+ Code + Text

Install

```
!pip install -q pandas numpy matplotlib seaborn scikit-learn
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler, LabelEncoder

import warnings
warnings.filterwarnings("ignore")
sns.set(style="whitegrid")
```

```
from google.colab import files
uploaded = files.upload()
```

Choose Files predictive_...tenance.csv

- **predictive_maintenance.csv**(text/csv) - 531014 bytes, last modified: 7/24/2025 - 100% done

```
Saving predictive_maintenance.csv to predictive_maintenance (1).csv
```

```
import io
```

```
df = pd.read_csv(io.BytesIO(uploaded['predictive_maintenance (1).csv']))
print("Shape:", df.shape)
df.head()
```

```
Shape: (10000, 10)
```

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target	Failure Type
0	1	M14860	M	298.1	308.6	1551	42.8	0	0	No Failure
1	2	L47181	L	298.2	308.7	1408	46.3	3	0	No Failure
2	3	L47182	L	298.1	308.5	1498	49.4	5	0	No Failure
3	4	L47183	L	298.2	308.6	1433	39.5	7	0	No Failure
4	5	L47184	L	298.2	308.7	1408	40.0	9	0	No Failure

Next steps: Generate code with df View recommended plots New interactive sheet

```
print(df.columns)
```

```
Index(['UDI', 'Product ID', 'Type', 'Air temperature [K]',
       'Process temperature [K]', 'Rotational speed [rpm]', 'Torque [Nm]',
       'Tool wear [min]', 'Target', 'Failure Type'],
      dtype='object')
```

```
if df['Failure Type'].dtype == 'object':
    le = LabelEncoder()
    df['Failure Type'] = le.fit_transform(df['Failure Type'])
    print("Label Mapping:", dict(zip(le.classes_, le.transform(le.classes_))))
```

```
Label Mapping: {'Heat Dissipation Failure': np.int64(0), 'No Failure': np.int64(1), 'Overstrain Failure': np.int64(2), 'Power Failur
```

```
X = df.drop("Failure Type", axis=1)
y = df["Failure Type"]

# Encode any categorical feature columns
for col in X.columns:
    if X[col].dtype == 'object':
        X[col] = LabelEncoder().fit_transform(X[col])

# Normalize numeric features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, stratify=y, random_state=42)
```

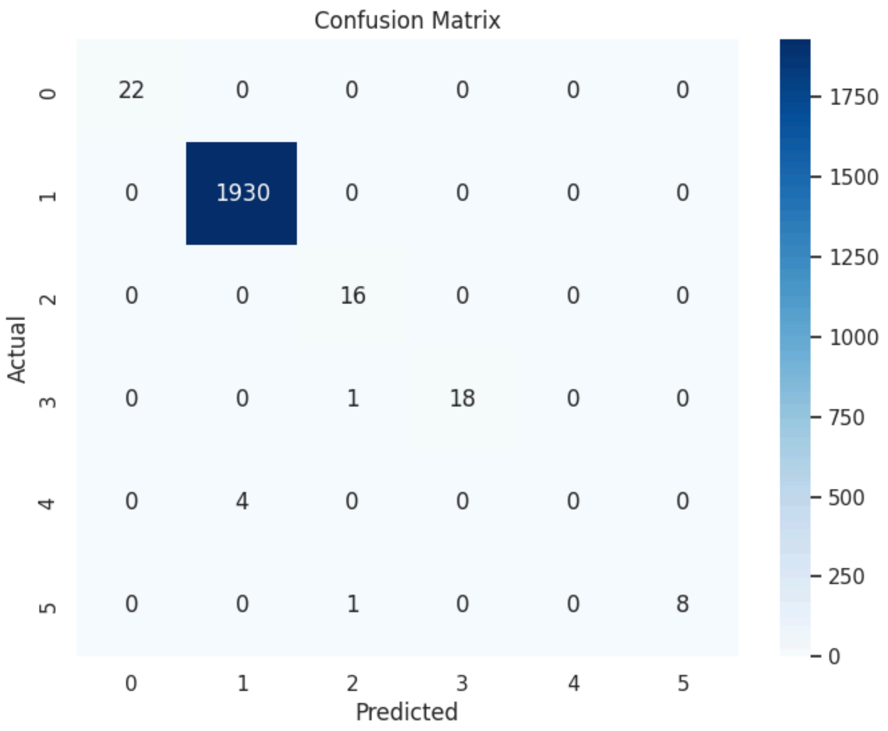
```
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

```
▾    RandomForestClassifier    ⓘ ?
RandomForestClassifier(random_state=42)
```

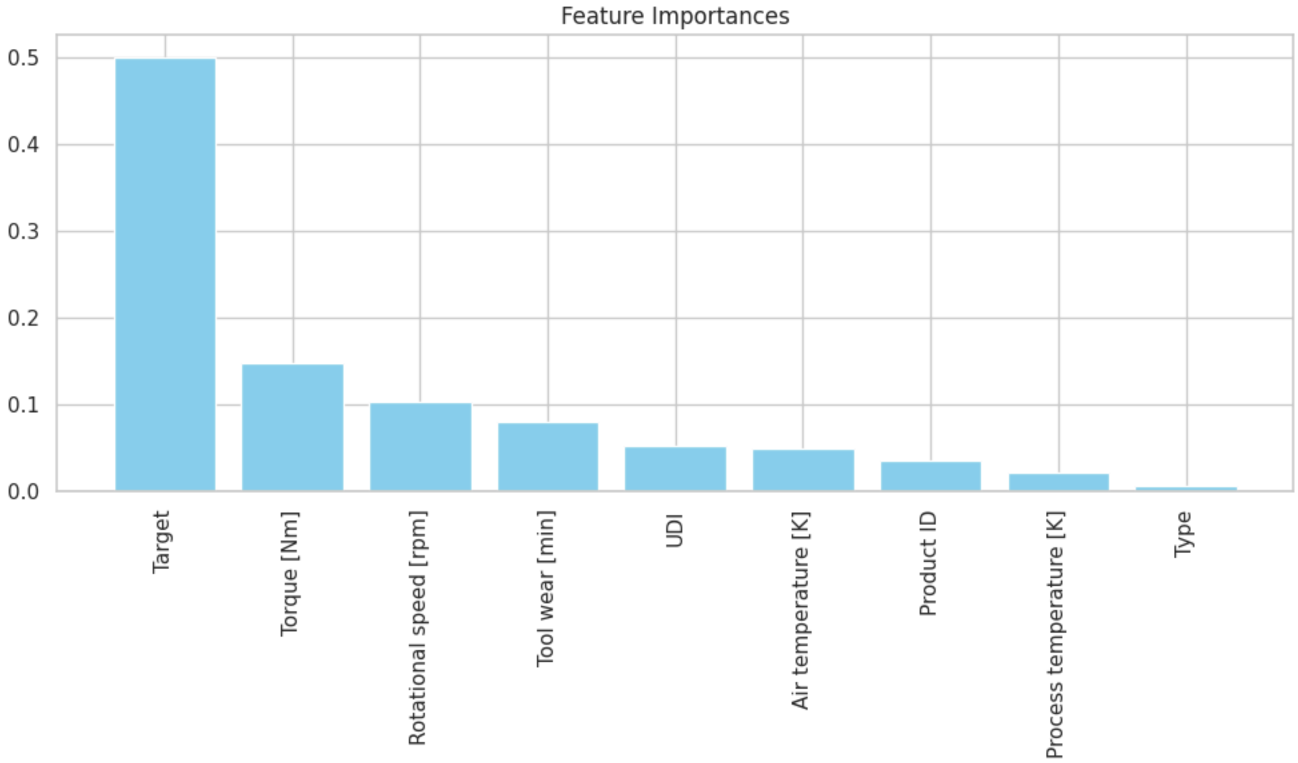
```
y_pred = model.predict(X_test)

print("Classification Report:\n")
print(classification_report(y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00        22
           1       1.00      1.00      1.00      1930
           2       0.89      1.00      0.94        16
           3       1.00      0.95      0.97        19
           4       0.00      0.00      0.00         4
           5       1.00      0.89      0.94         9

    accuracy                           1.00      2000
   macro avg       0.81      0.81      0.81      2000
weighted avg       1.00      1.00      1.00      2000
```

```
conf_matrix = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```



```
importances = model.feature_importances_
indices = np.argsort(importances)[::-1]

plt.figure(figsize=(10, 6))
plt.title("Feature Importances")
plt.bar(range(X.shape[1]), importances[indices], color="skyblue", align="center")
plt.xticks(range(X.shape[1]), X.columns[indices], rotation=90)
plt.tight_layout()
plt.show()
```


Feature Importances
0.5
0.4
0.3
0.2
0.1
0.0
Target
Torque [Nm]
Rotational speed [rpm]
Tool wear [min]
UDI
Air temperature [K]
Product ID
Process temperature [K]
Type