```
import kagglehub
stephanmatzka_predictive_maintenance_dataset_ai4i_2020_path = kagglehub.dataset_download('st


print('Data source import complete.')
```

```
Data source import complete.
```

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import warnings

# Ignore all warnings
warnings.filterwarnings("ignore")
```

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

UID: unique identifier ranging from 1 to 10000 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 type: just the product type L, M or H from column 2 air temperature [K]: generated using a random walk process later normalized to a standard deviation of 2 K around 300 K 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. rotational speed [rpm]: calculated from a power of 2860 W, overlaid with a normally distributed noise torque [Nm]: torque values are normally distributed around 40 Nm with a SD = 10 Nm and no negative values. tool wear [min]: The quality variants H/M/L add 5/3/2 minutes of tool wear to the used tool in the process. 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

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). 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. 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. 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. 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.

```
df=pd.read_csv("/kaggle/input/predictive-maintenance-dataset-ai4i-2020/ai4i2020.csv")
df # Displaying dataset to understand the structure
```

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure
0	1	M14860	M	298.1	308.6	1551	42.8	0	0
1	2	L47181	L	298.2	308.7	1408	46.3	3	0
2	3	L47182	L	298.1	308.5	1498	49.4	5	0
3	4	L47183	L	298.2	308.6	1433	39.5	7	0
4	5	L47184	L	298.2	308.7	1408	40.0	9	0
...	...	...	...	...	...	...	...	...	...
9995	9996	M24855	M	298.8	308.4	1604	29.5	14	0
9996	9997	H39410	H	298.9	308.4	1632	31.8	17	0
9997	9998	M24857	M	299.0	308.6	1645	33.4	22	0
9998	9999	H39412	H	299.0	308.7	1408	48.5	25	0
9999	10000	M24859	M	299.0	308.7	1500	40.2	30	0

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```
df[df["Machine failure"]==1] #data points shows Machine Failure
```

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure
50	51	L47230	L	298.9	309.1	2861	4.6	143	1
69	70	L47249	L	298.9	309.0	1410	65.7	191	1
77	78	L47257	L	298.8	308.9	1455	41.3	208	1
160	161	L47340	L	298.4	308.2	1282	60.7	216	1
161	162	L47341	L	298.3	308.1	1412	52.3	218	1
...	...	...	...	...	...	...	...	...	...
9758	9759	L56938	L	298.6	309.8	2271	16.2	218	1
9764	9765	L56944	L	298.5	309.5	1294	66.7	12	1
9822	9823	L57002	L	298.5	309.4	1360	60.9	187	1
9830	9831	L57010	L	298.3	309.3	1337	56.1	206	1
9974	9975	L57154	L	298.6	308.2	1361	68.2	172	1

DATA PREPROCESSING

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   UDI                      10000 non-null  int64
 1   Product ID               10000 non-null  object
 2   Type                     10000 non-null  object
 3   Air temperature [K]      10000 non-null  float64
 4   Process temperature [K]  10000 non-null  float64
 5   Rotational speed [rpm]   10000 non-null  int64
 6   Torque [Nm]              10000 non-null  float64
 7   Tool wear [min]          10000 non-null  int64
 8   Machine failure          10000 non-null  int64
 9   TWF                      10000 non-null  int64
 10  HDF                      10000 non-null  int64
 11  PWF                      10000 non-null  int64
 12  OSF                      10000 non-null  int64
 13  RNF                      10000 non-null  int64
dtypes: float64(3), int64(9), object(2)
memory usage: 1.1+ MB
```

```
# Checking for null values and duplicates
df.isnull().sum()
```

```
df.duplicated().sum()
```

```
np.int64(0)
```

```
# Understanding data types and unique values per column
df.dtypes
df.nunique()
```

	0
UDI	10000
Product ID	10000
Type	3
Air temperature [K]	93
Process temperature [K]	82
Rotational speed [rpm]	941
Torque [Nm]	577
Tool wear [min]	246
Machine failure	2
TWF	2
HDF	2
PWF	2
OSF	2
RNF	2

dtype: int64

```
df['Type'].value_counts()
df.drop(columns=['UDI','Product ID'],inplace=True)
```

Feature Engineering

```
# Creating new feature: temperature difference between process and air
df['temperature_difference']=df['Process temperature [K]']-df['Air temperature [K]']
```

```
# Creating new feature: mechanical power using torque and rotational speed
df['Mechanical Power [W]']=np.round((df['Torque [Nm]']*df['Rotational speed [rpm]']* 2 * np.
```

```
df
```

	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	TWF	HDF	PWF
0	M	298.1	308.6	1551	42.8	0	0	0	0	0
1	L	298.2	308.7	1408	46.3	3	0	0	0	0
2	L	298.1	308.5	1498	49.4	5	0	0	0	0
3	L	298.2	308.6	1433	39.5	7	0	0	0	0
4	L	298.2	308.7	1408	40.0	9	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
9995	M	298.8	308.4	1604	29.5	14	0	0	0	0
9996	H	298.9	308.4	1632	31.8	17	0	0	0	0
9997	M	299.0	308.6	1645	33.4	22	0	0	0	0
9998	H	299.0	308.7	1408	48.5	25	0	0	0	0
9999	M	299.0	308.7	1500	40.2	30	0	0	0	0

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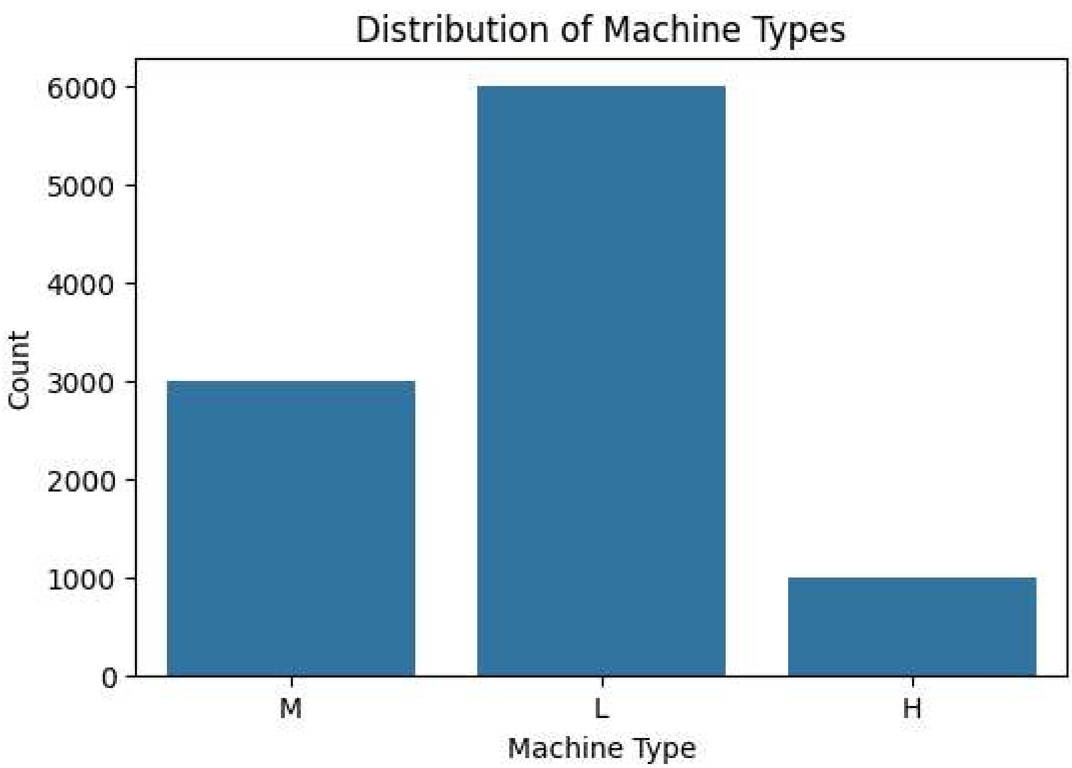
```
df.describe().T #statistical_description
```

	count	mean	std	min	25%	50%
Air temperature [K]	10000.0	300.004930	2.000259	295.3000	298.3000	300.10000
Process temperature [K]	10000.0	310.005560	1.483734	305.7000	308.8000	310.10000
Rotational speed [rpm]	10000.0	1538.776100	179.284096	1168.0000	1423.0000	1503.00000
Torque [Nm]	10000.0	39.986910	9.968934	3.8000	33.2000	40.10000
Tool wear [min]	10000.0	107.951000	63.654147	0.0000	53.0000	108.00000
Machine failure	10000.0	0.033900	0.180981	0.0000	0.0000	0.00000
TWF	10000.0	0.004600	0.067671	0.0000	0.0000	0.00000
HDF	10000.0	0.011500	0.106625	0.0000	0.0000	0.00000
PWF	10000.0	0.009500	0.097009	0.0000	0.0000	0.00000
OSF	10000.0	0.009800	0.098514	0.0000	0.0000	0.00000
RNF	10000.0	0.001900	0.043550	0.0000	0.0000	0.00000
temperature_difference	10000.0	10.000630	1.001094	7.6000	9.3000	9.80000

1) Plotting the Distribution of Machine Types Helps you to see how many machines belong to each type (L, M, H)

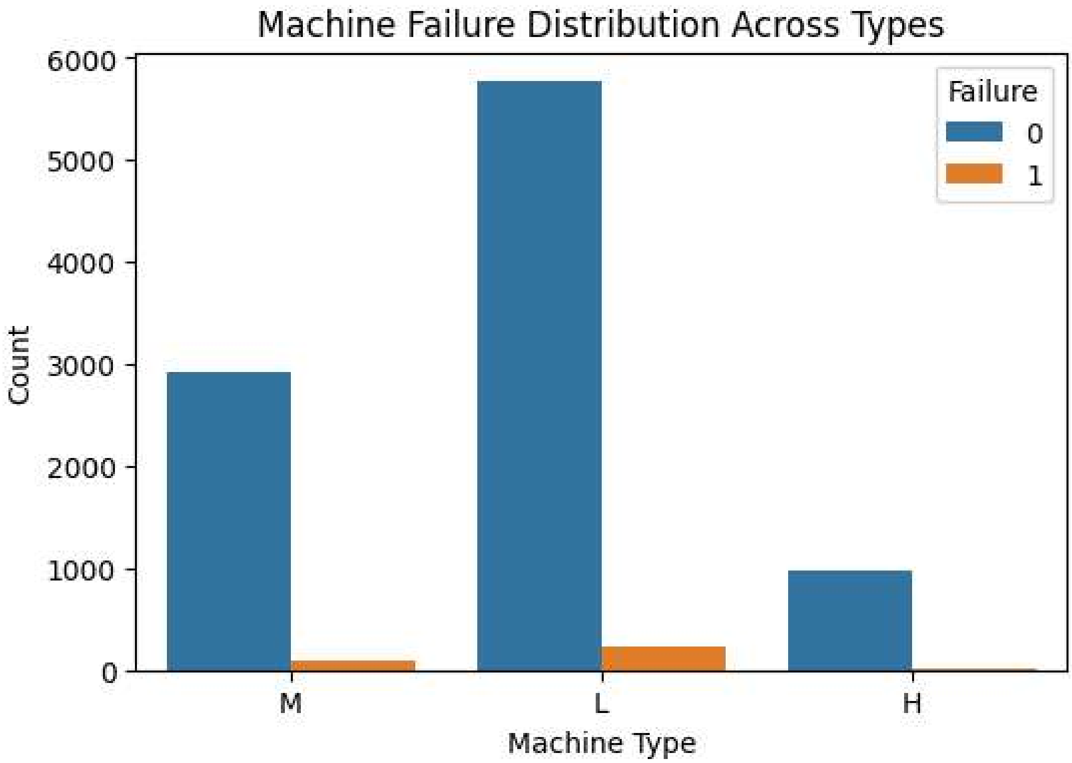
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(6,4))
sns.countplot(x='Type', data=df)
plt.title('Distribution of Machine Types')
plt.xlabel('Machine Type')
plt.ylabel('Count')
plt.show()
```



2) Visualizing Failure Distribution Across Product Types

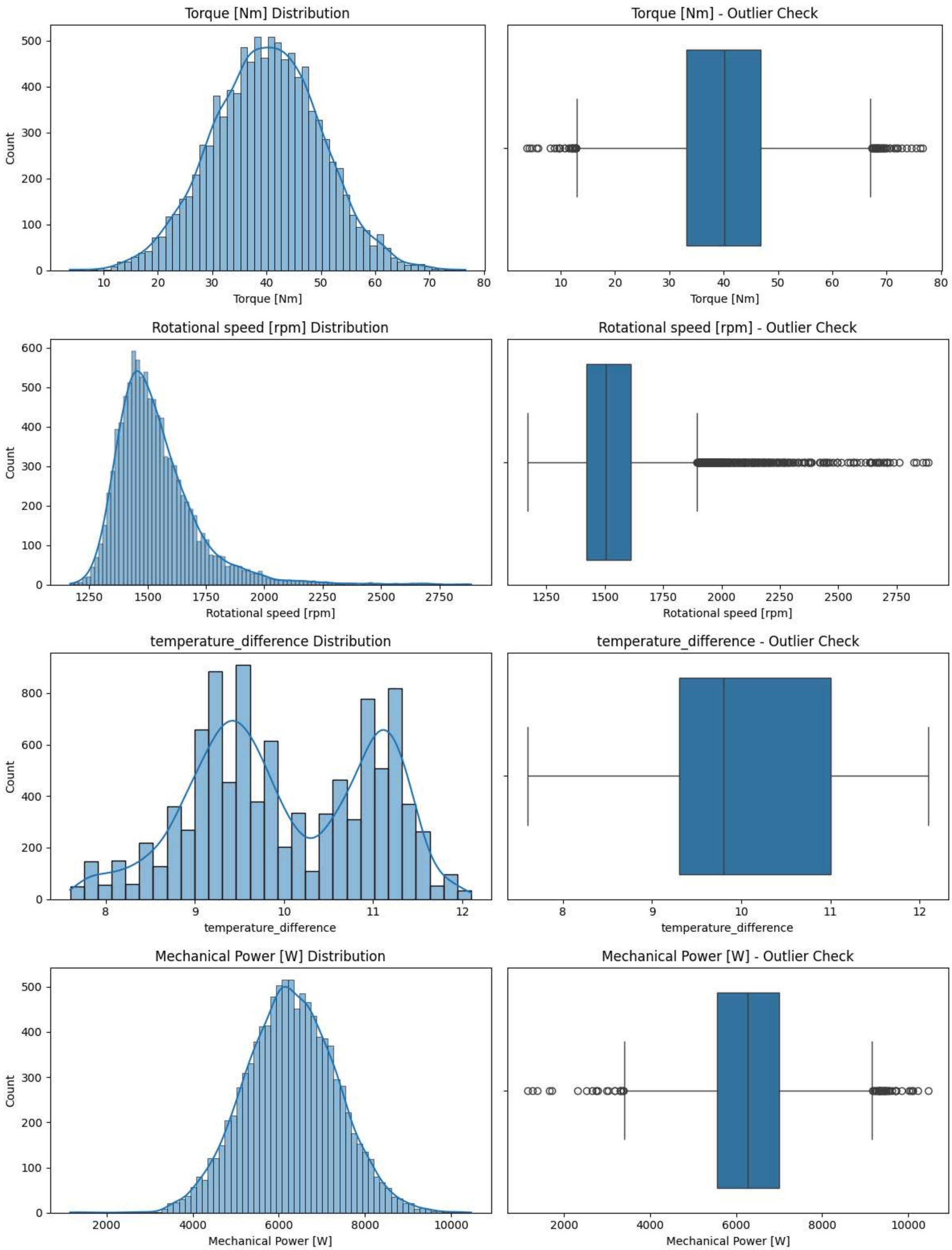
Shows how failures are spread across types — are some types failing more?

```
plt.figure(figsize=(6,4))
sns.countplot(x='Type', hue='Machine failure', data=df)
plt.title('Machine Failure Distribution Across Types')
plt.xlabel('Machine Type')
plt.ylabel('Count')
plt.legend(title='Failure')
plt.show()
```



3) Plotting Feature Distributions to Observe Patterns or Anomalies

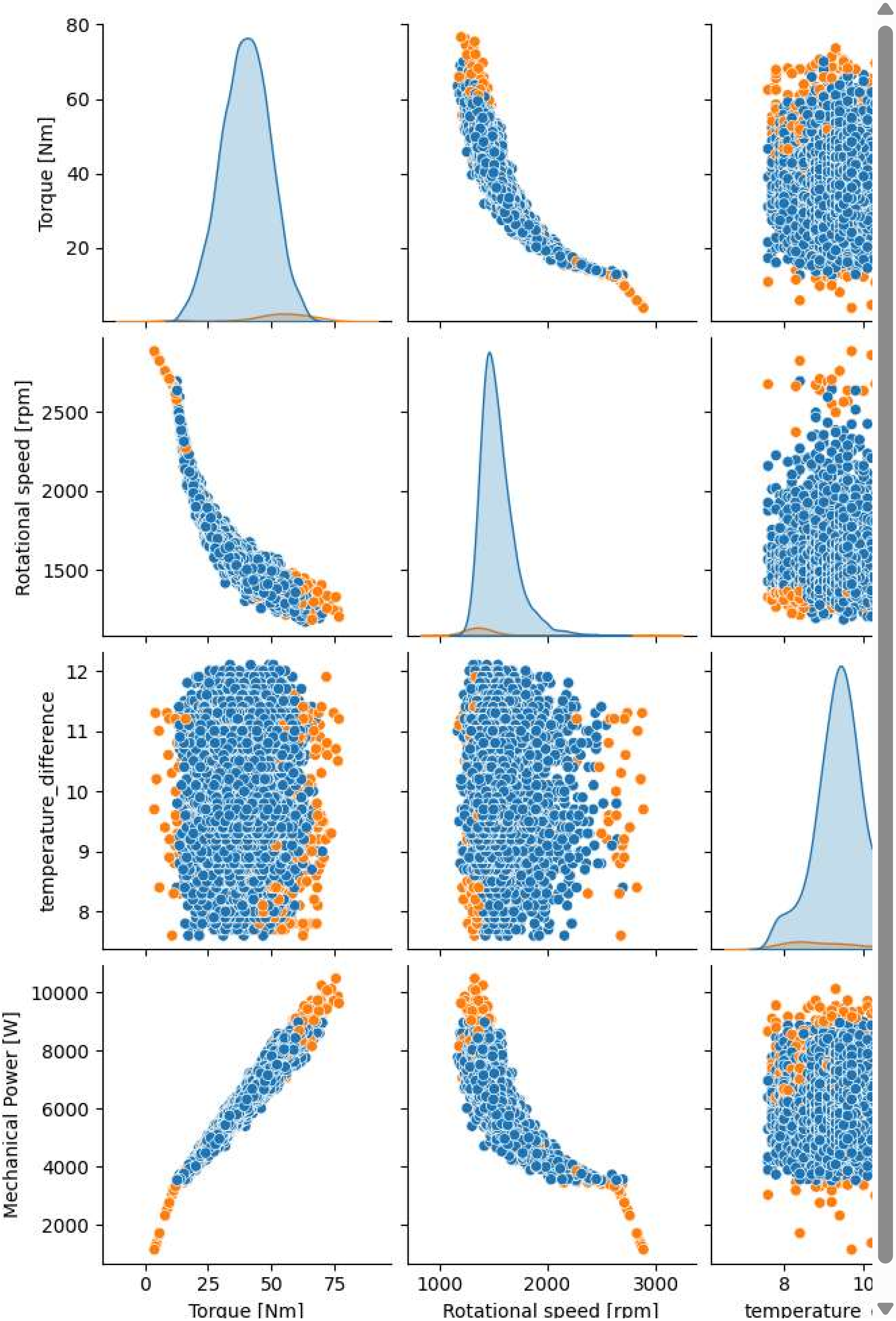
```
cols = ['Torque [Nm]', 'Rotational speed [rpm]', 'temperature_difference', 'Mechanical Power

for col in cols:
    fig, axes = plt.subplots(1, 2, figsize=(12, 4))  # 1 row, 2 columns

    # Histogram with KDE
    sns.histplot(data=df, x=col, kde=True, ax=axes[0])
    axes[0].set_title(f"{col} Distribution")

    # Boxplot
    sns.boxplot(data=df, x=col, ax=axes[1])
    axes[1].set_title(f"{col} - Outlier Check")

    plt.tight_layout()
    plt.show()
```



Torque [Nm] Distribution
Count
Torque [Nm]
Torque [Nm] - Outlier Check
Torque [Nm]
Rotational speed [rpm] Distribution
Count
Rotational speed [rpm]
Rotational speed [rpm] - Outlier Check
Rotational speed [rpm]
temperature_difference Distribution
Count
temperature_difference
temperature_difference - Outlier Check
temperature_difference
Mechanical Power [W] Distribution
Count
Mechanical Power [W]
Mechanical Power [W] - Outlier Check
Mechanical Power [W]

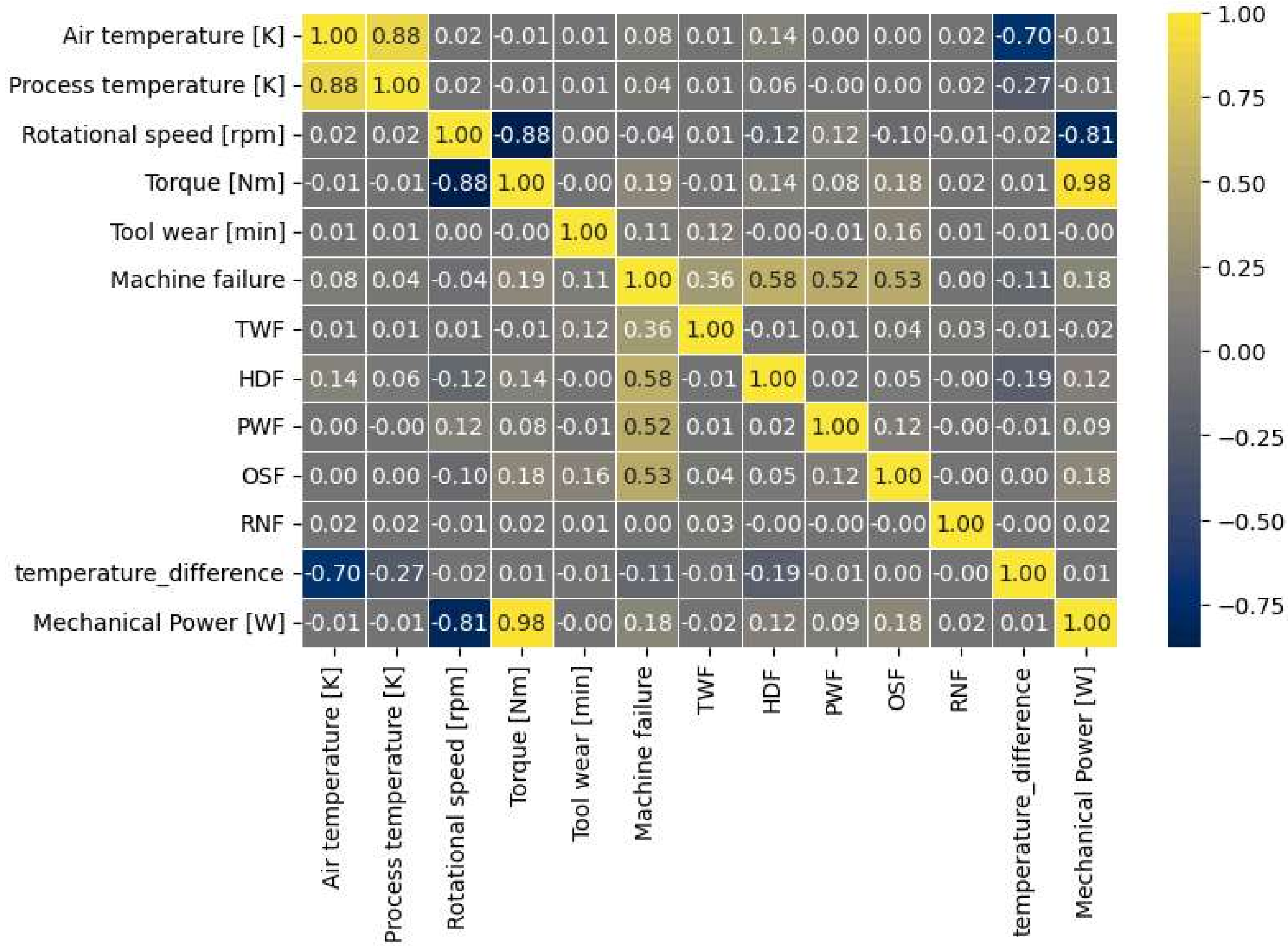
4) Pairplot for Feature Relationships

```
sns.pairplot(df[['Torque [Nm]', 'Rotational speed [rpm]', 'temperature_difference','Mechanic
plt.show()
```


Torque [Nm]
Rotational speed [rpm]
temperature_difference
Mechanical Power [W]
Torque [Nm]
Rotational speed [rpm]
temperature

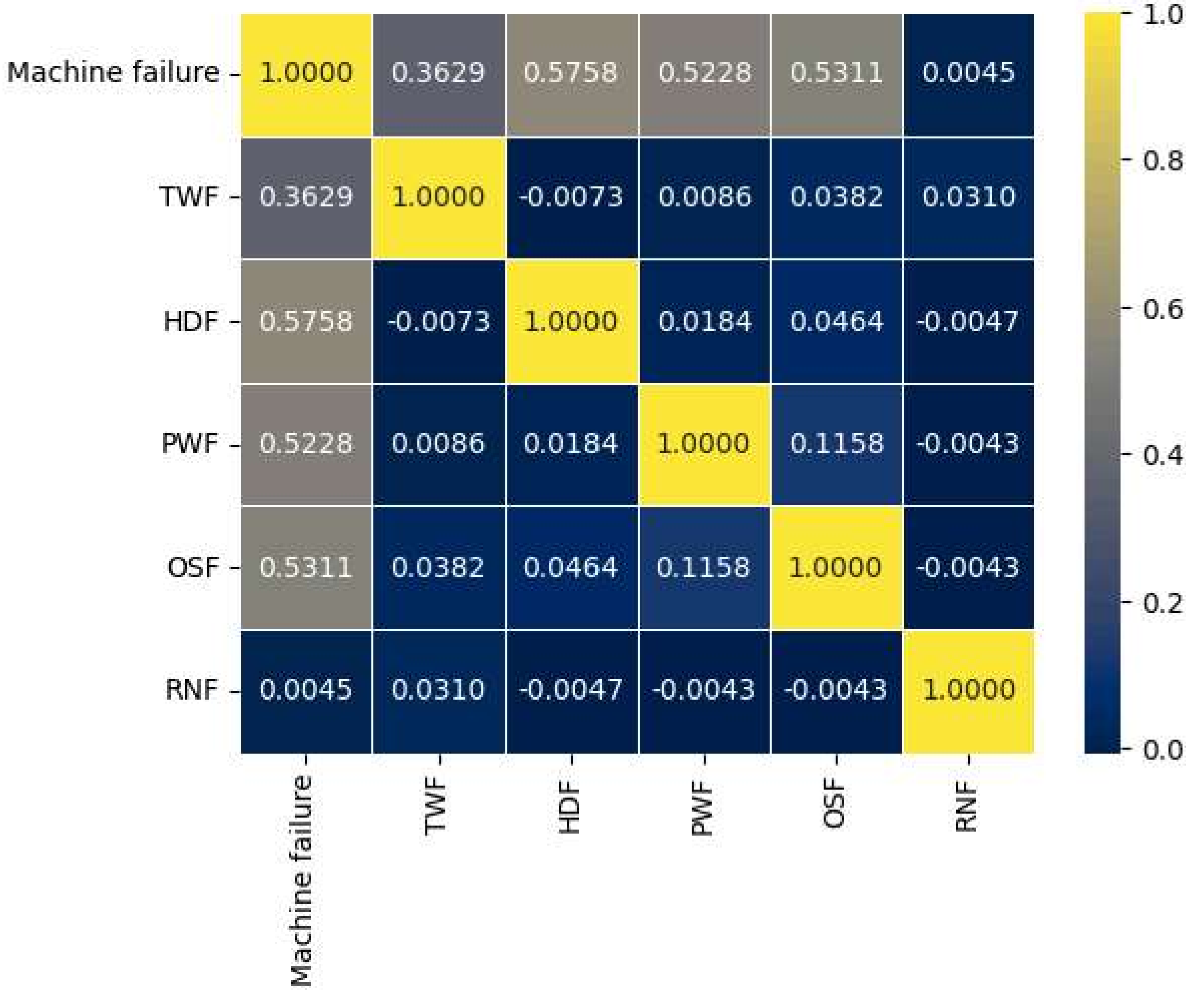
```
# Correlation of features

# Checking correlation between numerical features using a heatmap
corr_matrix=df.corr(numeric_only=True)
plt.figure(figsize=(8,5))
sns.heatmap(corr_matrix,annot=True,cmap='cividis',fmt=".2f", linewidths=0.5)
```

<Axes: >




```
# Checking correlation between different failure using a heatmap

target=df.iloc[:,[6,7,8,9,10,11]]
target_mat=target.corr()
sns.heatmap(target_mat,annot=True,cmap="cividis",fmt=".4f",linewidth=0.5)
```

```
<Axes: >
```



Tool wear failure (TWF), heat dissipation failure (HDF),power failure (PWF),overstrain failure (OSF) and random failures (RNF) shows more positive correlation with target variable i.e. machine failure. Thus dropping columns 'TWF','HDF','PWF','OSF','RNF'.

```
df.drop(columns=['TWF','HDF','PWF','OSF','RNF'],inplace=True)
df.sample(3)
```

	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	temperature_di
4505	L	302.4	310.1	1426	46.8	95	0	
8105	L	300.4	311.9	1476	48.7	189	0	

Encoding Columns & FEATURE SCALING

```
# Label encoding categorical variables (column- Type)
from sklearn.preprocessing import LabelEncoder
```

```
df['Type'] = LabelEncoder().fit_transform(df['Type'])

# Scaling numerical features using StandardScaler for model compatibility
from sklearn.preprocessing import StandardScaler
scale=StandardScaler()
data=pd.DataFrame(scale.fit_transform(df),columns=df.columns,index=df.index)
data.sample(10)
```

	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	tem
8134	-0.332223	-0.152453	0.737662	0.620409	-0.761093	-0.753343	-0.187322	
749	-0.332223	-1.702330	-1.351765	2.449999	-1.774292	1.571838	-0.187322	
9134	-0.332223	-1.152374	-0.879959	-0.500773	0.021376	-0.203469	-0.187322	
1263	-0.332223	-1.102378	-0.542955	-0.774096	1.696664	-1.161821	-0.187322	
5631	-0.332223	1.397424	1.479072	-0.132624	-0.319700	0.849147	-0.187322	
2113	-0.332223	-0.252445	-0.610355	1.808527	-1.754228	-0.454840	-0.187322	
5513	1.333889	1.397424	1.479072	-0.484039	1.034575	-0.753343	-0.187322	
6623	1.333889	0.847468	0.468059	-0.539819	0.111661	-0.297733	-0.187322	
2921	-0.332223	0.397503	-0.138549	0.659455	-0.891505	0.676329	-0.187322	

Splitting data into features (X) and target (y)

```
Y=df.pop("Machine failure")
X=df
```

```
X
```

	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	temperature_difference
0	2	298.1	308.6	1551	42.8	0	10.5
1	1	298.2	308.7	1408	46.3	3	10.5
2	1	298.1	308.5	1498	49.4	5	10.4
3	1	298.2	308.6	1433	39.5	7	10.4
4	1	298.2	308.7	1408	40.0	9	10.5
...	...	...	...	...	...	...	...
9995	2	298.8	308.4	1604	29.5	14	9.6
9996	0	298.9	308.4	1632	31.8	17	9.5
9997	2	299.0	308.6	1645	33.4	22	9.6
9998	0	299.0	308.7	1408	48.5	25	9.7
9999	2	299.0	308.7	1500	40.2	30	9.7

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Y

	Machine failure
0	0
1	0
2	0
3	0
4	0
...	...
9995	0
9996	0
9997	0
9998	0
9999	0

10000 rows × 1 columns

dtype: int64

Handling Imbalanced Data

```
# SMOTE- Synthetic Minority Over-sampling Technique
# SMOTE is a method for handling imbalanced datasets in machine learning.
# Goal: To increase the number of instances in the minority class by creating synthetic samp
# How it works: SMOTE generates new examples by interpolating between existing minority clas
# This helps the model learn better about the minority class and improves its performance or

# print distribution of class before SMOTE
from collections import Counter

counts = Counter(Y)
print(counts)
```

```
Counter({0: 9661, 1: 339})
```

```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, Y)
```

```
# print distribution of class AFTER SMOTE

from collections import Counter

counts = Counter(y_resampled )
print(counts)
```

```
Counter({0: 9661, 1: 9661})
```

Train Test Split

```
#Performing train-test split

from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X_resampled,y_resampled,test_size=0.1)
```

```
# Importing machine learning models

from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression,LogisticRegressionCV,SGDClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier,AdaBoostClas
from sklearn.tree import DecisionTreeClassifier
```