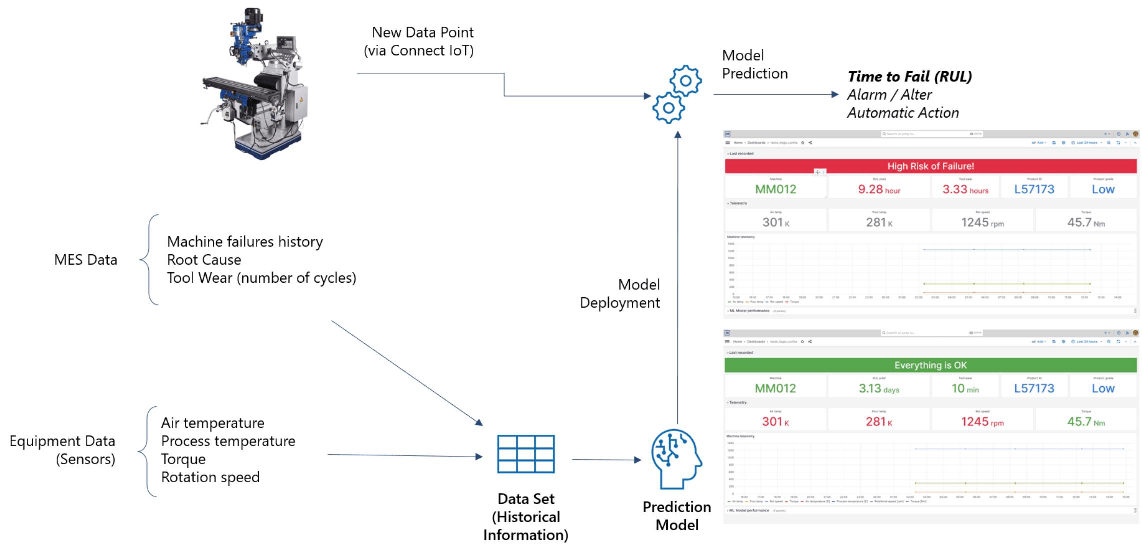
1. **Tool Wear Failure (TWF)**
2. **Heat Dissipation Failure (HDF)**
3. **Power Failure (PWF)**
4. **Overstrain Failure (OSF)**
5. **Random Failures (RNF)**

We will also estimate the Remaining Useful Life (RUL) of the milling machine based on observed time intervals between failures.

Preconditions

Before implementing predictive maintenance, ensure the following:

1. **Data Collection**:
    - Historical failure data with features such as tool wear, temperature, rotational speed, torque, and power usage.
2. **Analytical Tools**:
    - A data visualization platform (example: Grafana) and access to Data Platform ML Model.



Steps to Implement Predictive Maintenance

As context, let's consider a milling machine with the following failure scenarios:

- **TWF**: Tool wear reaches its limit (200-240 min).
- **HDF**: Heat dissipation fails when temp difference < 8.6 K and rotational speed < 1380 rpm.
- **PWF**: Power fails when P < 3500 W or P > 9000 W.
- **OSF**: ToolWear x Torque > 11000 minNm for load L, 12000 for M, 13000 for H.
- **RNF**: Rare random failures (<1%).

Step 1: Data Preprocessing

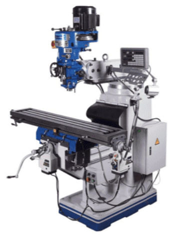
1. **Import Data**: Load the data via Post Event and store it in a Data Set. For more information, see Outlier Detection using Machine Learning. Ensure it contains fields you need.
2. **Clean Data**: Handle missing values and outliers. Standardize or normalize data for consistent analysis. This can be done for you in the ML Model wizard.
3. **Feature Engineering**:
   - Optionally, we may compute derived metrics like power using P = Torque * Rot. Speed (rad/s).

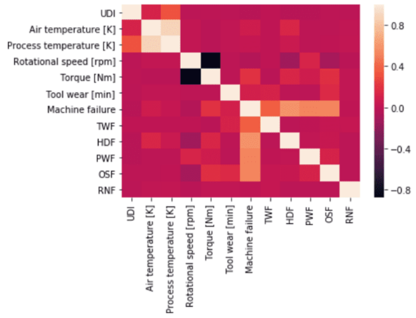
> **Info**
>
> Once again, these last steps may be performed within the ML Model.

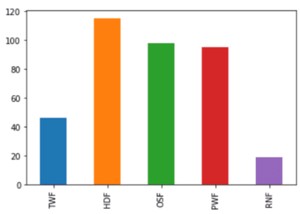
Step 2: Exploratory Data Analysis

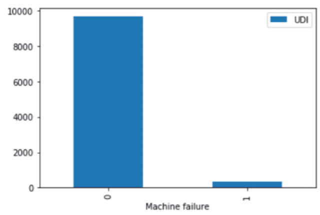
1. **Visualize Data**: Use graphs and dashboards to identify trends and patterns.
   - Example: Plot tool wear over time to observe failure intervals.
2. **Correlations**: Analyze correlations between failure events and parameters like tool wear, temperature, and power.
3. **Failure Insights**: Validate that failure conditions align with the thresholds provided:
   - Example: Check if failures occur when temp difference < 8.6 K and rotational speed < 1380 rpm (HDF).

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	TWF	HDF	PWF	OSF	RNF
0	1	M14860	M	298.1	308.6	1551	42.8	0	0	0	0	0	0	0
1	2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0	0
2	3	L47182	L	298.1	308.5	1498	49.4	5	0	0	0	0	0	0
3	4	L47183	L	298.2	308.6	1433	39.5	7	0	0	0	0	0	0
4	5	L47184	L	298.2	308.7	1408	40.0	9	0	0	0	0	0	0







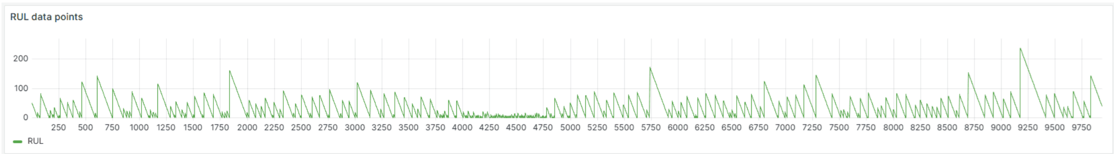


In the image, we can see the data structure along with their correlation matrix. For this particular dataset, we observe the dataset is not balanced - for classification problems, you may first consider apply over-sampling and/or under-sampling techniques.

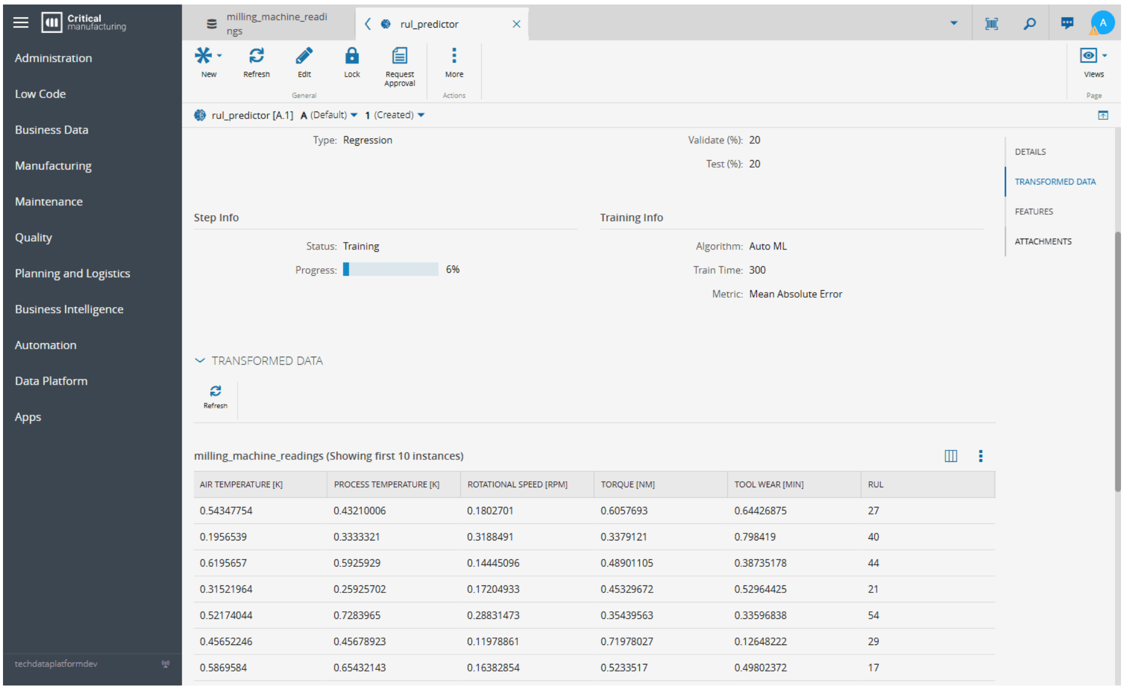
Step 3: Predictive Modeling

Let's divide the predictive modeling into two parts:

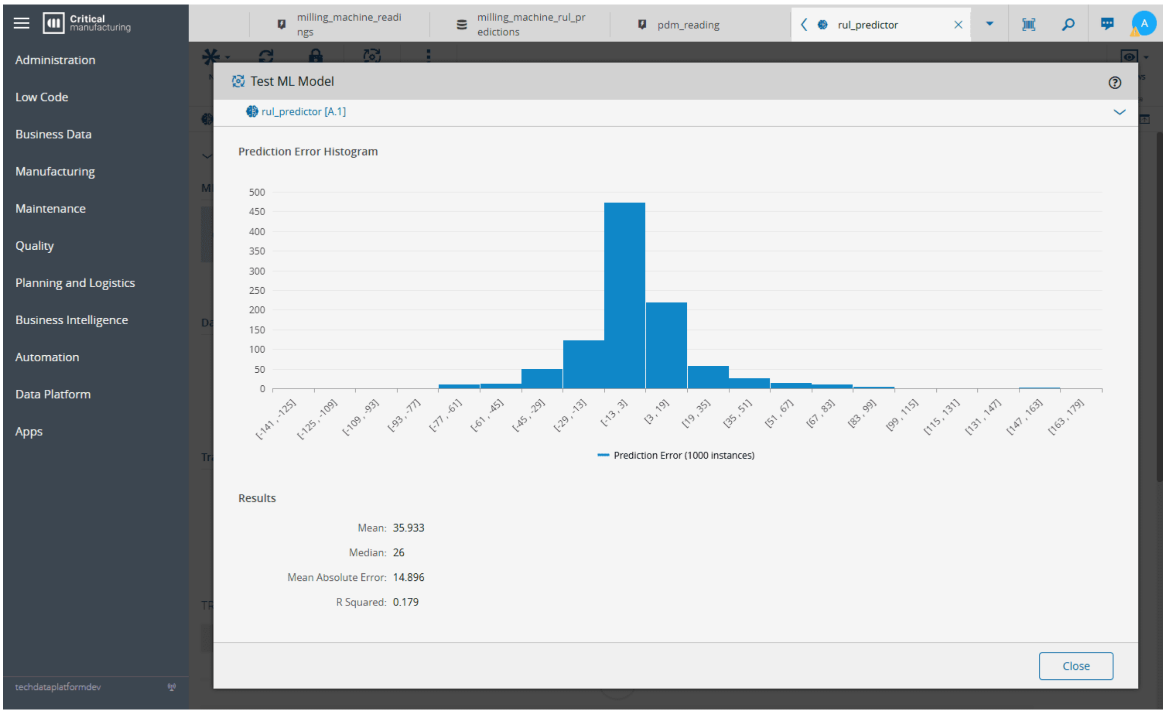
1. **Label RUL**:
   - Calculate the time remaining until the next failure for each data point.
   - Use a linear approximation based on the observed time intervals between failures.



2. **Train RUL Model**:
   - Train the model using features like tool wear, temperature, power, and torque. Select, during the ML Model wizard, the RUL column as label. This will define the experiment as a regression problem - you can check the Details view later on.
   - Use the ML Model to predict RUL. Validate the ML Model's performance.



As this is a regression problem, choose a metric that fits your needs. When it is trained, you only need to set it effective to deploy the model in MES ecosystem.

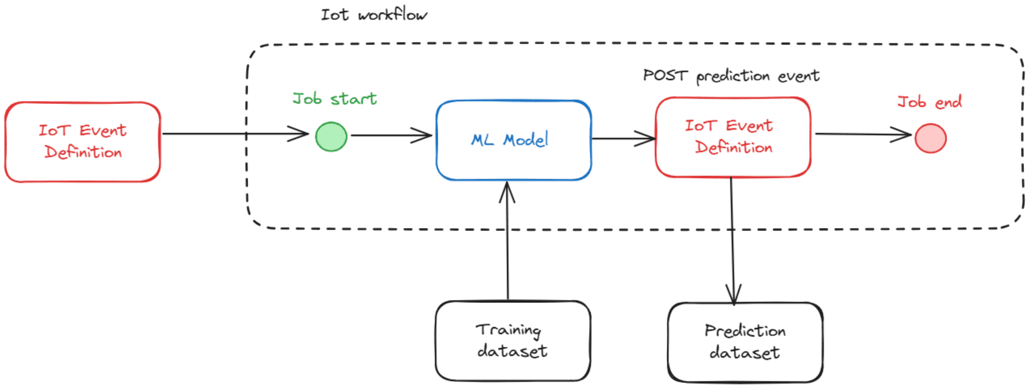


> **Info**
>
> Remember that the ML Model consist in an AutoML framework, thus, it will automatically select the best model for your problem. For more information, see this link.

Step 4: Integrate with Real-Time Monitoring

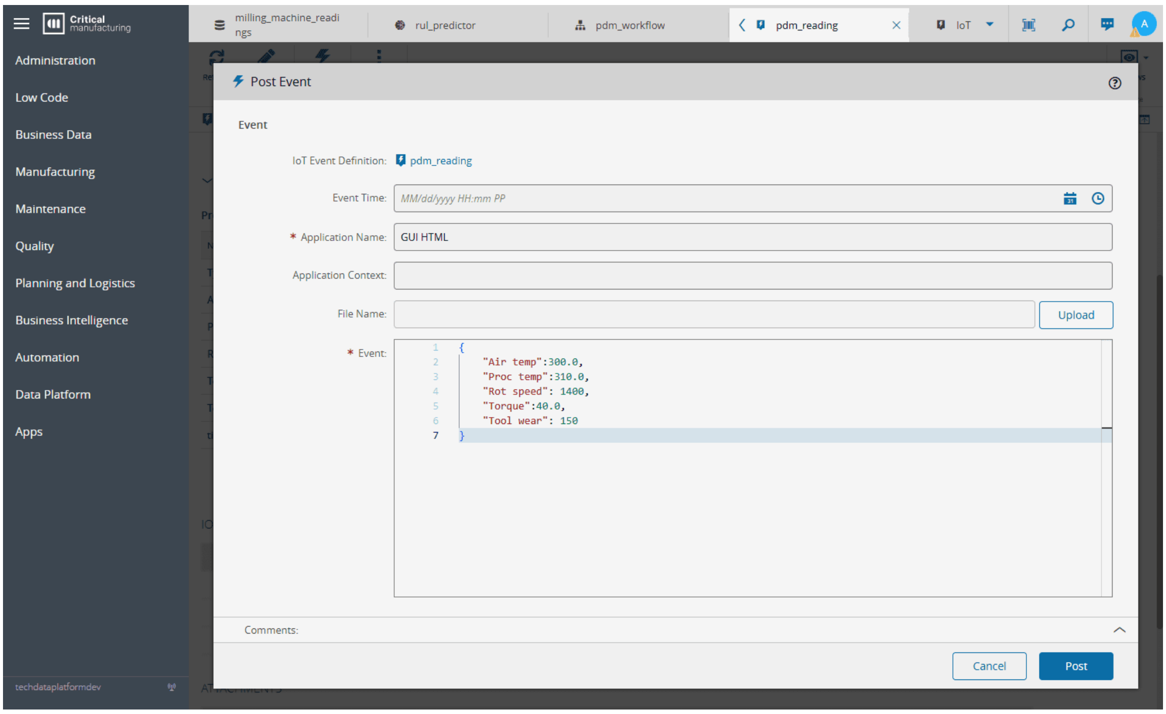
1. **Set Up IoT workflow**:

- Assign an IoT workflow to post the readings. The workflows, when triggered, will then predict the time to fail and record the value in a Data Set via Post Event, as shown in the image:



2. **Add ML Task**:
   - Drag the ML Task and connect the inputs, but first you must select the right IoT Event Definition - select the settings button to do so. For more information, see Outlier Detection using Machine Learning.
3. **Add API Post Event Task**:
   - Add API Post Event Task to record the predicted RUL in a Data Set.
   - Select the settings button to choose the right event definition.

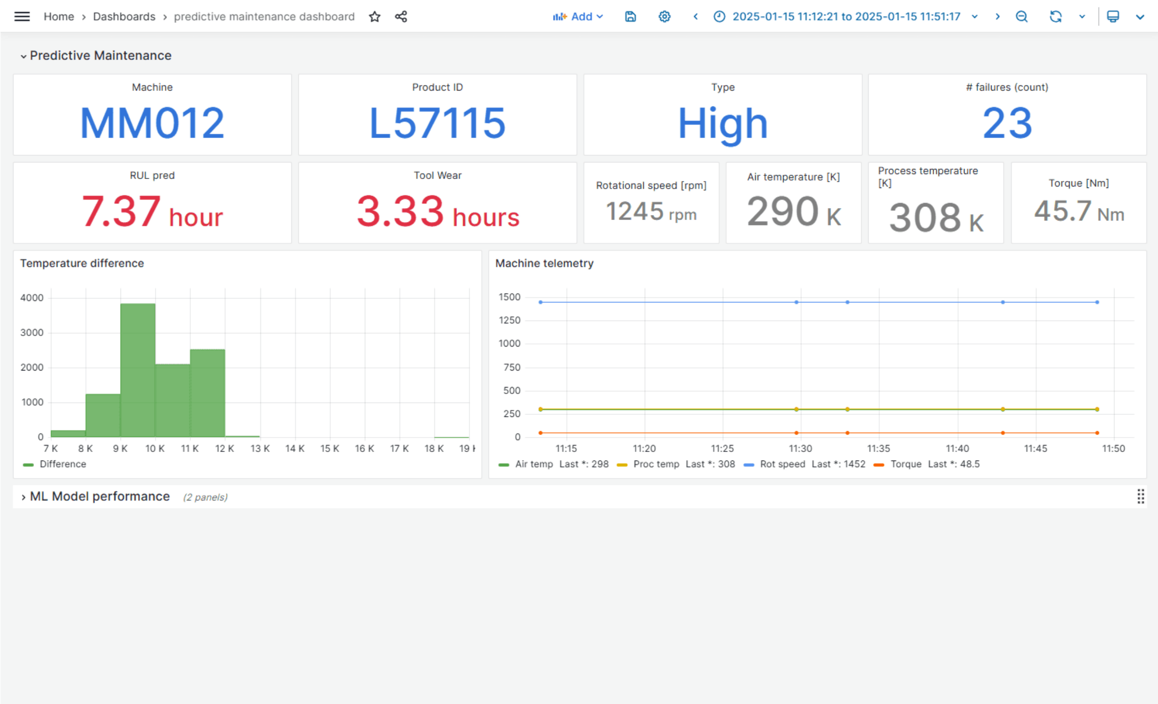
When this is done, connect the blocks and run the workflow by manually posting an event. Example:



You should see a new record in the predicted RUL Data Set.

Step 5: Validate and Optimize

1. **Create Dashboards**:
   - Display real-time RUL estimates, failure type predictions, and key parameters (example: tool wear, power).
2. **Test Predictions**:
   - Compare model predictions with actual failures to evaluate accuracy.
3. **Adjust Models**:
   - Refine thresholds and retrain models with updated data to improve predictions.
4. **Monitor Performance**:
   - Continuously monitor the workflow to ensure reliability.



Final remarks

The example dashboard for the milling machine could include:

- **Tool Wear Monitor**: Visualize tool wear over time, highlighting when it nears failure thresholds.
- **Telemetry Trends**: Show temperature differences and power consumption to detect anomalies.
- **RUL Estimation**: Display predicted RUL in minutes.

By following this tutorial, you can build a predictive maintenance workflow for a milling machine that improves uptime, reduces costs, and ensures smooth production processes. For further assistance, refer to your data analytics platform documentation or consult with your engineering team.

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