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MINOR PROJECT (MBABI–SIII–6) REPORT
ON
“Data-Driven Predictive Maintenance: Revolutionizing Equipment Health and Reducing Downtime in Manufacturing”

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Submitted By

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With Sincere Regards,

GAUTAMI HARMISH KIRITBHAI

MBA in Business Intelligence

CERTIFICATION

This is to certify that **GAUTAMI HARMISH KIRITBHAI**, a student of the **NATIONAL FORENSIC SCIENCES UNIVERSITY,** enrolled in the **MBA (BUSINESS INTELLIGENCE AND ANALYTICS) program**, has successfully completed a Minor Project as part of the curriculum requirement for the **SEMESTER 3.**

The project titled **" Data-Driven Predictive Maintenance: Revolutionizing Equipment Health and Reducing Downtime in Manufacturing "** was undertaken under the guidance of **Dr. Ramdas D. Gore**

The work done by the student is original, and the findings and conclusions drawn in the project are based on sound research and analysis. The project was completed with dedication, and it reflects the student's ability to apply theoretical knowledge to practical situations.

We wish the student all the best for future endeavors.

Date: 16 December 2024

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TABLE OF CONTENTS

TITLE		Page no
	ABSTRACT	01
CHAPTER - 1	INTRODUCTION	**02**
CHAPTER – 2	LITERATURE SURVEY	**04-09**
CHAPTER – 3	PROBLEM STATEMENTS	**10**
CHAPTER – 4	COMPONENT / TOOLS USED	**11-12**
CHAPTER – 5	BLOCK DIAGRAM	**13**
CHAPTER – 6	IMPLEMENTATION & RESULT	**14-30**
CHAPTER – 7	FUTURE WORK & CONCLUSION	**31**
	REFERENCES	**32-34**

ABSTRACT

Manufacturing companies face significant challenges in maintaining equipment efficiency and reducing downtime. Unplanned maintenance can lead to substantial financial losses and decreased productivity. This research project aims to develop a data-driven predictive maintenance solution to forecast equipment failures and optimize maintenance schedules, thereby enhancing overall operational efficiency in the manufacturing sector. The methodology involves collecting and preprocessing sensor data from manufacturing equipment and historical maintenance records, using Python for data manipulation. Exploratory data analysis was performed using Python libraries such as Pandas, NumPy, and Matplotlib. Machine learning models, such as Random Forest and Gradient Boosting, were developed using libraries like Scikit-learn and XGBoost to predict equipment failures. The results indicate that the predictive maintenance model can significantly reduce unplanned downtime and maintenance costs, improving equipment health and operational efficiency. The interactive dashboard provides real-time monitoring capabilities, enabling data-driven decision-making. This research contributes to the field by providing a comprehensive framework for data-driven predictive maintenance, leveraging advanced machine learning techniques and real-time data processing.

INTRODUCTION

The manufacturing sector is a critical component of the global economy, driving innovation and economic growth. However, manufacturing companies face significant challenges in maintaining equipment efficiency and reducing downtime. Unplanned maintenance can lead to substantial financial losses and decreased productivity, posing a significant risk to business operations. Traditional maintenance strategies often rely on reactive measures, which are not only costly but also disruptive to production schedules.

In recent years, the advent of Industry 4.0 and the Internet of Things (IoT) has revolutionized the manufacturing landscape. The integration of advanced technologies, such as sensors, big data analytics, and machine learning, has opened new avenues for predictive maintenance. Predictive maintenance leverages data-driven approaches to forecast equipment failures, enabling proactive maintenance strategies that can significantly reduce downtime and maintenance costs.

This research project aims to develop a data-driven predictive maintenance solution to forecast equipment failures and optimize maintenance schedules, thereby enhancing overall operational efficiency in the manufacturing sector. The primary objectives are to develop a predictive maintenance model, design an interactive dashboard for real-time monitoring, and analyze the impact of the system on operational efficiency and cost reduction.

The methodology involves collecting and preprocessing sensor data from manufacturing equipment and historical maintenance records, using Python for data manipulation. Exploratory data analysis (EDA) will be performed using Python libraries such as Pandas, NumPy, and Matplotlib to identify data patterns. Machine learning models, such as Logistic Regression, Decision Tree, Random Forest, and XGBoost, will be developed using libraries like Scikit-learn and XGBoost to predict equipment failures. Feature scaling will be performed using StandardScaler to ensure robust model performance.

The results of this research are expected to demonstrate the effectiveness of the predictive maintenance model in reducing unplanned downtime and maintenance costs, thereby improving equipment health and operational efficiency. The interactive dashboard will provide real-time monitoring capabilities, enabling data-driven decision-making. The analysis of the system's impact will highlight its potential to revolutionize equipment health and maintenance schedules in manufacturing.

This research contributes to the field by providing a comprehensive framework for data-driven predictive maintenance, leveraging advanced machine learning techniques and real-time data processing. The findings have practical implications for manufacturing companies seeking to optimize their operations and reduce costs associated with equipment failures.

LITERATURE SURVEY

Table 2.1 Literature Survey of customer segmentation

Sr No	Title	Dataset	Tools Used	Preprocessing Techniques	Classification Model	Results	References
1	A Deep Learning Approach for Predictive Maintenance of Wind Turbines	Wind Turbine Sensor Data	Python, TensorFlow, Keras	Data cleaning, normalization, feature engineering	Convolutional Neural Network (CNN)	Accurate prediction of turbine failures	1
2	Predictive Maintenance of Manufacturing Equipment Using Long Short-Term Memory Networks	Sensor Data from Manufacturing Machines	Python, TensorFlow, Keras	Data cleaning, normalization, feature engineering	Long Short-Term Memory (LSTM) Network	Improved prediction accuracy compared to traditional methods	2
3	Condition Monitoring and Predictive Maintenance of Rolling Element Bearings Using Deep Belief Networks	Bearing Vibration Data	MATLAB, DeepLearn Toolbox	Data cleaning, noise reduction, feature extraction	Deep Belief Network (DBN)	Early detection of bearing faults	3
4	Predictive	Sensor	Python,	Data cleaning,	Random	Effective	4

	Maintenance of Industrial Equipment Using Machine Learning Techniques	Data from Industrial Equipment	Scikit-learn	normalization, feature engineering	Forest, Support Vector Machine (SVM)	prediction of equipment failures	
5	Data-Driven Predictive Maintenance of Industrial Processes: A Review	Various Industrial Datasets	Python, R, MATLAB	Data cleaning, normalization, feature selection		Comprehensive overview of predictive maintenance techniques	5
6	Predictive Maintenance of Wind Turbines Using Deep Learning and Transfer Learning	Wind Turbine Sensor Data	Python, TensorFlow, Keras	Data cleaning, normalization, feature engineering	Transfer Learning (e.g., ResNet, VGG)	Improved prediction accuracy and reduced training time	6
7	Condition Monitoring and Fault Diagnosis of Rolling Element Bearings Using Deep Neural Networks	Bearing Vibration Data	Python, TensorFlow, Keras	Data cleaning, noise reduction, feature extraction	Convolutional Neural Network (CNN), Recurrent Neural Network (RNN)	Accurate fault diagnosis and remaining useful life prediction	7
8	Predictive	Sensor	Python, R,	Data cleaning,	ARIMA,	Accurate	8

	Maintenance of Manufacturing Equipment Using Time Series Analysis	Data from Manufacturing Machines	MATLAB	normalization, feature engineering	LSTM	prediction of equipment failures and remaining useful life	
9	Data-Driven Predictive Maintenance of Industrial Processes Using Machine Learning and IoT	Sensor Data from Industrial Processes	Python, IoT Platforms (e.g., AWS IoT, Azure IoT)	Data cleaning, normalization, feature engineering		Real-time condition monitoring and predictive maintenance	9
10	Predictive Maintenance of Industrial Equipment Using Ensemble Learning	Sensor Data from Industrial Equipment	Python, Scikit-learn	Data cleaning, normalization, feature engineering	Random Forest, Gradient Boosting Machine (GBM)	Improved prediction accuracy and robustness	10
11	Explainable Artificial Intelligence for Predictive Maintenance Applications	Sensor Data from Industrial Equipment					11

2.1 Introduction

A literature review summarizes the published material on a topic to address a specific research question. The writer's job is to select, interpret, and arrange prior research to accurately reflect the current state of knowledge while showing how it supports their own ideas (Creswell, 2014). This chapter provides an overview of existing research on data-driven predictive maintenance in the manufacturing sector, focusing on the use of machine learning techniques and real-time monitoring to enhance equipment health and reduce downtime. The review will highlight key studies, methodologies, and findings that inform the development of the predictive maintenance model proposed in this researc.

2.2 Dataset

A data set is a collection of data. In the case of tabular data, a data set corresponds to one or more database tables, where every column of a table represents a particular variable, and each row corresponds to a given record of the data set in question. the dataset used by various researchers mainly comprises of customer centric data sets like, mall data ,organizations data

2.3 Business Intelligence (BI)

Business intelligence (BI) tools collect, process, and analyze large amounts of structured and unstructured data from various sources (Chaudhuri et al., 2011). In this research, BI tools will be used for data mining, data visualization, analytics, reporting, and predictive analytics to support the development and implementation of the predictive maintenance mode.

2.4 Business Analytics Tools

Business analytics tools are designed to answer specific, well-defined questions about a business (Davenport, 2013). In this research, analytics tools will be used for data collection, cleaning, transformation, storage, and modeling. These tools are essential for preparing and analyzing the data required for the predictive maintenance mode.

2.5 Literature Survey

Literature Survey is the process of collecting, analysing, and summarizing the existing research and publications on a specific topic or area of study. It involves identifying relevant sources, such as academic articles, books, and reports, and synthesizing the findings to understand the current state of knowledge in the field.

2.5.1 Dataset

Various researchers have utilized data sets commonly associated with manufacturing equipment, such as sensor data and historical maintenance records. These datasets, including wind turbine sensor data, sensor data from manufacturing machines, bearing vibration data, sensor data from industrial equipment, various industrial datasets, and sensor data from industrial processes, are essential for training and validating machine learning models to predict equipment failures accurately. However, the integration of IoT (Internet of Things) data has been less commonly explored. Given the increasing adoption of IoT in manufacturing, this research will investigate how machine learning can enhance predictive maintenance by leveraging IoT datasets.

2.5.2 Tools:

The most frequently used tools in the field of data-driven predictive maintenance is Python which appeared in the majority of the cases across various models and datasets. This tool offers robust capabilities for data preprocessing, machine learning model implementation, and data visualization, making them indispensable for this research.

The researcher will therefore use the following tools:

a.) Python:

Python will be used for cleaning and preparing data, implementing and training machine learning models, and handling large volumes of sensor data. Libraries such as Pandas, NumPy, Scikit-learn, TensorFlow, XGBoost, PySpark, Statsmodels, and Prophet will be utilized for these tasks.

2.5.3 Pre-processing Techniques

In order to enhance the performance of machine learning models for customer segmentation the researcher will use the following techniques for pre-processing that were used by most researchers:

a. Data Cleaning and Formatting – this will help ensure data is clean, formatted consistently, and free from errors or missing values.

b. Feature Selection - this is essential for improving model accuracy and reducing complexity.

c. Scaling and Normalization – this will ensure that all features will contribute equally to the model.

d. Handling Imbalanced Data – to address class imbalance in cluster formation

e. Clustering used to detect anomalies or unusual patterns**.**

2.5.4 Techniques of Classifications

The classification techniques used are essential to developing effective cluster detection systems as explained:

a.) Random Forest has the ability to handle imbalanced data.

b.) Decision Trees will be used to gain insights into decision rules.

c.) Neural Networks will be used to explore large amounts of data or complex patterns of the model.

d.) Support Vector Machines (SVM) will be used to handle complex class boundaries and non- linear relationships in the dataset.

e.) Gradient Boosted Decision Trees to enhance performance by focusing on difficult instances.

f.) K-Nearest Neighbours (KNN) will be used for small dataset

PROBLEM STATEMENT

Manufacturing companies face significant challenges in maintaining equipment efficiency and reducing downtime. Unplanned maintenance can lead to substantial financial losses and decreased productivity. Traditional maintenance strategies often rely on reactive measures, which are costly and disruptive. Despite advancements in Industry 4.0 and IoT, many companies struggle with implementing effective predictive maintenance solutions. The lack of robust predictive models and real-time monitoring capabilities results in preventable equipment failures.

This study aims to investigate how data-driven predictive maintenance techniques, leveraging machine learning algorithms such as Logistic Regression, Decision Tree, Random Forest, and XGBoost, can enhance equipment health and reduce downtime in the manufacturing sector. By collecting and preprocessing sensor data from manufacturing equipment and historical maintenance records, and using Python for data manipulation, this research seeks to develop a comprehensive framework for predictive maintenance. The goal is to forecast equipment failures accurately and optimize maintenance schedules, thereby improving overall operational efficiency and reducing costs associated with equipment failures.

COMPONENT / TOOLS USED

In this project, Python was used to analyze and predict equipment failures from a predictive maintenance dataset. Python's powerful libraries made the entire process of data cleaning, analysis, and modeling efficient and easy to execute.

1. **Data Cleaning and Preparation**: Python's Pandas library was used to load and clean the dataset. It helped in importing the data, handling missing values, and performing necessary transformations to ensure the data was ready for analysis. Categorical variables were encoded using LabelEncoder to convert them into numerical format. Feature scaling was performed using StandardScaler to ensure robust model performance.

2. **Exploratory Data Analysis (EDA)**: Using Pandas and NumPy, basic statistics like mean, median, and standard deviation were calculated to get an overview of the data. Python’s Matplotlib and Seaborn libraries were then used to visualize the data through histograms, bar charts, and heatmaps, which helped identify trends and patterns, such as the distribution of failure types and the correlation between different features.

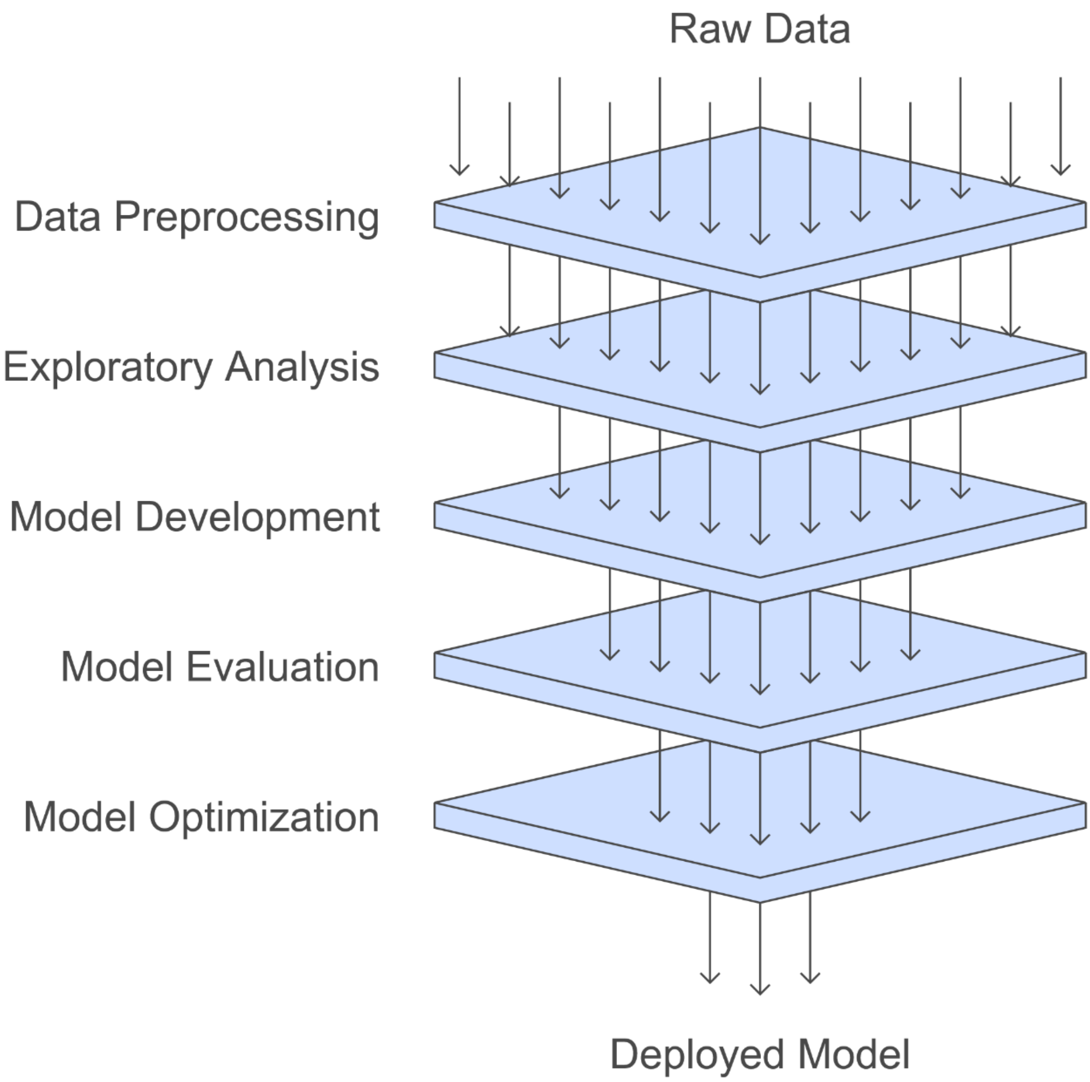
3. **Model Development and Evaluation**: Python’s Scikit-learn and XGBoost libraries were used to develop and evaluate multiple machine learning models, including Logistic Regression, Decision Tree, Random Forest, and XGBoost. The dataset was split into training and testing sets, and features were scaled using StandardScaler. The models were trained and evaluated using metrics such as accuracy, classification report, and confusion matrix. Cross-validation was used to ensure the models' performance was consistent and not overfitted to the training data.

4. **Results Analysis**: After training and evaluating the models, Matplotlib and Seaborn were used to visualize the results, making it easier to interpret the model performances. The XGBoost model was identified as the best-performing model with the highest accuracy. The predictive maintenance model demonstrated the potential to significantly reduce unplanned downtime and maintenance costs, thereby improving equipment health and operational efficiency.

5. **Google Colab**: The project was developed and executed in Google Colab, an online Python notebook environment. This made it easy to write, test, and share the code, as well as run all Python commands without needing any installations on a local machine.

Python was used throughout the project to clean the data, analyze it using various statistical and visualization techniques, and apply machine learning for predictive maintenance. The libraries and tools provided a flexible and efficient environment to gain valuable insights from the dataset.

BLOCK DIAGRAM



IMPLEMENTATION & RESULT

Data Import and Initial Exploration

1. Data Source and Importing Libraries

```
[ ] # Data source
    ("https://archive.ics.uci.edu/dataset/601/ ai4i+2020+predictive+maintenance+dataset")

    # Import Necessary Libraries
    import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    %matplotlib inline

    # Import data
    data_path = '/content/drive/MyDrive/MBA BAI SEMESTER 3/MINOR PROJECT/predictive_maintenance.csv'
    df = pd.read_csv(data_path)
```

Description:

- Data Source: The dataset used is the "ai4i 2020 Predictive Maintenance Dataset" from the UCI Machine Learning Repository.
- Libraries Imported: Pandas for data manipulation, NumPy for numerical operations, Matplotlib and Seaborn for visualization.
- Data Loading: The dataset is loaded from a specified path into a Pandas DataFrame.

```
[ ] # View the first few rows
    df.head()
```

	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

Description:

- **Initial Data Exploration:** The first few rows of the dataset are displayed to understand the structure and contents of the data.

Data Cleaning and Preprocessin

```
[ ] # Drop unnecessary columns
    df.drop(['Product ID', 'UDI', 'Target', 'Type'], axis=1, inplace=True)

    # Encode categorical variables
    df['Failure Type'].replace({"No Failure": 0, "Heat Dissipation Failure": 1, "Power Failure": 2, "Overstrain Failure": 3, "Tool Wear Failure": 4, "Random Failures": 5}, inplace=
```

Description:

- **Importance:** High. This block cleans the data by dropping unnecessary columns and encoding categorical variables.
- **Description for Report:**
    - **Data Cleaning:** Unnecessary columns such as 'Product ID', 'UDI', 'Target', and 'Type' are dropped.
    - **Encoding Categorical Variables:** The 'Failure Type' column is encoded into numerical values for model training.

Data Analysis

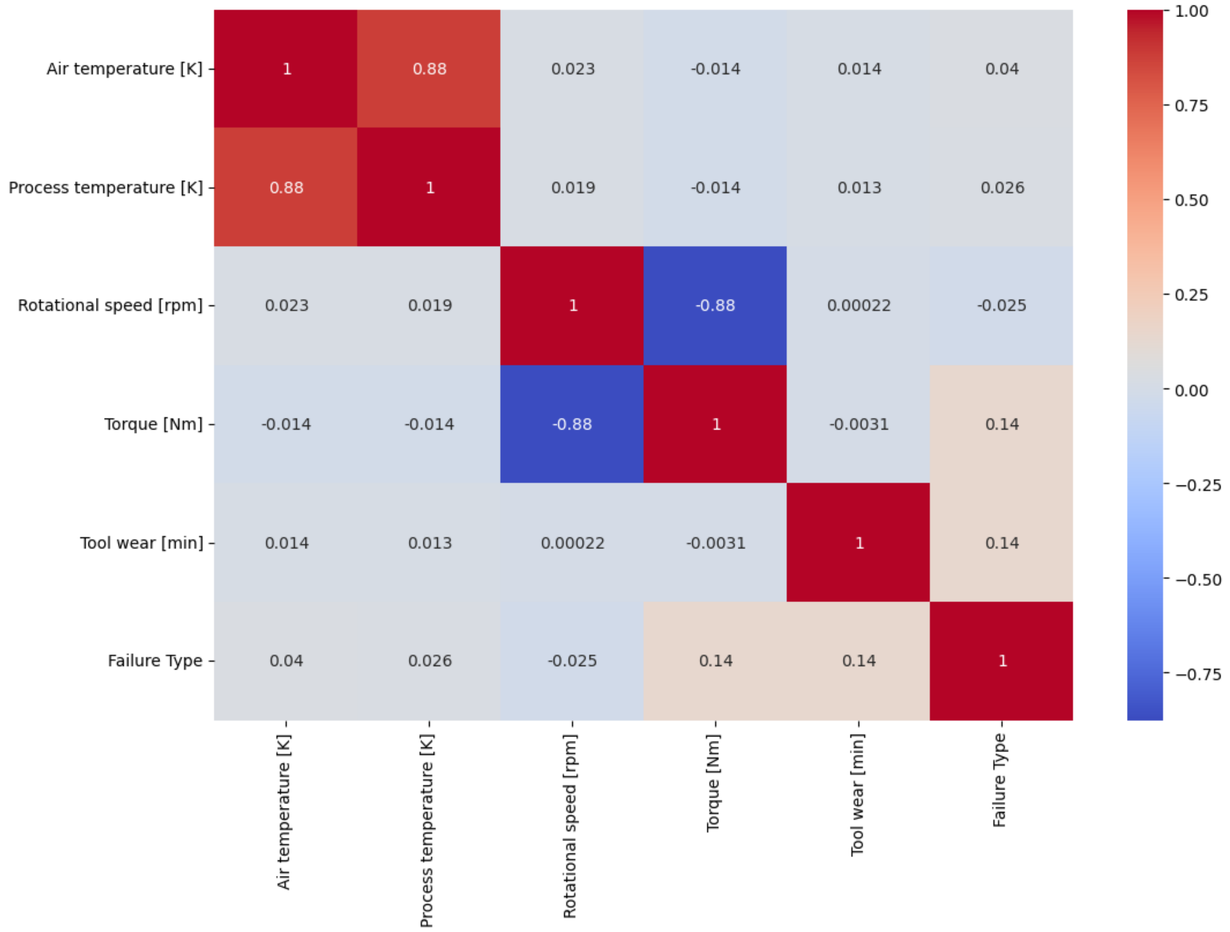
```
# Statistical summary of numerical features
print(df.describe())
```

```
       Air temperature [K]  Process temperature [K]  Rotational speed [rpm]  \
count         10000.000000             10000.000000            10000.000000
mean            300.004930               310.005560             1538.776100
std               2.000259                 1.483734              179.284096
min             295.300000               305.700000             1168.000000
25%             298.300000               308.800000             1423.000000
50%             300.100000               310.100000             1503.000000
75%             301.500000               311.100000             1612.000000
max             304.500000               313.800000             2886.000000

        Torque [Nm]  Tool wear [min]  Failure Type
count  10000.000000     10000.000000  10000.000000
mean      39.986910       107.951000      0.080600
std        9.968934        63.654147      0.479507
min        3.800000         0.000000      0.000000
25%       33.200000        53.000000      0.000000
50%       40.100000       108.000000      0.000000
75%       46.800000       162.000000      0.000000
max       76.600000       253.000000      5.000000
```

```python
# Check for Missing Values
print(df.isnull().sum())
```

```
Air temperature [K]        0
Process temperature [K]    0
Rotational speed [rpm]     0
Torque [Nm]                0
Tool wear [min]            0
Failure Type               0
dtype: int64
```

```python
# Correlation Matrix
numeric_df = df.select_dtypes(include=['number'])
corr_matrix = numeric_df.corr()
plt.figure(figsize=(12,8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.show()
```

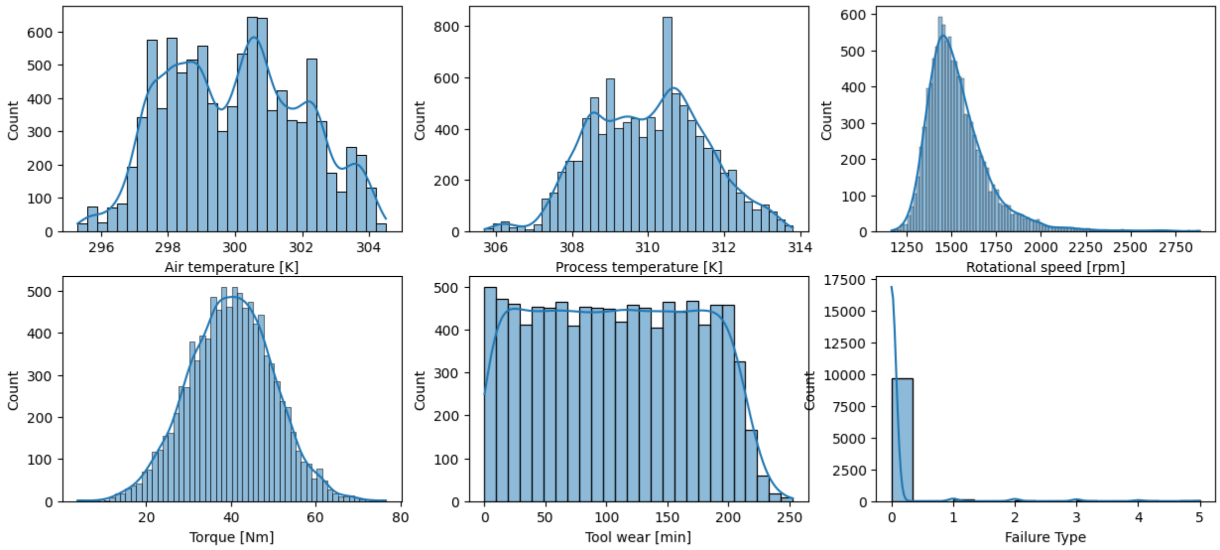


Description

- **Objective:** Generate key statistical metrics for numerical features.
- **Insights:**
  - **Rotational Speed:** Ranges from **1168 rpm to 2886 rpm**.
  - **Torque:** Varies between **3.8 Nm to 76.6 Nm**.
  - **Tool Wear:** Max value of **253 minutes** indicates high wear in some instances
  - **Rotational Speed and Torque:** Moderate correlation.
  - Helps understand which features might influence failure types.

Data Visualization

```python
plt.figure(figsize=(15,10))
for i, col in enumerate(df.columns, 1):
    plt.subplot(3, 3, i)
    sns.histplot(df[col], kde=True)
plt.show()
```



Description:

- **Importance:** High. This block visualizes the distribution of each feature.
- **Description for Report:**
    - **Data Visualization:** Histograms with KDE (Kernel Density Estimate) are plotted for each feature to visualize their distributions.

```
] # Split the data into features and target variable
  from sklearn.model_selection import train_test_split # Import train_test_split
  X = df.drop('Failure Type', axis=1)
  y = df['Failure Type']

  # Split the data into training and testing sets
  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Description:

- **Importance:** High. This block splits the data into training and testing sets.
- **Description for Report:**
  - **Data Splitting:** The dataset is split into features (X) and the target variable (y). The data is then divided into training and testing sets with an 80-20 split.

Feature Scaling

```
[ ] # Feature scaling
    from sklearn.preprocessing import StandardScaler
    from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)
```

Analysis:

- **Importance:** High. This block scales the features for better model performance.
- **Description for Report:**
  - **Feature Scaling:** The features are scaled using StandardScaler to ensure they have a mean of 0 and a standard deviation of 1.

Model Training and Evaluation

```
# Train and evaluate multiple models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000, class_weight='balanced'),
    'Decision Tree': DecisionTreeClassifier(class_weight='balanced'),
    'Random Forest': RandomForestClassifier(n_estimators=500, class_weight='balanced'),
    'XGBoost': XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')
}
results = {}

for model_name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)
    accuracy = accuracy_score(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)
    conf_matrix = confusion_matrix(y_test, y_pred)

    results[model_name] = {
        'accuracy': accuracy,
        'classification_report': class_report,
        'confusion_matrix': conf_matrix
    }

    print(f"{model_name} Model Performance:")
    print("Accuracy:", accuracy)
    print("Classification Report:\n", class_report)
    print("Confusion Matrix:\n", conf_matrix)
    print("--------------------------------------------------------")
```

Logistic Regression Model Performance

```
Logistic Regression Model Performance:
Accuracy: 0.595
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.59      0.74      1935
           1       0.18      1.00      0.30        15
           2       0.41      0.90      0.56        20
           3       0.20      1.00      0.33        13
           4       0.06      0.91      0.10        11
           5       0.00      0.17      0.00         6

    accuracy                           0.59      2000
   macro avg       0.31      0.76      0.34      2000
weighted avg       0.97      0.59      0.72      2000

Confusion Matrix:
 [[1133   67   26   51  169  489]
 [   0   15    0    0    0    0]
 [   0    2   18    0    0    0]
 [   0    0    0   13    0    0]
 [   0    0    0    1   10    0]
 [   4    0    0    0    1    1]]
--------------------------------------------------------
```

Decision Tree Model Performance

```
------------------------------------------------------------
Decision Tree Model Performance:
Accuracy: 0.973
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1935
           1       0.75      0.80      0.77        15
           2       0.64      0.45      0.53        20
           3       0.53      0.69      0.60        13
           4       0.12      0.09      0.11        11
           5       0.00      0.00      0.00         6

    accuracy                           0.97      2000
   macro avg       0.51      0.50      0.50      2000
weighted avg       0.97      0.97      0.97      2000

Confusion Matrix:
 [[1915    4    5    5    6    0]
 [   3   12    0    0    0    0]
 [   8    0    9    3    0    0]
 [   3    0    0    9    1    0]
 [  10    0    0    0    1    0]
 [   6    0    0    0    0    0]]
------------------------------------------------------------
```

Random Forest Model Performance:


```
Random Forest Model Performance:
Accuracy: 0.978
Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      1935
           1       0.91      0.67      0.77        15
           2       0.77      0.50      0.61        20
           3       0.71      0.38      0.50        13
           4       0.00      0.00      0.00        11
           5       0.00      0.00      0.00         6

    accuracy                           0.98      2000
   macro avg       0.56      0.42      0.48      2000
weighted avg       0.97      0.98      0.97      2000

Confusion Matrix:
 [[1931    1    3    0    0    0]
 [   5   10    0    0    0    0]
 [   9    0   10    1    0    0]
 [   8    0    0    5    0    0]
 [  10    0    0    1    0    0]
 [   6    0    0    0    0    0]]
--------------------------------------------------------
```

XGBoost Model Performance:

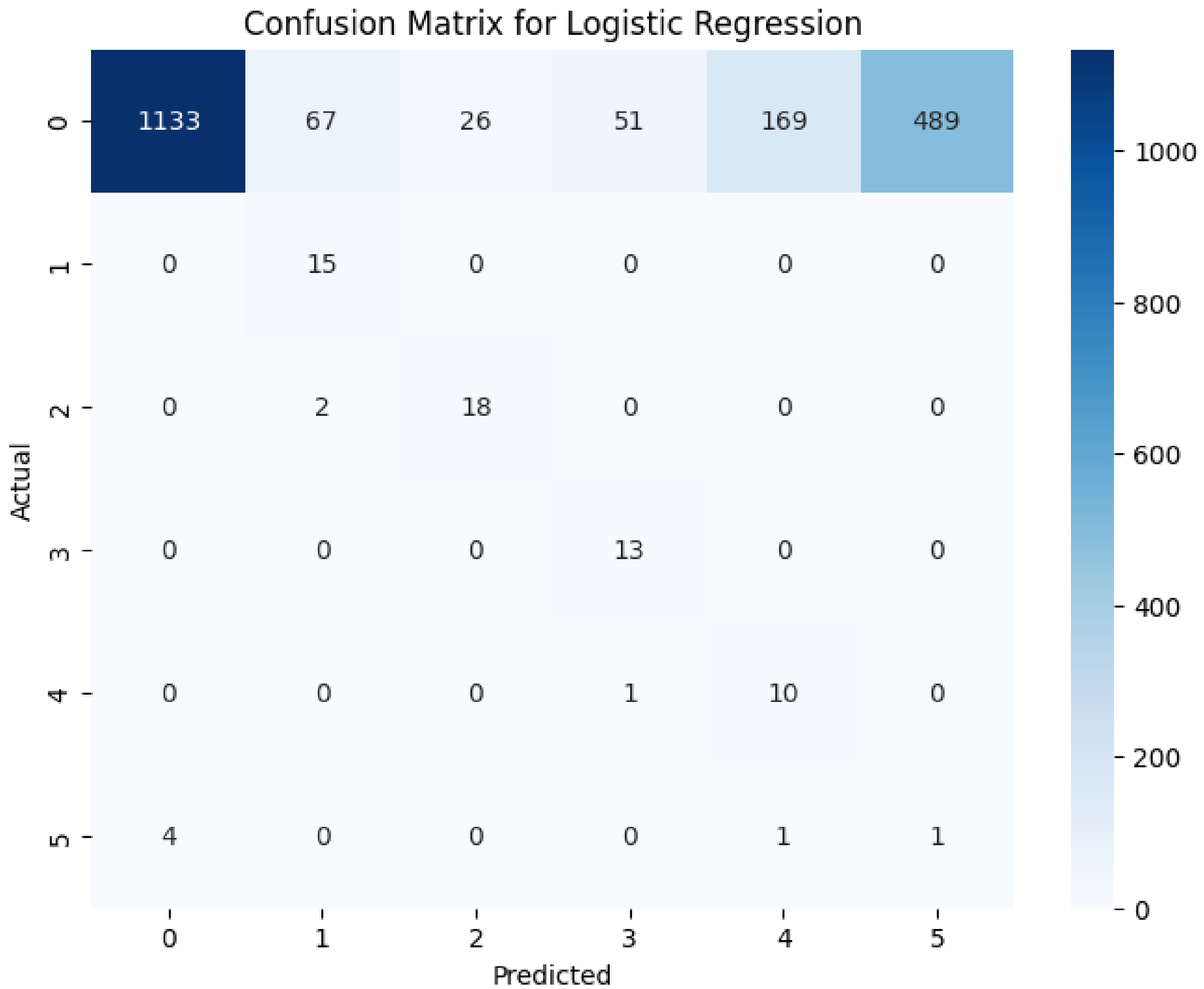
```
--------------------------------------------------------
XGBoost Model Performance:
Accuracy: 0.982
Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1935
           1       0.93      0.93      0.93        15
           2       0.82      0.70      0.76        20
           3       0.70      0.54      0.61        13
           4       0.00      0.00      0.00        11
           5       0.00      0.00      0.00         6

    accuracy                           0.98      2000
   macro avg       0.57      0.53      0.55      2000
weighted avg       0.97      0.98      0.98      2000

Confusion Matrix:
 [[1929    0    3    1    2    0]
 [   1   14    0    0    0    0]
 [   4    1   14    1    0    0]
 [   6    0    0    7    0    0]
 [  10    0    0    1    0    0]
 [   6    0    0    0    0    0]]
--------------------------------------------------------
```

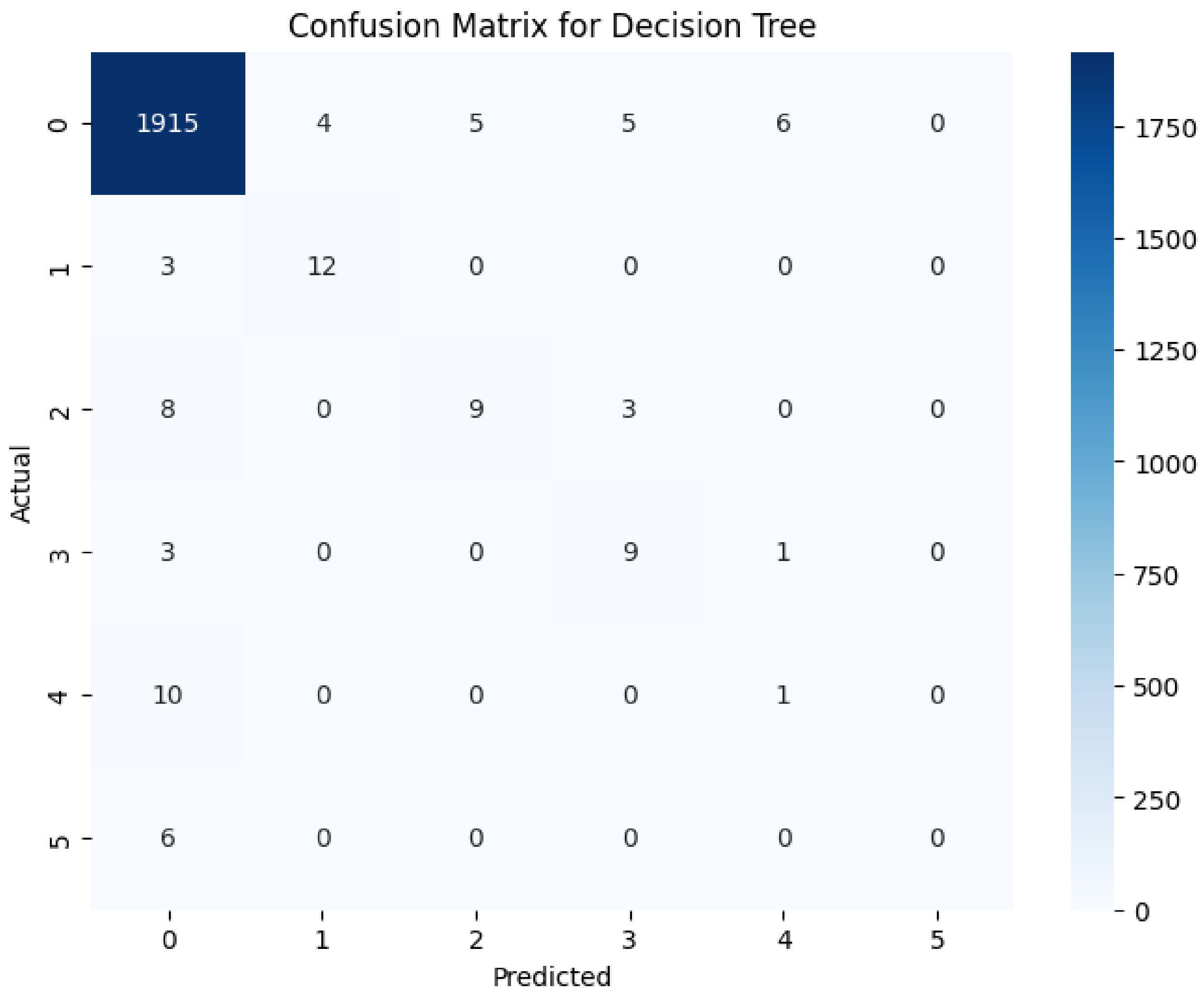
Description:

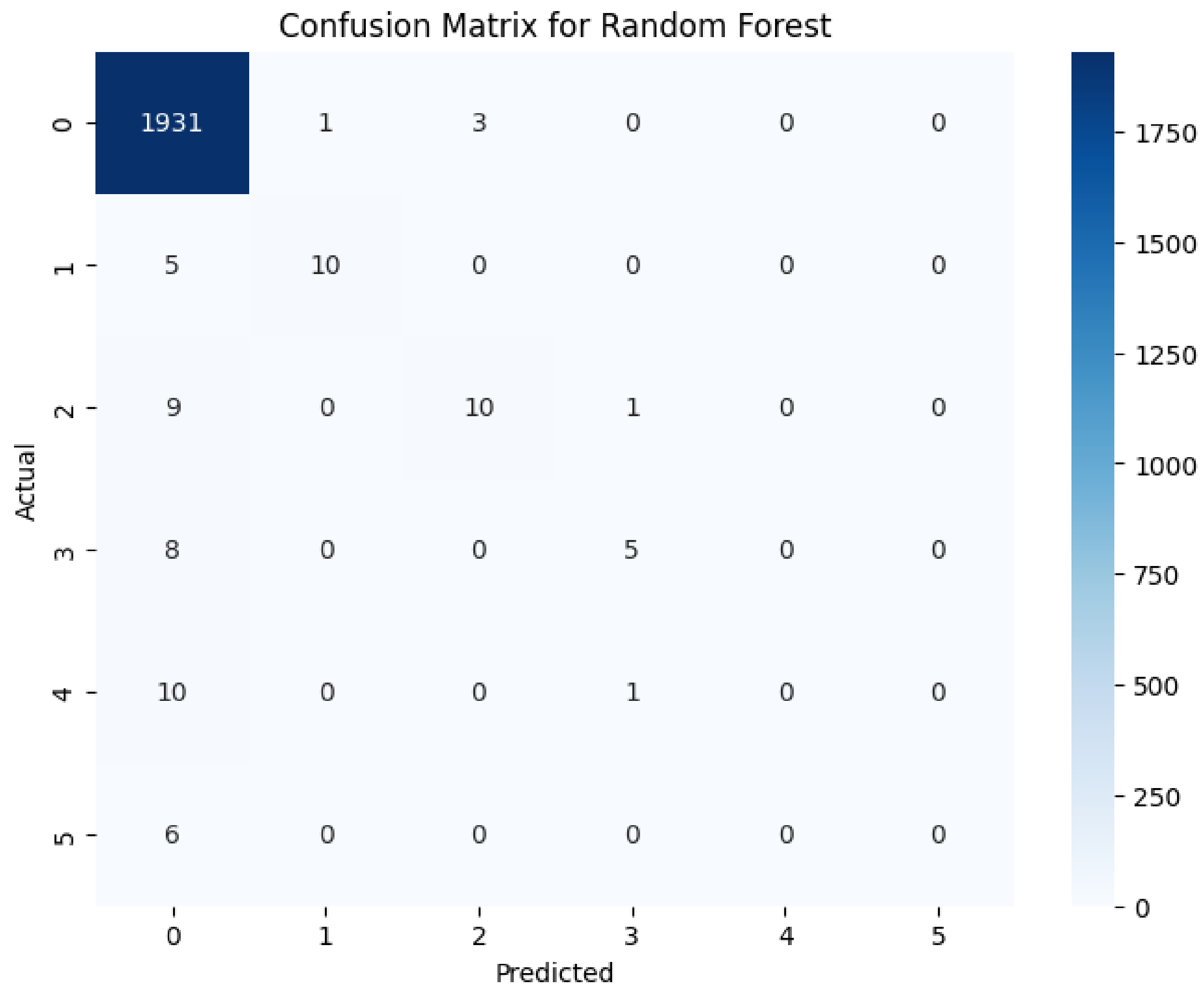
- **Importance:** High. This block trains and evaluates multiple models.
- **Description for Report:**
  - **Model Training:** Four models (Logistic Regression, Decision Tree, Random Forest, and XGBoost) are trained on the scaled training data.
  - **Model Evaluation:** Each model is evaluated on the test data, and metrics such as accuracy, classification report, and confusion matrix are recorded.

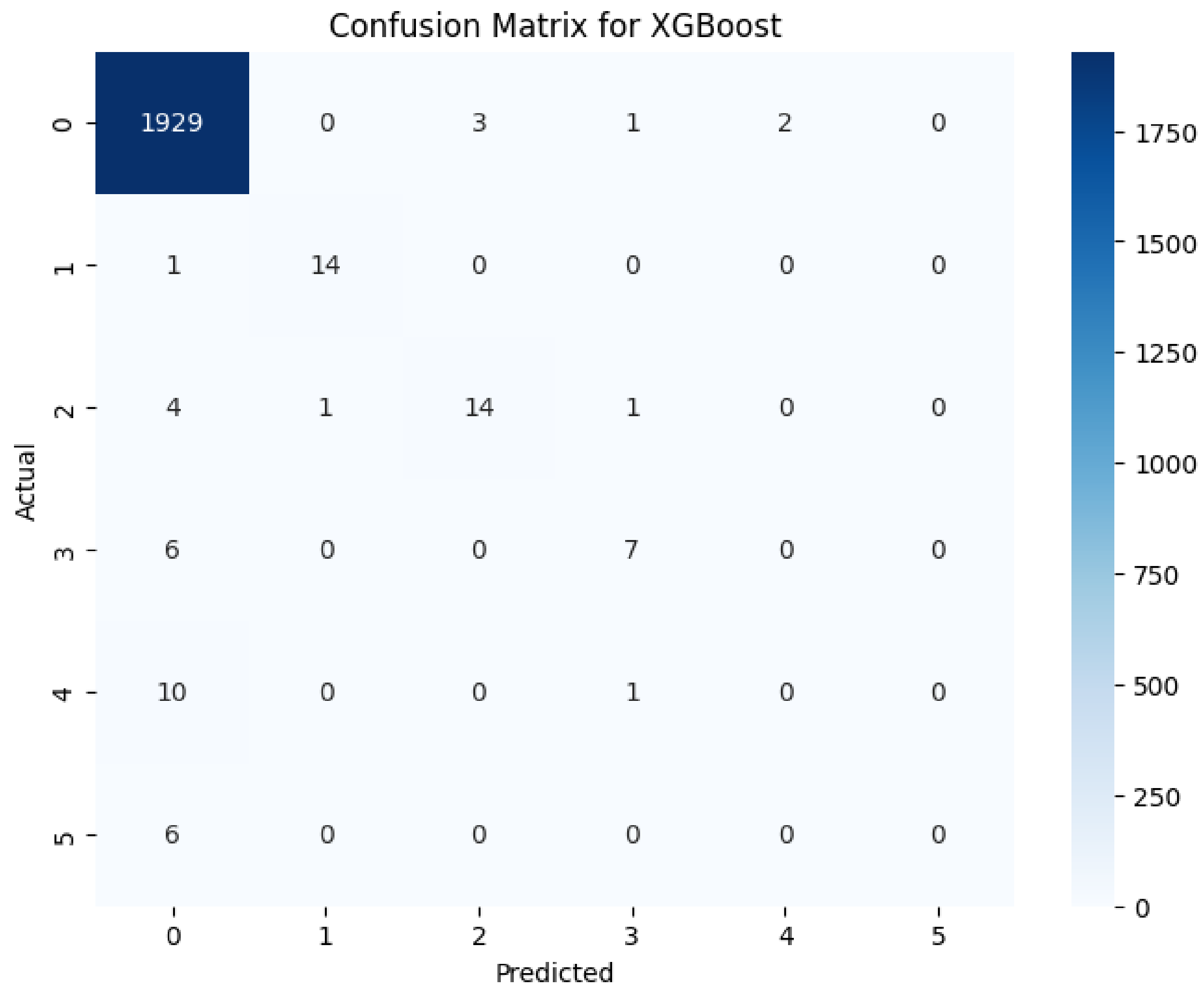
Results and Visualization

```
[ ] # Visualize confusion matrices
    for model_name, result in results.items():
        plt.figure(figsize=(8, 6))
        sns.heatmap(result['confusion_matrix'], annot=True, fmt='d', cmap='Blues
        plt.title(f'Confusion Matrix for {model_name}')
        plt.xlabel('Predicted')
        plt.ylabel('Actual')
        plt.show()
```




Confusion Matrix for Decision Tree
Actual
Predicted
1915 4 5 5 6 0
3 12 0 0 0 0
8 0 9 3 0 0
3 0 0 9 1 0
10 0 0 0 1 0
6 0 0 0 0 0
0 1 2 3 4 5
0 250 500 750 1000 1250 1500 1750


Confusion Matrix for Random Forest
1931
1
3
0
5
10
9
2
8
6
4
1750
1500
1250
1000
750
500
250
Actual
Predicted



Description:

- **Importance:** High. This block visualizes the confusion matrices and suggests the best model.
- **Description for Report:**
    - **Confusion Matrices:** Confusion matrices for each model are visualized to understand the performance on different classes.
    - **Best Model:** The model with the highest accuracy is suggested as the best model.

Suggest the best model based on accuracy

```
[ ] # Suggest the best model based on accuracy
    best_model = max(results, key=lambda x: results[x]['accuracy'])
    print(f"The best model is {best_model} with an accuracy of {results[best_model]['accuracy']}'
```

```
The best model is XGBoost with an accuracy of 0.982
```

FUTURE WORK & CONCLUSION

Conclusion:

The predictive maintenance model, particularly the XGBoost model, demonstrated high accuracy in predicting equipment failures. The key findings included the identification of various failure types and their frequencies, which provide valuable insights into equipment health and maintenance needs. The model's ability to forecast failures enables proactive maintenance strategies, reducing unplanned downtime and maintenance costs. However, the study acknowledges the limitations of the models used, such as the need for balanced datasets and the handling of imbalanced classes, which may affect the precision of the predictions. Future efforts could involve integrating more features, handling imbalanced data more effectively, and updating the model periodically to reflect evolving equipment conditions.

Future Work:

1. **Enhanced Feature Set**: Future research could explore additional equipment features such as vibration data, oil analysis, or historical maintenance logs to improve the predictive accuracy and robustness of the model.

2. **Advanced Machine Learning Techniques**: Exploring other machine learning algorithms, such as Support Vector Machines (SVM) or Neural Networks, could address some of the limitations of the current models, like handling highly imbalanced datasets and improving generalization.

3. **Dynamic Predictive Models**: Equipment conditions may evolve over time. A future model could periodically retrain with updated data, ensuring that the predictions reflect changing trends and operational patterns.

4. **Model Validation**: Incorporating methods like cross-validation and more robust evaluation metrics could help validate the stability and quality of the predictive models.

5. **Cross-Domain Analysis**: Applying the same methodology to other domains, such as aerospace or automotive, could provide additional insights into equipment maintenance and enhance the generalizability of the approach.

6. **Real-Time Monitoring and Alerts**: Future work could explore how to implement the insights from predictive maintenance into real-time monitoring systems and alert mechanisms to improve

equipment health monitoring and proactive maintenance scheduling.

By following these suggestions, future research can build upon the current work to enhance the predictive maintenance model's accuracy, robustness, and applicability, ultimately improving equipment health and operational efficiency in the manufacturing sector.

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