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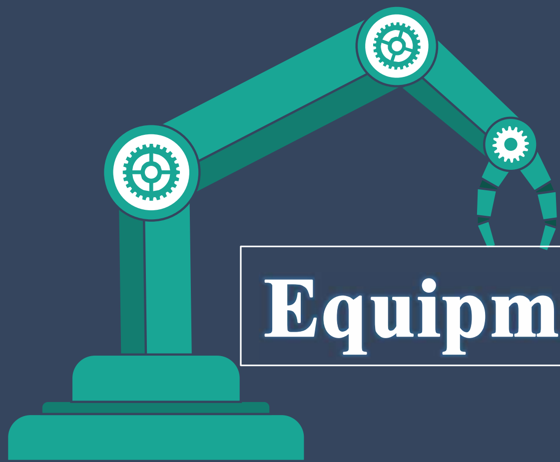

Equipment Failure for Maintenance

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Our Team Infographic

TEAM RRR

TEAM MEMBERS

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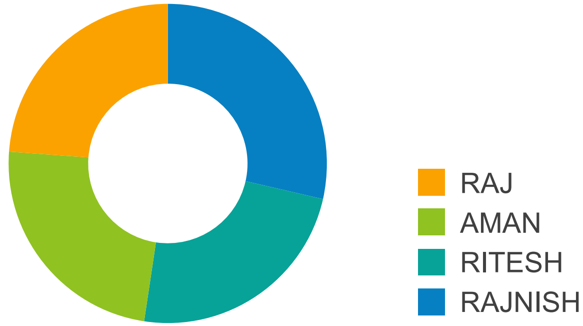
TEAM PROGRESS



https://github.com/rajnish1602/Equipment-Failure-on-Sensor-Data.git

Agenda

01 INTRODUCTION

02 ABOUT PROJECT

03 DATA PREPARATION

04 DATA VISUALIZATION

05 STEPS OF EDA

06 DATA ANALYSIS

07 INSIGHTS

08 CONCLUSION

INTRODUCTION

Predictive maintenance plays a crucial role in various industries to ensure the reliability and efficiency of equipment. This paper presents a comprehensive methodology for predictive maintenance, leveraging advanced machine learning (ML) and deep learning techniques. The objective is to develop a predictive maintenance system capable of pre-emptively identifying equipment failures, thereby enabling proactive maintenance interventions. The methodology encompasses data collection, preprocessing, feature engineering, model selection, training, and deployment. Various tools and technologies such as Python programming language, TensorFlow, and cloud computing platforms are employed to enhance scalability and flexibility. The proposed framework is applicable across diverse domains, offering significant impacts such as reduced downtime, lower maintenance costs, and improved operational efficiency.

TRADITIONAL WAY OF MAINTENANCE

Reactive Maintenance: This strategy involves fixing equipment and systems after they have already broken. While this approach requires less staffing and maintenance training fees.

Preventive Maintenance: This approach involves performing maintenance tasks on a fixed schedule, such as replacing parts or conducting inspections, regardless of whether or not the equipment is showing signs of wear or malfunction. This can lead to unnecessary maintenance activities and wasted resources.

Lack of Real-Time Data: Traditional maintenance methods often lack real-time data monitoring, which can lead to unexpected equipment failures.

Higher Costs: Traditional maintenance methods can lead to higher costs due to unnecessary preventive maintenance and the costs associated with equipment failure.

Lack of Efficiency: Traditional maintenance methods can be less efficient as they do not utilize data to optimize maintenance schedules.

Why equipment failure for maintenance required ?

Proper training and adherence to operating procedures can help prevent this

Improper Operation

Regular maintenance is essential for optimal performance. Neglecting preventive maintenance can lead to equipment failure

Failure to Perform Preventive Maintenance

While preventive maintenance is important, too much of it can also lead to problems. Over-maintenance can result in unnecessary downtime and increased costs.

Too Much Preventive Maintenance

Continuous monitoring of equipment can help detect issues early and prevent equipment failure. Without it, problems might go unnoticed until it's too late

Failure to Continuously Monitor Equipment

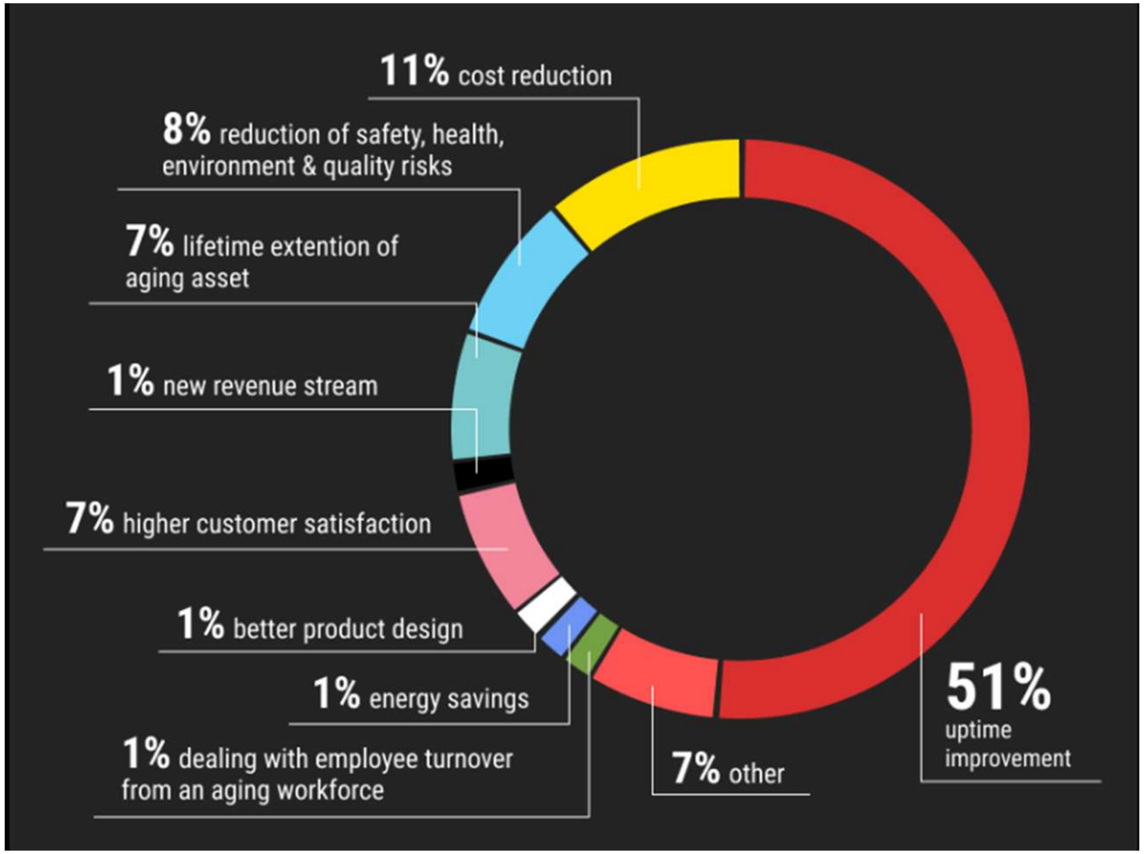
Equipment maintenance is crucial to prevent failures and ensure smooth operations. Here are some common reasons why equipment failure occurs and why maintenance is required

EQUIPMENT FAILURE FOR MAINTENANCE

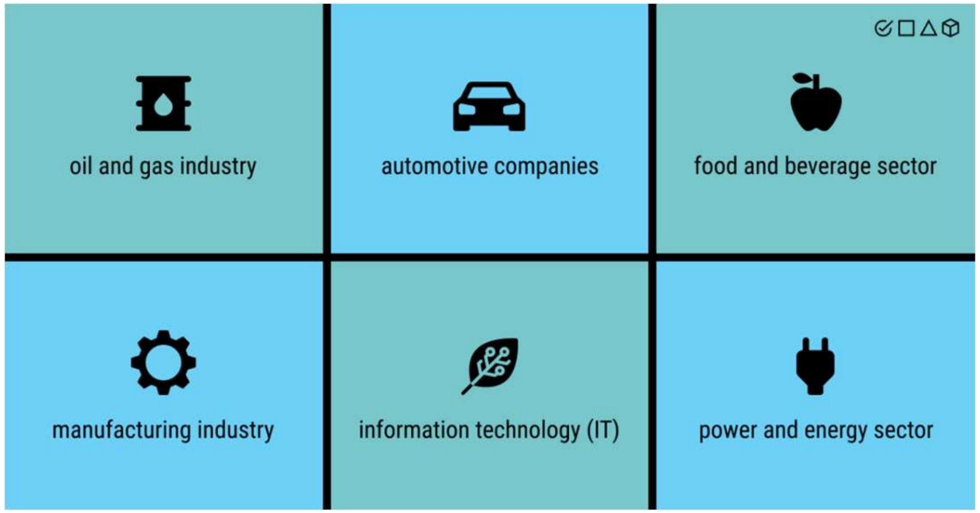
Bad (or No) Reliability Culture

A strong reliability culture emphasizes the importance of regular maintenance and encourages everyone to play their part in maintaining equipment

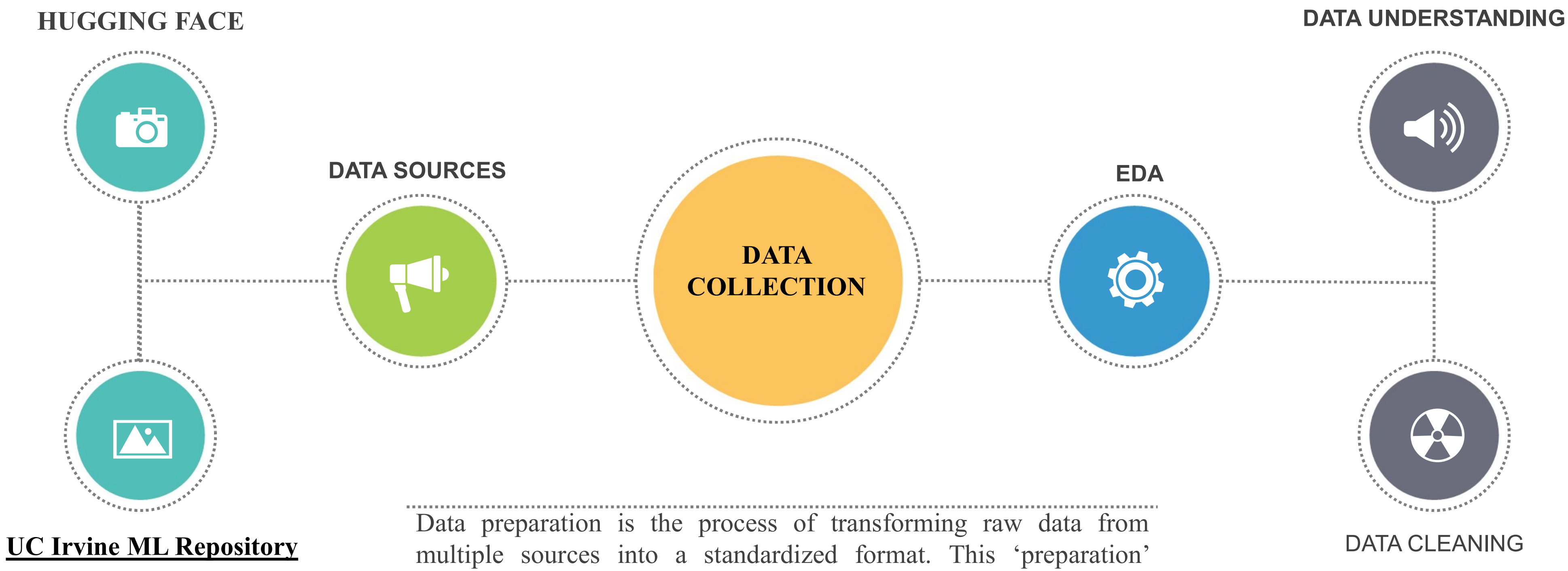
Impact of Equipment Failure Prediction



Major Impact Industries

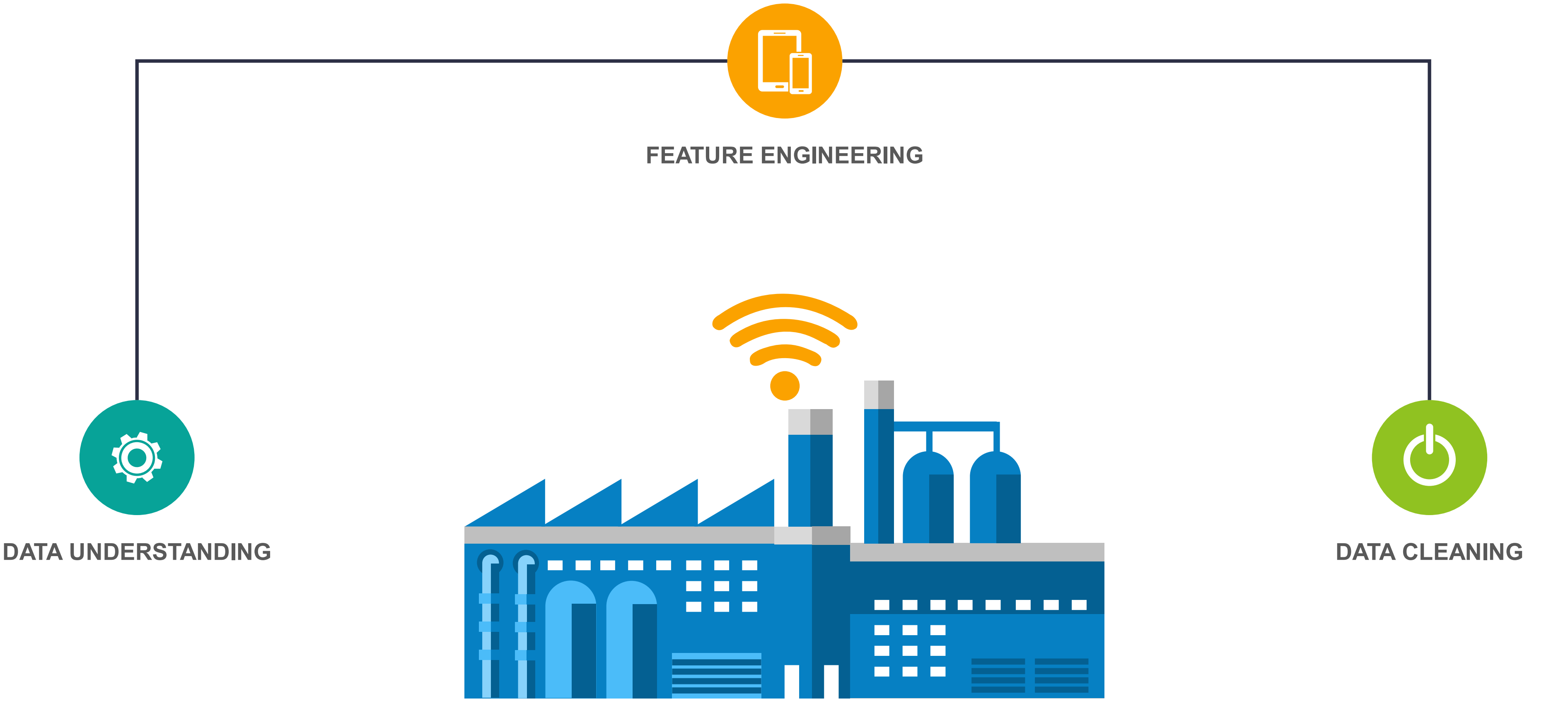


DATA PREPARATION



Data preparation is the process of transforming raw data from multiple sources into a standardized format. This 'preparation' makes the data ready for use by business intelligence tools and is thus a prerequisite to analysis.

EXPLORATORY DATA ANALYSIS



DATA UNDERSTANDING

- There are 10000 rows and 14 columns
- In this graph, it contains 1st and last five rows.
- Columns Details

1. UDI: Serial no.
2. Product ID: Equipment ID
3. Type: Type of Equipment
4. Air Temperature: in K
5. Process Temperature: in K
6. Rotational Speed: Revolutions per minute
7. Torque: in Newton meter
8. Tool wear: minutes
9. Machine Failure: 0 or 1
10. MWF, HDF, PWF, OSF, RNF : MACHINE COMPONENTS

```
1 df.head()
```

	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

```
1 df.tail()
```

	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
9995	9996	M24855	M	298.8	308.4	1604	29.5	14	0	0	0	0	0	0
9996	9997	H39410	H	298.9	308.4	1632	31.8	17	0	0	0	0	0	0
9997	9998	M24857	M	299.0	308.6	1645	33.4	22	0	0	0	0	0	0
9998	9999	H39412	H	299.0	308.7	1408	48.5	25	0	0	0	0	0	0
9999	10000	M24859	M	299.0	308.7	1500	40.2	30	0	0	0	0	0	0

Statical Summary

	UDI	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	TWF	HDF	PWF	OSF	RNF
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000
mean	5000.50000	300.004930	310.005560	1538.776100	39.986910	107.951000	0.033900	0.004600	0.011500	0.009500	0.009800	0.00190
std	2886.89568	2.000259	1.483734	179.284096	9.968934	63.654147	0.180981	0.067671	0.106625	0.097009	0.098514	0.04355
min	1.00000	295.300000	305.700000	1168.000000	3.800000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	2500.75000	298.300000	308.800000	1423.000000	33.200000	53.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
50%	5000.50000	300.100000	310.100000	1503.000000	40.100000	108.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
75%	7500.25000	301.500000	311.100000	1612.000000	46.800000	162.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
max	10000.00000	304.500000	313.800000	2886.000000	76.600000	253.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00000

Count: All columns have a count of 10,000, indicating there are no missing values.

Mean: This row represents the average value for each column.

Std: This row shows the standard deviation, which measures the amount of variation in each column.

Min: This row shows the minimum value in each column.

25%: This is the first quartile, indicating that 25% of the data in each column is below this value.

50%: This is the median, indicating that 50% of the data in each column is below this value.

75%: This is the third quartile, indicating that 75% of the data in each column is below this value.

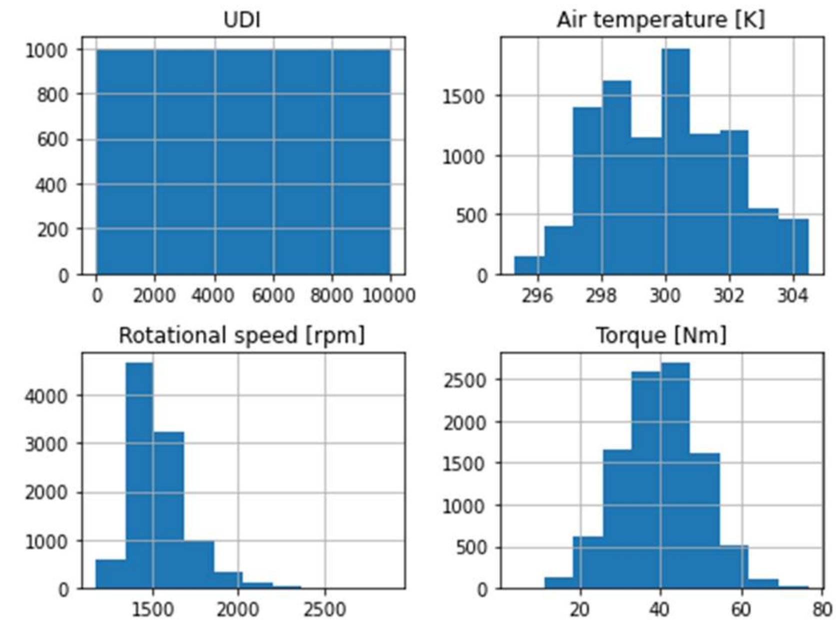
Max: This row shows the maximum value in each column.

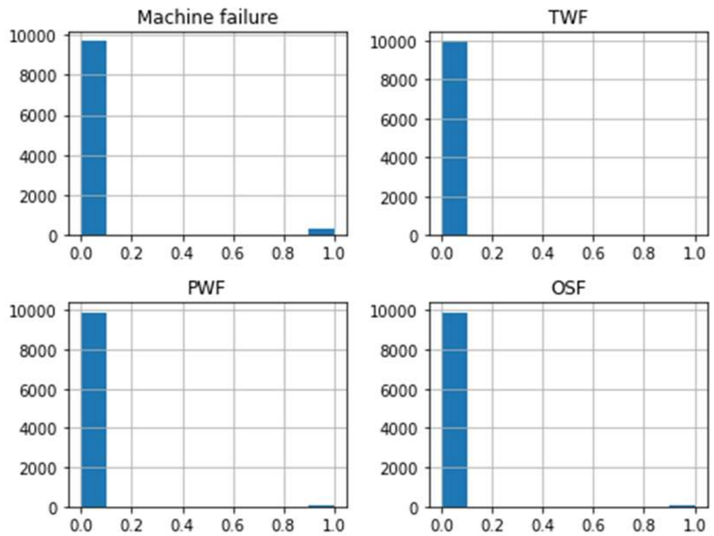
Missing Values Summary

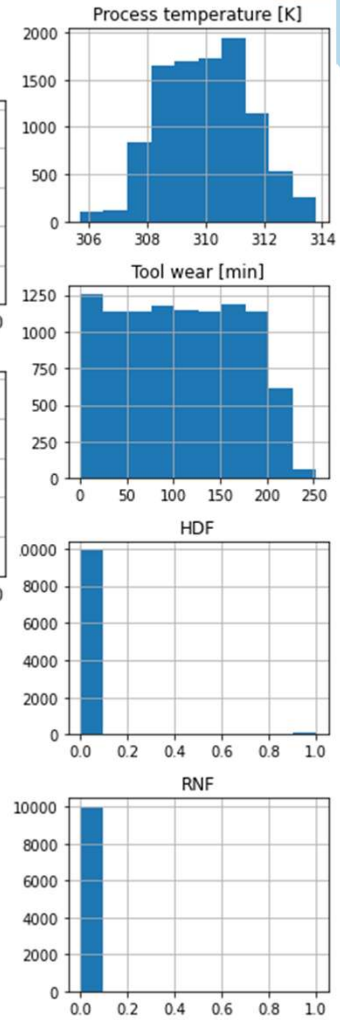
Here, is the brief about the graph

- As there is no missing value in any columns.

- So further we analyse each columns by univariant, bivariant and multivariant, and data transformation

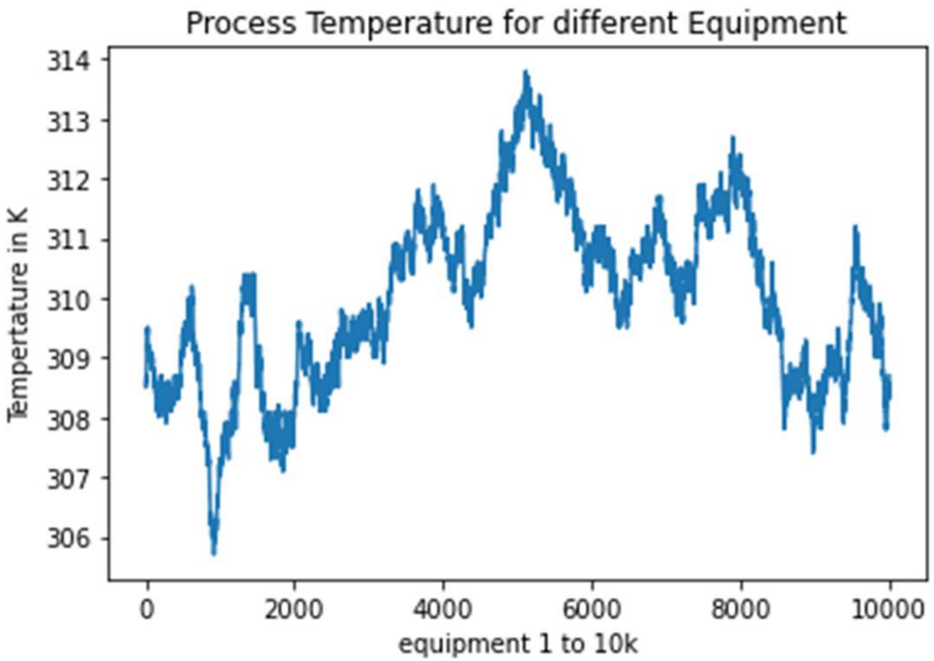


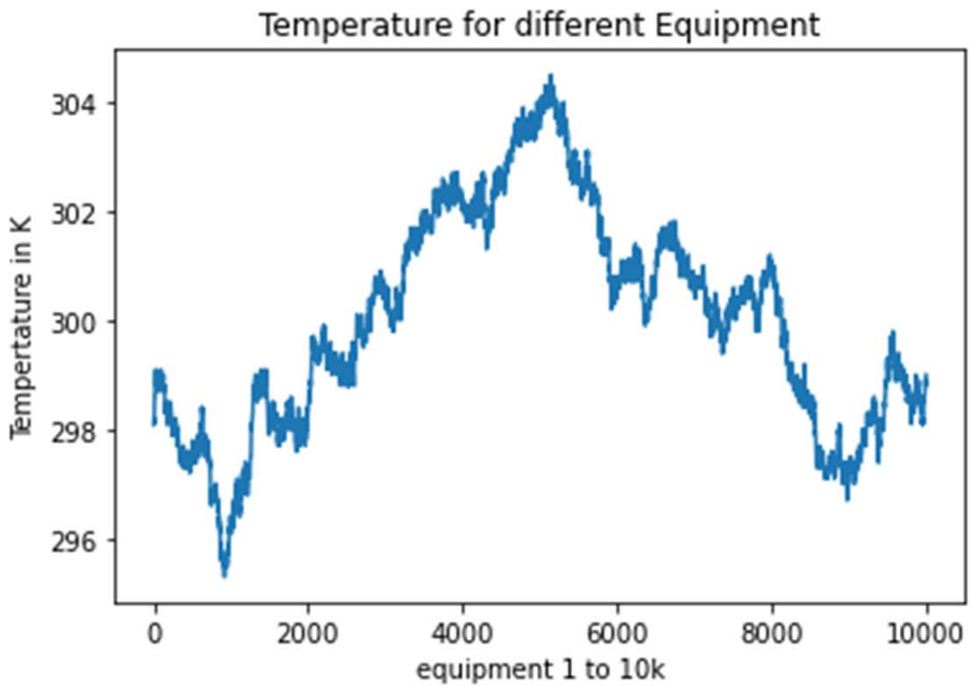




Distribution Plot

Here, All the graph represent distribution of data in each columns



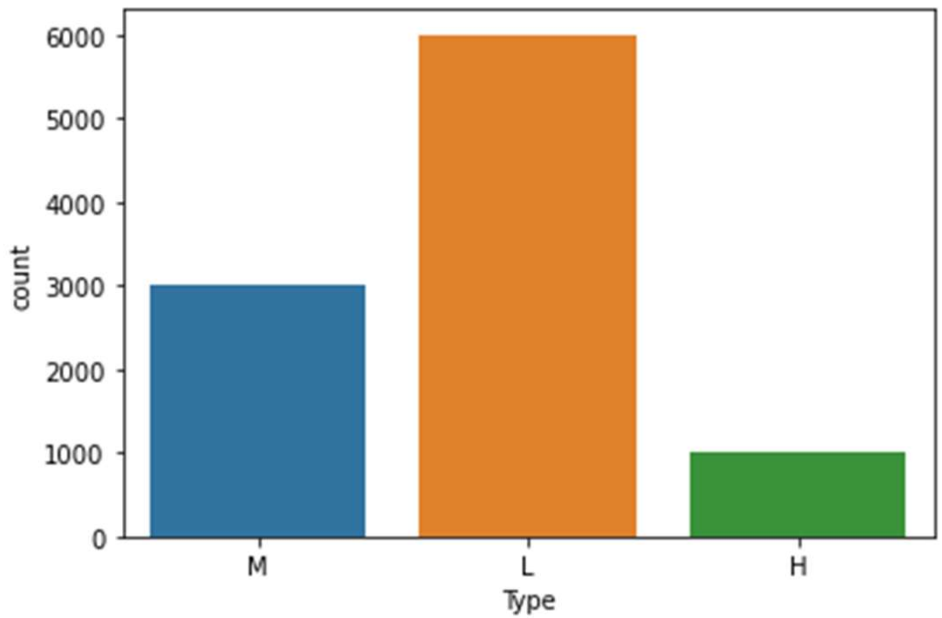


Line Graph of Air Temperature & Process Temperature Columns

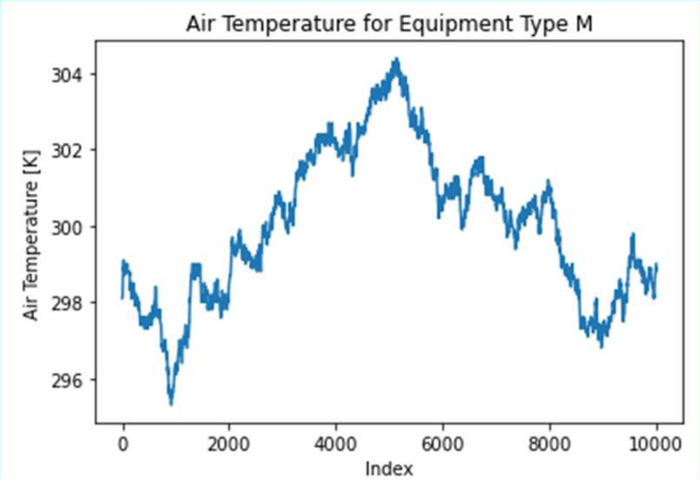
In this graph, Equipment are of three type M,L,H

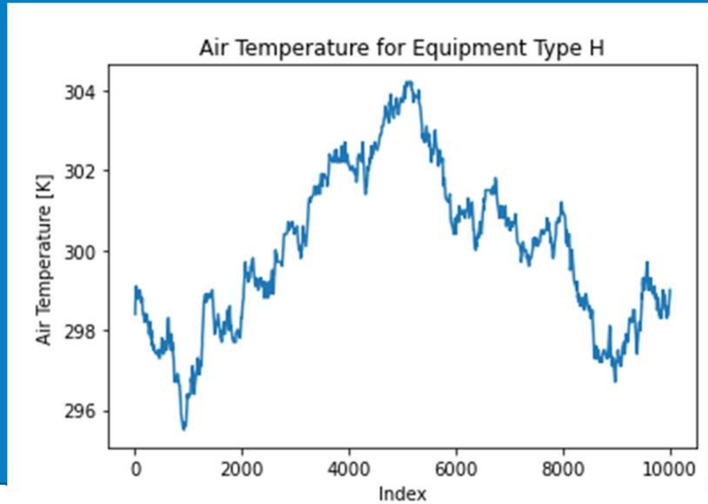
- M Type: 3000 equipment's
- L Type: 6000 equipment's
- H Type: 1000 equipment’s

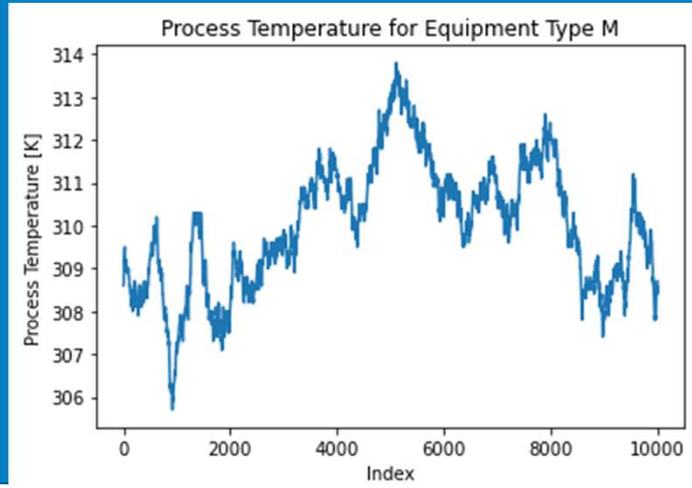
Further, we can split this columns to into 3 parts M_type, L_type, H_type

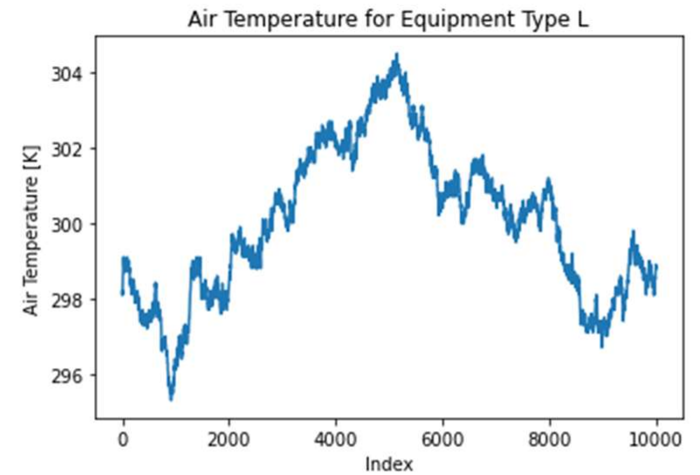


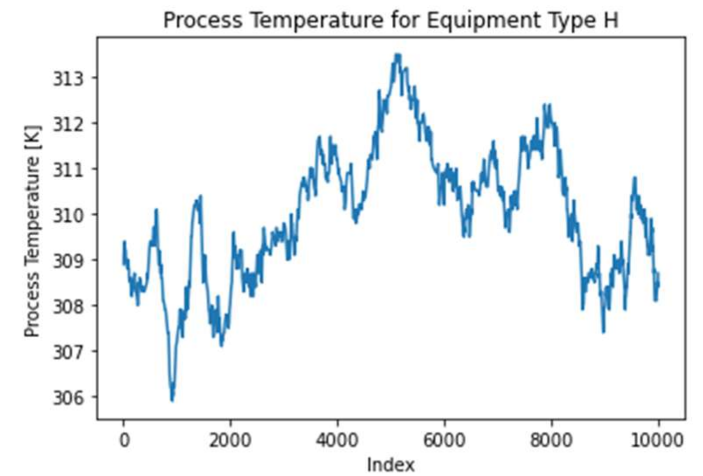
Bivariant and Multivariant Analysis

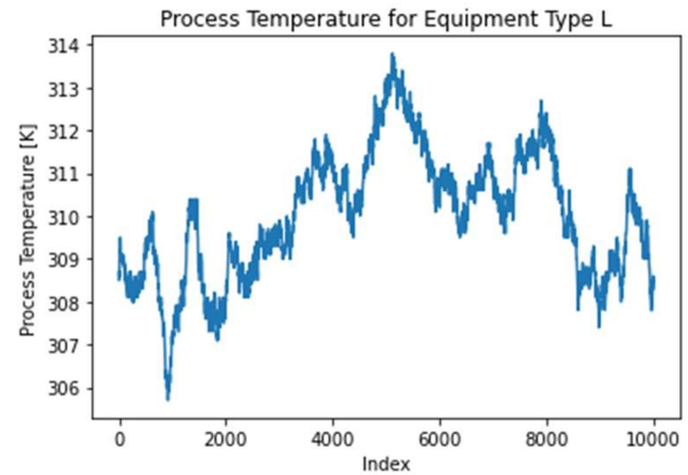






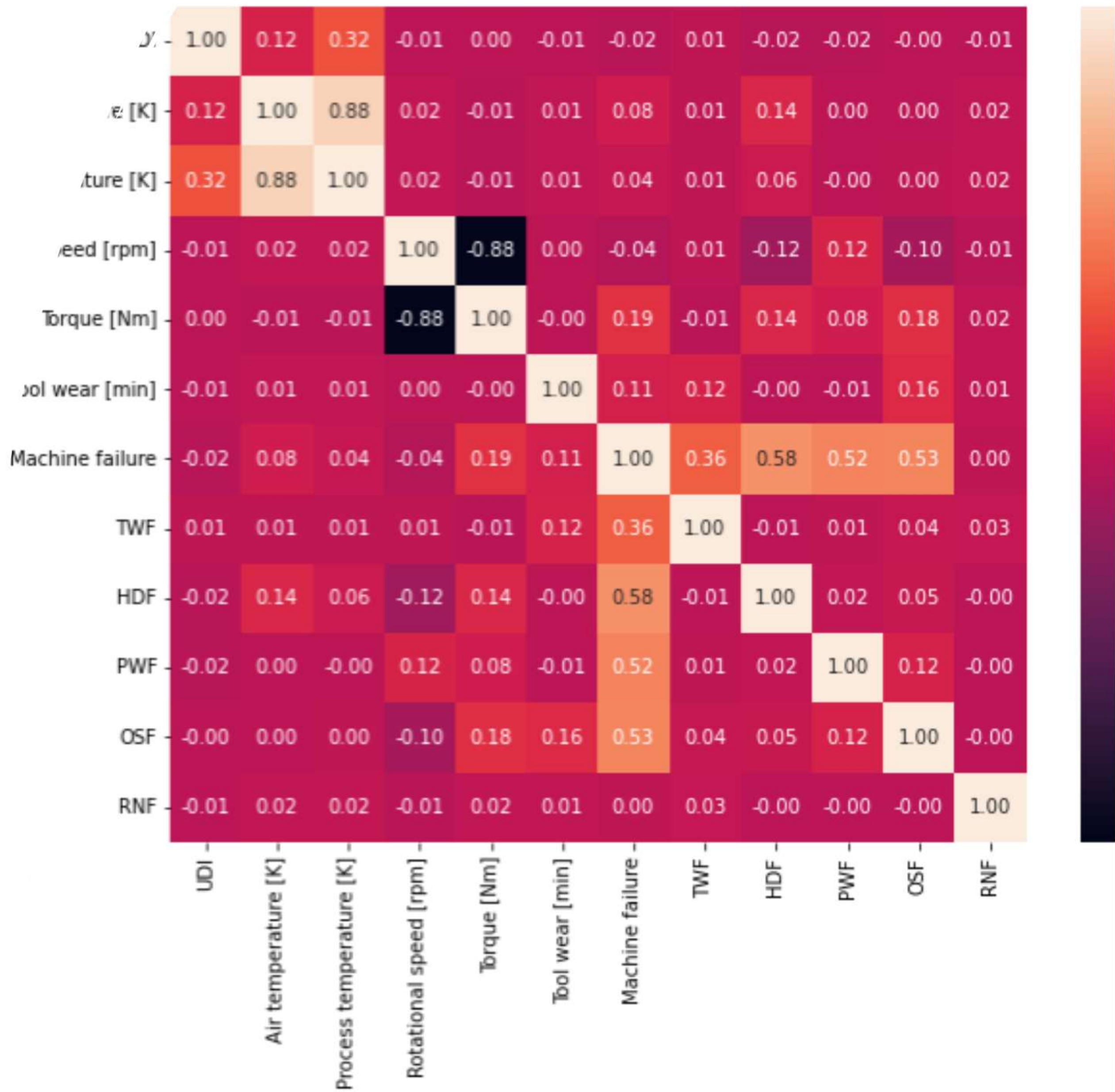






Checking Co-relation Coefficients

- **Parameters**: The parameters include UDI, Air temperature [K], Process temperature [K], Rotational speed [rpm], Torque [Nm], Tool wear [min], Machine failure, TWF, HDF, PWF, OSF, and RNF.
- **Colour Gradient**: The cells are coloured from dark purple to white to dark red indicating the range of correlation from -1 through 0 to 1 respectively. Dark red cells with a value of 1 indicate a perfect positive correlation.
- **Interpretation**: Most correlations appear weak as indicated by colours close to white and values close to zero; however, there are stronger correlations visible such as between Air temperature and Process temperature.

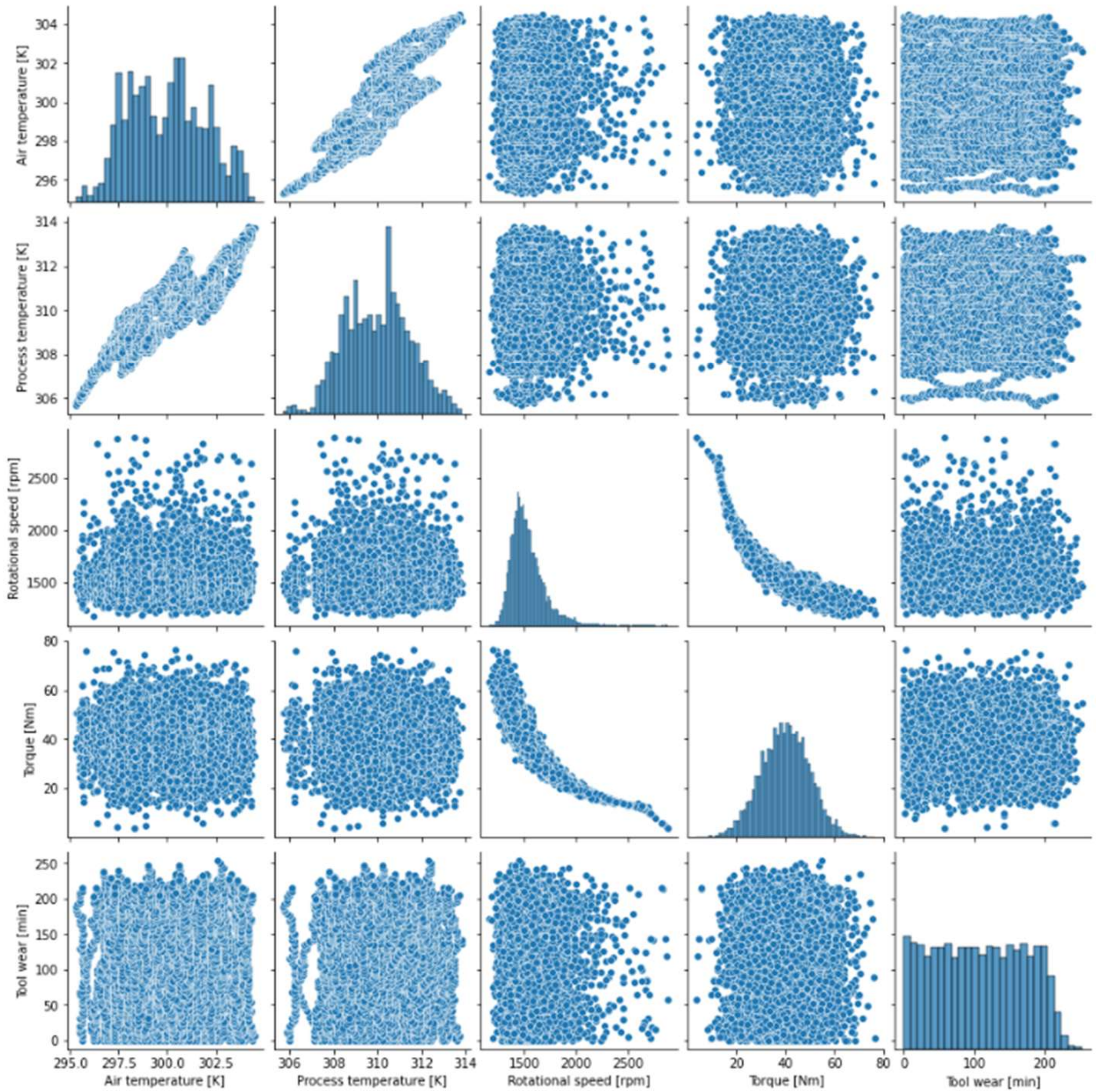


Matrix of Pairplot that visualize the relationships between different variables such as Air Temperature, Process Temperature, Rotational Speed, Torque, and Tool Wear. Here's a summary for your PowerPoint presentation:

•**Variable Distributions**: The histograms on the diagonal show the distribution of each variable. For instance, Air Temperature appears to have a normal distribution, while Tool Wear shows an increasing trend.

•**Variable Relationships**: The scatter plots off the diagonal illustrate how two variables relate to each other. For example, there's a plot comparing Process Temperature against Air Temperature.

•**Data Representation**: Data points are depicted as blue dots in scatter plots and blue bars in histograms, providing a clear visual representation of the data.



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Equipment Failure For Maintenance
Thank You