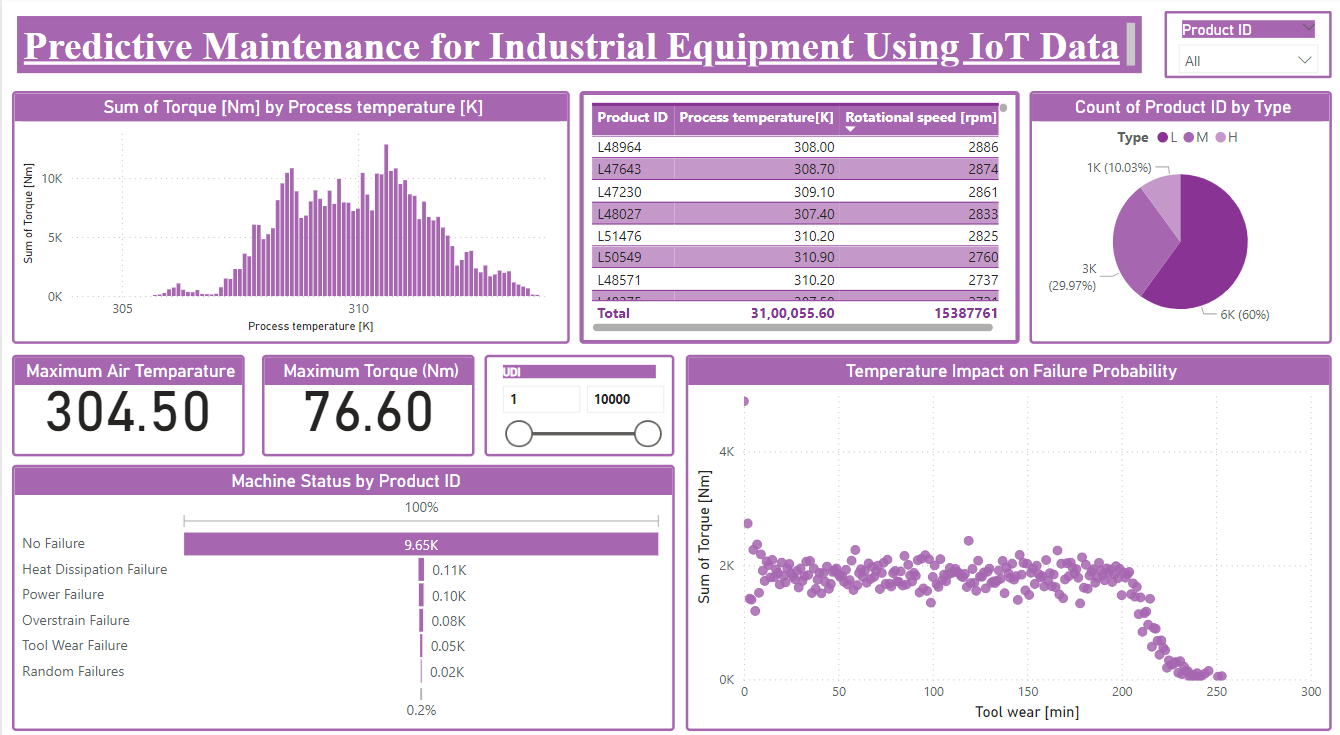
Predictive Maintenance for Industrial Equipment Using IoT Data: A Comprehensive Analysis



**Introduction:**

The aim of this report is to utilize Internet of Things (IoT) data to predict and prevent machine failures in an industrial setting. Predictive maintenance, powered by data analysis and machine learning, can help industries reduce downtime, enhance machine efficiency, and prevent costly failures. This report analyses key metrics such as temperature, torque, and tool wear to predict failure types, based on real-time IoT data.

**Key Metrics Overview:**

This section highlights the most significant performance indicators in predictive maintenance.

1. Sum of Torque by Process Temperature:

- A bar graph illustrates the relationship between process temperature and the torque exerted by machines. The chart shows how the total torque changes across various temperature ranges, offering insight into temperature's impact on machine performance.

2. Maximum Air Temperature and Maximum Torque:

- Peak air temperature recorded is 304.50 K, and the highest torque observed is 76.60 Nm. These maximum values provide reference points for monitoring abnormal machine behaviors.

3. Machine Status by Product ID (Failure Type Analysis):

- A categorical breakdown of failure types such as "No Failure," "Heat Dissipation Failure," and "Power Failure" across different machine Product IDs, gives insight into the frequency of various failure modes. The majority of machines exhibit "No Failure," but heat-related failures are the most common among those that fail.

4. Count of Product ID by Type:

- A pie chart representing the distribution of machines across three types of Product IDs (L, M, H). Most products fall into the "H" category, indicating potentially high-stress operational environments for this group.

5. Tool Wear and Temperature Impact on Failure Probability:

- This scatter plot explores the relationship between tool wear (in minutes) and torque values. As tool wear increases, torque values tend to decrease, suggesting that worn-out tools affect the machine’s overall performance and increase the probability of failure.

**Data Preparation:**

The IoT dataset underwent thorough preparation and cleaning processes to ensure that the analysis would be robust and accurate.

1. Handling Missing Data:

- Missing values were imputed using forward fill to maintain consistency in the dataset, ensuring no gaps that could skew machine learning results.

2. Outlier Detection and Removal:

- Z-scores were used to identify extreme outliers in air temperature values, which were subsequently removed. Outliers in the data can distort the model’s predictions and therefore were handled carefully.

3. Feature Engineering:

- A dummy timestamp feature was created to simulate real-time data and derive useful time-based features such as the hour of the day and rolling averages of air temperature. These features added valuable context to the machine's operational behavior over time.

4. Scaling and Normalization:

- Min-Max scaling was applied to temperature features, while torque was standardized to balance the scales of different features and improve the model's efficiency.

**Machine Learning Modelling:**

A Random Forest Classifier was selected for predicting machine failures based on the pre-processed IoT data. The choice of Random Forest was due to its robustness and ability to handle large datasets with multiple features.

1. Initial Model:

- Initial training of the Random Forest model on features like air temperature, torque, tool wear, and time-based features yielded an accuracy of 85.35%. This showed promise but left room for improvement.

2. Model Evaluation:

- The confusion matrix demonstrated that the model was effective in correctly predicting most failure types.

- The Receiver Operating Characteristic (ROC) curve achieved an Area Under the Curve (AUC) score of 0.89, indicating good overall model performance.

- The Precision-Recall curve showed that the model had high precision, especially in identifying cases of machine failure.

3. Hyperparameter Tuning:

- Using GridSearchCV, the model’s hyperparameters were optimized. The final parameters included 200 decision trees, a max depth of 20, and a minimum sample split of 5. After tuning, the model accuracy increased to 88.65%.

4. Feature Importance:

- Air temperature, torque, and tool wear were the three most significant features driving failure predictions. Air temperature emerged as the most influential factor, suggesting it plays a crucial role in machine health.

**The Code:**

import os

import pandas as pd

import numpy as np

from sklearn.preprocessing import MinMaxScaler, StandardScaler

from sklearn.model\_selection import train\_test\_split, GridSearchCV

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy\_score, classification\_report, confusion\_matrix, roc\_curve, auc, precision\_recall\_curve

import seaborn as sns

import matplotlib.pyplot as plt

import time

# Define the file path

file\_path = 'C:/Users/HP/Downloads/predict\_iot.xlsx'

# Check if the file exists

if os.path.exists(file\_path):

    print("File exists. Loading file...")

    # Load the Excel file into a DataFrame

    df = pd.read\_excel(file\_path)

    print("Excel file loaded successfully!")

    print(df.head())  # Show the first few rows of the dataset

else:

    print("File does not exist. Please check the file path.")

    exit()  # Exit if the file doesn't exist

# Display the data types of each column

print("\nColumn Data Types:")

print(df.info())

# Show a summary of numerical columns

print("\nSummary of Numerical Columns:")

print(df.describe())

# Check for missing values

print("\nMissing Values in Each Column:")

print(df.isnull().sum())

# Fill missing values using forward fill method

df.ffill(inplace=True)

# Calculate Z-scores to identify outliers for 'Air temperature [K]'

df['z\_score\_air\_temp'] = (df['Air temperature [K]'] - df['Air temperature [K]'].mean()) / df['Air temperature [K]'].std()

# Filter out rows where the absolute Z-score for 'Air temperature [K]' is greater than 3 (i.e., outliers)

df\_filtered = df[np.abs(df['z\_score\_air\_temp']) < 3]

# Drop the 'z\_score\_air\_temp' column after filtering

df\_filtered.drop(columns=['z\_score\_air\_temp'], inplace=True)

# Check the cleaned DataFrame

print("\nData after handling missing values and outliers:")

print(df\_filtered.head())

# Create a dummy timestamp column for this example

df\_filtered['timestamp'] = pd.date\_range(start='2023-01-01', periods=len(df\_filtered), freq='H')

# Extract time features (like hour of the day)

df\_filtered['hour'] = df\_filtered['timestamp'].dt.hour

df\_filtered['day'] = df\_filtered['timestamp'].dt.day

# Create rolling mean features

df\_filtered['rolling\_mean\_air\_temp'] = df\_filtered['Air temperature [K]'].rolling(window=5).mean()

# Check the DataFrame after adding time-based features

print("\nData after adding time-based features and rolling mean:")

print(df\_filtered.head())

# Apply scaling to numerical columns

# Min-Max scaling for 'Air temperature [K]'

scaler = MinMaxScaler()

df\_filtered[['Air temperature [K]']] = scaler.fit\_transform(df\_filtered[['Air temperature [K]']])

# Standardization for 'Torque [Nm]'

scaler = StandardScaler()

df\_filtered[['Torque [Nm]']] = scaler.fit\_transform(df\_filtered[['Torque [Nm]']])

# Check the scaled DataFrame

print("\nData after scaling 'Air temperature [K]' and 'Torque [Nm]':")

print(df\_filtered.head())

# Create new features: Difference between consecutive 'Torque [Nm]' values and cumulative sum of 'Tool wear [min]'

df\_filtered['diff\_torque'] = df\_filtered['Torque [Nm]'].diff()

df\_filtered['cumulative\_wear'] = df\_filtered['Tool wear [min]'].cumsum()

# Check the new features

print("\nData with new features:")

print(df\_filtered.head())

# Define features and target variable

features = ['Air temperature [K]', 'Torque [Nm]', 'Tool wear [min]', 'hour', 'day', 'rolling\_mean\_air\_temp']

X = df\_filtered[features]

y = df\_filtered['Target']  # Target variable

# Split the data (80% for training, 20% for testing)

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

print("Training and testing sets created.")

# Initialize the Random Forest Classifier

model = RandomForestClassifier(n\_estimators=100, random\_state=42)

# Train the model

model.fit(X\_train, y\_train)

# Make predictions on the test set

y\_pred = model.predict(X\_test)

# Evaluate the model

accuracy = accuracy\_score(y\_test, y\_pred)

print(f"Model Accuracy: {accuracy \* 100:.2f}%")

# Classification report for detailed evaluation

print("\nClassification Report:")

print(classification\_report(y\_test, y\_pred))

# Plot Correlation Heatmap

plt.figure(figsize=(10, 8))

correlation\_matrix = df\_filtered[features].corr()

sns.heatmap(correlation\_matrix, annot=True, cmap='coolwarm', linewidths=0.5)

plt.title("Correlation Heatmap", fontsize=18)

plt.show()

# Plot Pair Plot of Features

sns.pairplot(df\_filtered[features + ['Target']], hue='Target', diag\_kind='kde', palette='coolwarm', height=2.5)

plt.title("Pair Plot of Features", fontsize=18)

plt.show()

# Compute confusion matrix

cm = confusion\_matrix(y\_test, y\_pred)

# Plot the confusion matrix

plt.figure(figsize=(8, 6))

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', linewidths=0.5, cbar=False)

plt.xlabel('Predicted', fontsize=14)

plt.ylabel('Actual', fontsize=14)

plt.title('Confusion Matrix', fontsize=18)

plt.show()

# ROC Curve

fpr, tpr, \_ = roc\_curve(y\_test, y\_pred)

roc\_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))

plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc\_auc:.2f})')

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')

plt.xlim([0.0, 1.0])

plt.ylim([0.0, 1.05])

plt.xlabel('False Positive Rate', fontsize=14)

plt.ylabel('True Positive Rate', fontsize=14)

plt.title('Receiver Operating Characteristic (ROC)', fontsize=18)

plt.legend(loc="lower right")

plt.show()

# Precision-Recall Curve

precision, recall, \_ = precision\_recall\_curve(y\_test, y\_pred)

plt.figure(figsize=(8, 6))

plt.plot(recall, precision, color='green', lw=2)

plt.xlabel('Recall', fontsize=14)

plt.ylabel('Precision', fontsize=14)

plt.title('Precision-Recall Curve', fontsize=18)

plt.show()

# Hyperparameter tuning using GridSearchCV

param\_grid = {

    'n\_estimators': [100, 200, 300],

    'max\_depth': [10, 20, 30],

    'min\_samples\_split': [2, 5, 10],

}

# Initialize the grid search

grid\_search = GridSearchCV(RandomForestClassifier(random\_state=42), param\_grid, cv=5, scoring='accuracy')

# Fit the grid search

grid\_search.fit(X\_train, y\_train)

# Print the best parameters

print(f"Best Hyperparameters: {grid\_search.best\_params\_}")

# Train the model with the best parameters

best\_model = grid\_search.best\_estimator\_

y\_pred\_best = best\_model.predict(X\_test)

# Evaluate the tuned model

accuracy\_best = accuracy\_score(y\_test, y\_pred\_best)

print(f"Model Accuracy after Tuning: {accuracy\_best \* 100:.2f}%")

print("\nClassification Report after Tuning:")

print(classification\_report(y\_test, y\_pred\_best))

# Get feature importance from the trained Random Forest model

feature\_importances = best\_model.feature\_importances\_

features = X\_train.columns

# Plot feature importance

plt.figure(figsize=(10, 6))

sns.barplot(x=feature\_importances, y=features, palette='viridis')

plt.xlabel('Importance', fontsize=14)

plt.ylabel('Features', fontsize=14)

plt.title('Feature Importance in Predicting Machine Failures', fontsize=18)

plt.show()

# Real-time prediction simulation

print("\nStarting real-time prediction simulation...")

for i in range(len(X\_test)):

    # Simulate real-time prediction

    prediction = best\_model.predict([X\_test.iloc[i]])

    # Print the prediction (1 = failure, 0 = no failure)

    print(f"Real-Time Prediction for sample {i+1}: {prediction[0]}")

    # Simulate a delay (e.g., 1 second between readings)

    time.sleep(0.01)

**Insights and Findings:**

1. Process Temperature vs Torque:

- Torque values surged significantly within the 308-310 K temperature range. This could imply that machines either operate more efficiently or face more stress in this range, warranting closer monitoring.

2. Failure Type Distribution:

- A large majority of the machines exhibited no failures, but among those that did, heat dissipation failure was the most common issue. This points to a potential area of improvement in thermal management for machines.

3. Temperature and Tool Wear Impact:

- There was a clear negative correlation between tool wear and torque output, especially at higher tool wear levels. This suggests that machine components become less effective over time, increasing the likelihood of failure.

4. Product Type Distribution:

- The high percentage of type "H" products in the dataset suggests that these products are more susceptible to issues, potentially due to more stressful operating conditions.

**Recommendations:**

1. Monitor Process Temperatures:

- Machines operating within the 308-310 K range should be monitored closely, as this is where the highest torque values—and potentially the most stress—are observed. Implementing real-time temperature monitoring systems can help identify problems early.

2. Heat Dissipation Solutions:

- Since heat dissipation failure was the most frequent cause of machine issues, investing in improved cooling systems or heat management solutions for machinery would likely reduce the occurrence of failures.

3. Tool Wear Monitoring:

- A scheduled maintenance program focused on tool wear management would help prevent torque degradation and extend machine life. Regular inspection and replacement of worn tools are recommended to maintain optimal performance.

4. Product Type "H" Focus:

- Special attention should be given to type "H" products, which appear to face more frequent issues. Implementing preventive maintenance strategies and enhanced monitoring could significantly reduce failure rates.

**Conclusion:**

The analysis of IoT data for predictive maintenance reveals several key insights into machine behaviour and failure patterns. Temperature, torque, and tool wear are critical factors in predicting machine health, with air temperature playing a particularly important role. The deployment of a Random Forest model enabled accurate failure predictions, reaching an improved accuracy of 88.65% after tuning.

By focusing on specific failure types—especially heat dissipation issues—and leveraging real-time data monitoring, industrial organizations can greatly enhance their maintenance strategies. Implementing preventive measures, particularly in high-stress temperature ranges, will likely reduce machine downtime, improve operational efficiency, and extend equipment lifespan. Ultimately, a data-driven approach to predictive maintenance will provide long-term savings and reliability for industrial operations.