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Application of Machine Learning and Artificial Intelligence in Smart Manufacturing Systems

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Abstract: “Artificial intelligence” and “machine learning” are important components of smart “manufacturing systems” that maximize operational efficiency and minimize unanticipated equipment breakdowns. This study examines how “machine learning” models can be used to predict maintenance based on the “Machine Predictive Maintenance Classification” dataset. Diagnostic variables that include “air temperature”, “process temperature”, “rotational speed”, “torque”, and “tool wear” are computed to forecast machine failure. Before training the model, data preprocessing, exploratory analysis, and feature scaling are carried out. Three classification algorithms, such as “Logistic Regression”, “Random Forest”, and “Support Vector Machine”, are applied and compared. The experimental results show that “Random Forest” has the highest performance of 0.98 accuracy and 0.965 ROC AUC, which is a high predictive maintenance ability in smart manufacturing settings.

Keywords: Smart Manufacturing, Predictive Maintenance, “Machine Learning”, “Random Forest”, “Support Vector Machine”, “Logistic Regression”, Machine Failure Prediction.

I. INTRODUCTION

Background of Smart Manufacturing

Smart manufacturing is a technological advancement of legacy industrial structures via digital transformation, automation, and the use of analytics to make decisions. Sensors, connected devices, and sophisticated computing technologies are becoming an essential part of manufacturing industries to provide real-time monitoring of machine performance and production processes. This digital connection allows the manufacturers to gather vast amounts of equipment functioning data of temperature sensors, rotational speed sensors, and torque measurement systems. This kind of data gives useful information about machine behavior and production efficiency. Sudden failure of equipment, however, is a significant issue in the industrial setting, where it usually leads to production loss and disruption in operations. Smart manufacturing systems are the solution to this problem because they integrate data analytics and smart monitoring systems to enhance operational efficacy and reliability. Predictive maintenance is now a key part of modern manufacturing systems, and industries are acting to identify what is likely going wrong with equipment before it fails.

Role of Machine Learning and AI

“Artificial Intelligence (AI)” and “Machine Learning (ML)” are instrumental in improving intelligent manufacturing systems to perform intelligent analysis of industrial data. The technologies also enable manufacturing systems to detect the latent trends in vast datasets of machine sensors and processes. In predictive maintenance, parameters can include “air temperature”, “process temperature”, “rotational speed”, “torque”, and “tool wear”, which the ML algorithm uses to indicate a machine is prone to failure. The classification algorithms are able to differentiate normal operating

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conditions and possible failure states, early detecting equipment faults. The application of MLs to sensor information can assist manufacturers in better planning of maintenance, minimize unforeseen machine failures, and optimize output. As a result, AI-based predictive maintenance systems lead to greater reliability and sustainability of the contemporary manufacturing setting.

Aim and Objectives

The purpose of this study is to analyses how smart manufacturing systems using "machine learning" methods can be utilized in predictive maintenance. This study uses the Machine Predictive Maintenance "Classification" dataset in order to design classification models that are able to predict machine breakdown depending on operational sensor data. The goals are to analyses the features of machine sensors, test various classification algorithms, and focus on their levels of predictability to find potential equipment failure in manufacturing facilities.

II. LITERATURE REVIEW

Smart Manufacturing Systems

Modern industries apply smart manufacturing systems to enhance digital improvement of manufacturing and machine observation. These systems combine intelligent technologies like connected machines, sensors, and communication networks to gather and analyses manufacturing data. The primary objective of smart manufacturing is to enhance efficiency, productivity, and reliability in industrial processes. Operational data such as the temperature, speed of equipment, and tool usage can be shared among machines through these technologies, and they are used to monitor the state of equipment in real-time.

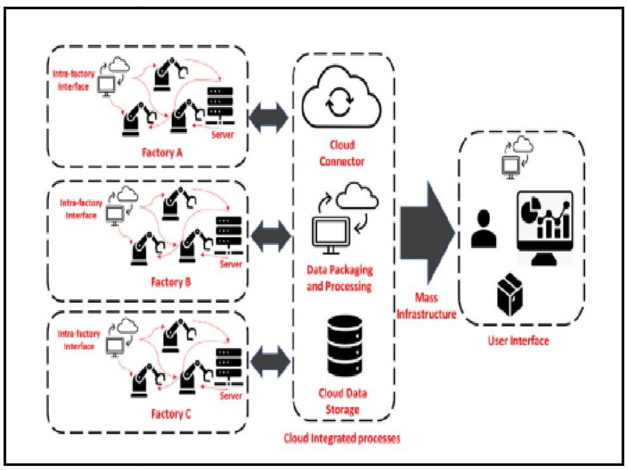

Fig 1: Smart Manufacturing Framework for Industrial Data Integration

The diagram shows integrated factories in which machines transmit working data to cloud platforms to be processed and stored (Atieh *et al.* 2023). This digitalization facilitates analysis of data, facilitating smart manufacturing systems to provide intelligent checking and predictive maintenance. This data-driven climate makes predictive maintenance possible by using "machine learning" and "artificial intelligence". When the manufacturers interpret machine sensor data, they will be informed of possible equipment failures beforehand and minimize unplanned downtime. Accordingly, intelligent manufacturing systems are a significant source of enhancement of efficiency in production and aid in smart decision-making in advanced manufacturing settings.

AI in Industrial Automation

"Machine Learning (ML)" and "Artificial Intelligence (AI)" can be significant in enhancing automation in contemporary manufacturing systems. The technologies also examine high volumes of machine and sensor data to enhance operational efficiency, productivity, and system reliability. In a factory setup, AI tools can detect abnormal

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patterns and use different measurements of temperatures, rotational velocity, torque, and tool wear to determine the workings of a machine.

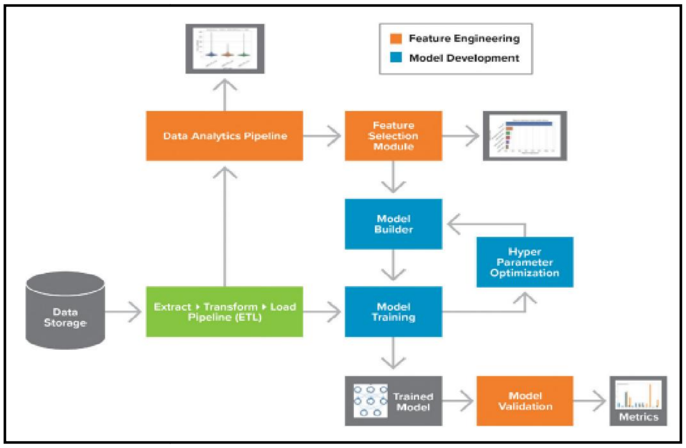

Fig 2: Machine Learning Pipeline for AI-Driven Industrial Automation

The figure shows a machine learning pipeline in which the industrial data is to be processed, features are to be selected, and models are to be trained and tested. The workflow is used to assist in predictive maintenance and intelligent decision-making within manufacturing systems (Plathottam *et al.* 2023). This facility helps in predictive maintenance since it detects the possible failure of the equipment in advance. This leads to the manufacturing systems being able to minimize the unnecessary downtime and enhance the planning process of production. Some issues remain, such as issues with gathering good-quality industrial data, handling massive data, and system security. Irrespective of these concerns, the application of AI-driven automation remains useful in facilitating smarter and more efficient manufacturing processes.

Predictive Maintenance using Machine Learning

“Machine learning” with predictive maintenance is a valuable application of machine learning to smart manufacturing. As with other fields of predictive analytics, machine learning methods examine intricate data interactions with the goal of creating useful information that can be used to accomplish prediction tasks. In manufacturing, machine learning models can be used to process machine sensor data, including machine air temperature, process temperature, rotational speed, torque, and tool wear to detect trends based on equipment conditions (Badawy *et al.* 2023). These models can be used to predict the probability of a machine failing by using historical data on the operational characteristics of the machine. Proper forecasting aids in assisting the manufacturers to schedule maintenance procedures before breakdowns take place. This minimizes the occurrence of unforeseen unproductiveness and enhances productivity. Predictive maintenance and decision-making in modern manufacturing systems need the support of reliable machine learning models to enhance performance.

Research Gap

The need to use smart manufacturing systems, artificial intelligence, and predictive analytics has been previously studied as a means of enhancing industrial operations. Numerous studies are dedicated to the implementation of “machine learning” methods in manufacturing industries for predictive maintenance and monitoring equipment. A number of the studies, however, primarily cover theoretical frameworks or broad industrial applications without testing the results of multiple classification models on machine sensor datasets. Moreover, limited studies have compared the performance of various “machine learning” models based on such operational variables as “temperature”, “rotational speed”, “torque”, and “tool wear”. Classification algorithms comparing real or simulated manufacturing data to predict machine failure should be further analyzed and compared to underpin reliable predictive maintenance systems.

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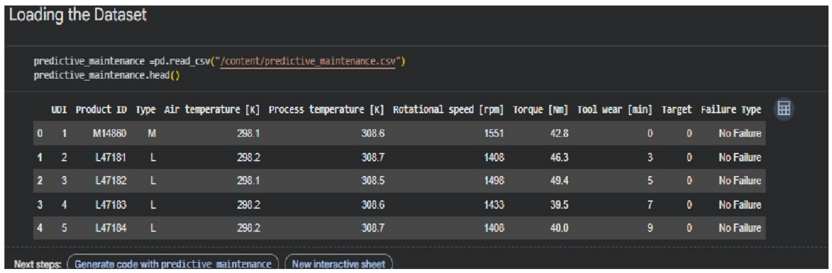
III. METHODOLOGY

Dataset Description

This study involves the utilization of data in the "Machine Predictive Maintenance Classification" dataset, which comprises 10,000 records and various machine sensor characteristics recorded in a simulated manufacturing setting. Variables indeed comprise "air temperature", "process temperature", "rotational speed", "torque", "machine type" and "tool wear".


Loading the Dataset

```
predictive_maintenance =pd.read_csv("/content/predictive_maintenance.csv")
predictive_maintenance.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

Next steps: Generate code with predictive_maintenance New interactive sheet

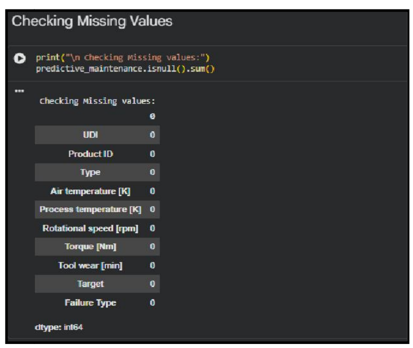
Fig 3: Displaying the dataset

These attributes denote operational states of manufacturing machines and are involved in the forecasting of equipment failure. There is also a target variable in the dataset that shows whether there was a machine failure. Data inspection shows the initial rows of data and gives details of column types, data structure, and the number of observations to use to perform an analysis.

Dataset Source:

https://www.kaggle.com/datasets/shivamb/machine-predictive-maintenance-classification

Data Preprocessing


Checking Missing Values

```
print("\n Checking Missing values:")
predictive_maintenance.isnull().sum()
```

Checking Missing values:

	0
UDI	0
Product ID	0
Type	0
Air temperature [K]	0
Process temperature [K]	0
Rotational speed [rpm]	0
Torque [Nm]	0
Tool wear [min]	0
Target	0
Failure Type	0

dtype: int64

Fig 4: Checking Missing Values

The output supports the fact that there are no missing values in all variables of the dataset. This validation makes the data complete and reliable to enable the preprocessing phase and machine learning models to work without data quality problems.

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DATA PREPROCESSING

Encode categorical variable

```
df = predictive_maintenance.copy()

# Dropping unnecessary columns

df = predictive_maintenance.drop(['UDI','Product ID','Failure Type'], axis=1)

le = LabelEncoder()
df['Type'] = le.fit_transform(df['Type'])
# Defining features and target
X = df.drop('Target', axis=1)
y = df['Target']
```

Fig 5: Encoding Categorical variable

The figure shows the preprocessing stage in which the extraneous columns like “UDI”, “Product ID” and “Failure Type” will be dropped, and the categorical variable Type will be encoded with LabelEncoder. This is followed by the definition of the “features” and “target” variables. The step is important to prepare the dataset to be used in “machine learning” algorithms by transforming categorical data to numerical data, or preparing inputs in order to train the model.

Train-Test Split

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

Fig 6: Splitting the dataset into train and test

Feature Scaling

```
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
print("Training set shape:", X_train.shape)
print("Testing set shape:", X_test.shape)

print("\nTarget distribution in training set:")
print(y_train.value_counts())

print("\nTarget distribution in testing set:")
print(y_test.value_counts())

Training set shape: (8000, 6)
Testing set shape: (2000, 6)

Target distribution in training set:
Target
0    7729
1     271
Name: count, dtype: int64

Target distribution in testing set:
Target
0    1932
1      68
Name: count, dtype: int64
```

Fig 7: Performing Feature Scaling

Two subsets are created based on a train-test split to help in the stable evaluation of “machine learning” models. StandardScaler is then used to scale numeric variables which of “temperature”, “rotational speed”, “torque” and “tool wear” to standard values. Such measures guarantee even distribution of data and the ability of the model to learn more efficiently when it comes to predicting machine failure in the predictive maintenance dataset.

Machine Learning Models

MODEL TRAINING AND EVALUATION

Model 1 -Logistic Regression

```python
# Train model
lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)

# Predictions
y_pred_lr = lr_model.predict(X_test)

# Classification Report
print("Classification Report (Logistic Regression)")
print(classification_report(y_test, y_pred_lr))
```

```
Classification Report (Logistic Regression)
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1932
           1       0.67      0.12      0.20        68

    accuracy                           0.97      2000
   macro avg       0.82      0.56      0.59      2000
weighted avg       0.96      0.97      0.96      2000
```

Fig 8: Performing Logistic Regression

"Logistic Regression" is used to predict machine failure based on sensor variables within the predictive maintenance dataset. The classification report demonstrates that there is an overall accuracy of 0.97 on 2000 test observations. The accuracy of the non-failure score is 0.97, with the recall rate 1.00, whereas the failure score accuracy is 0.67 at a recall rate 0.12, which attests to the evaluation of the baseline model.

Model 2 -Random Forest

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

# Predictions
y_pred_rf = rf_model.predict(X_test)

# Classification Report
print("Classification Report (Random Forest)")
print(classification_report(y_test, y_pred_rf))
```

```
Classification Report (Random Forest)
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      1932
           1       0.88      0.65      0.75        68

    accuracy                           0.98      2000
   macro avg       0.93      0.82      0.87      2000
weighted avg       0.98      0.98      0.98      2000
```

Fig 9: Performing Random Forest

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Model 3-Support Vector Machine (SVM)

```
# Train model
svm_model = SVC(probability=True)
svm_model.fit(X_train, y_train)

# Predictions
y_pred_svm = svm_model.predict(X_test)

# Classification Report
print("Classification Report (SVM)")
print(classification_report(y_test, y_pred_svm))
```

```
Classification Report (SVM)
              precision    recall  f1-score   support

           0       0.97      1.00      0.99      1932
           1       0.88      0.21      0.33        68

    accuracy                           0.97      2000
   macro avg       0.92      0.60      0.66      2000
weighted avg       0.97      0.97      0.96      2000
```

Figure 10: Performing SVM

The models used to classify machine failure are the "Random Forest" and the "Support Vector Machine" to use sensor data in the predictive maintenance dataset. "Random Forest" has an "accuracy" of 0.98, a "precision" of 0.88 and a "recall" of 0.66 to detect failure. The "SVM" achieves 0.97 "accuracy", 0.88 "precision" and 0.21 "recall" failure. The findings validate the comparative assessment of "machine learning" models in predictive maintenance in smarter manufacturing systems.

IV. ANALYSIS

Summary Statistics

```
# Summary statistics
print("\n Summary statistics:")
predictive_maintenance.describe()

# Including categorical columns
predictive_maintenance.describe(include='all')
```

Summary statistics:

	UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target	Failure Type
count	10000.00000	10000	10000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000
unique	NaN	10000	3	NaN	NaN	NaN	NaN	NaN	NaN	6
top	NaN	L57163	L	NaN	NaN	NaN	NaN	NaN	NaN	No Failure
freq	NaN	1	6000	NaN	NaN	NaN	NaN	NaN	NaN	9652
mean	5000.50000	NaN	NaN	300.004930	310.005560	1538.776100	39.986910	107.951000	0.033900	NaN
std	2886.89568	NaN	NaN	2.000259	1.483734	179.284096	9.968934	63.654147	0.180981	NaN
min	1.00000	NaN	NaN	295.300000	305.700000	1168.000000	3.800000	0.000000	0.000000	NaN
25%	2500.75000	NaN	NaN	298.300000	308.800000	1423.000000	33.200000	53.000000	0.000000	NaN
50%	5000.50000	NaN	NaN	300.100000	310.100000	1503.000000	40.100000	108.000000	0.000000	NaN
75%	7500.25000	NaN	NaN	301.500000	311.100000	1612.000000	46.800000	162.000000	0.000000	NaN

Figure 11: Displaying Summary Statistics

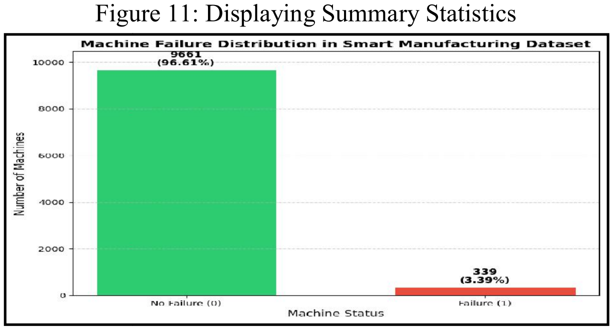

Fig 12: Graphical visualization of Failure distribution

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The summary statistics provide some important features of the machine sensor variables, including “air temperature”, “process temperature”, “rotational speed”, “torque”, and “subtractive wear” of tools. The failure distribution graph represents a normal case of 9,661 (96.61%) and failure cases of 339 (3.39%). The findings can be used to learn about dataset structure and class imbalance, which can be followed by additional machine learning modelling of predictive maintenance analysis.

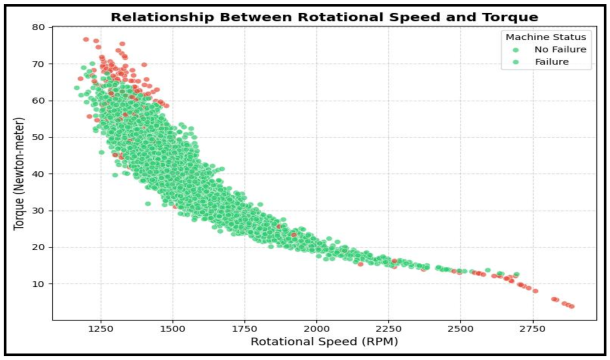

Fig 13: Scatter plot of Rotational speed and Torque

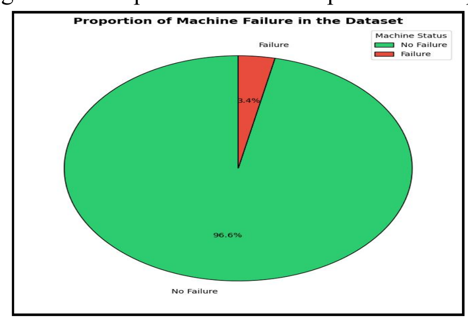

Fig 14: Pie chart of machine failure proportion

The scatter diagram represents the “correlation” between the “rotational speed” and “torque” when machines are operating, whereby high speed is correlated with low torque and vice versa. The pie chart reflects the class distribution, with the majority of observations indicating normal machine conditions and a low percentage indicating machine failures. These visualizations aid in the interpretation of the relationship between features and the balance of classes before the machine learning modelling.

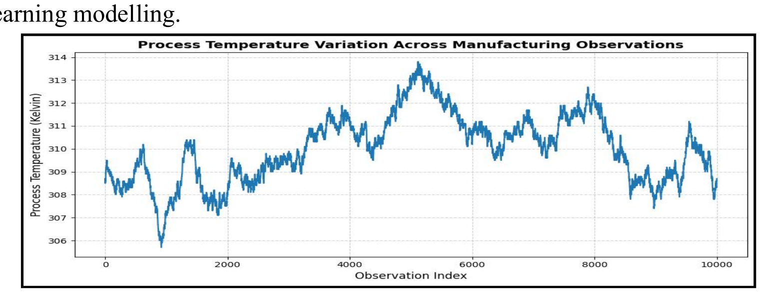

Fig 15: Line plot of temperature variation across manufacturing observations

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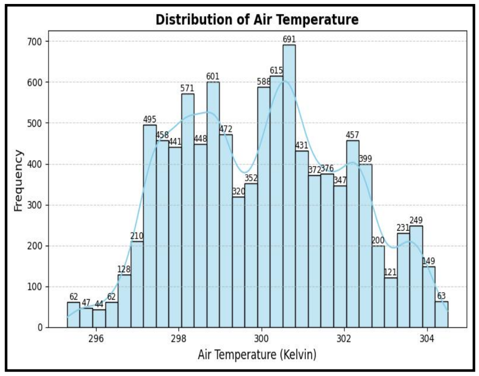

Fig 16: Histogram of air temperature distribution

The line plot shows the variation in process temperature on 10,000 manufacturing measurements, a fact that shows that the measurements vary around 306 K to 314 K and these values do not exceed 314 K, which means stable operating conditions. The histogram indicates that the air temperature is centered on 298 to 302 with a peak frequency of about 300. These visualizations aid in comprehending the patterns of temperatures that affect the functioning of the machine and the modelling of predictive maintenance.

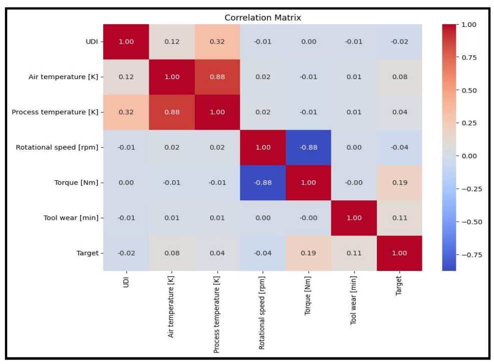

Fig 17: Correlational analysis

The correlation matrix shows relationships among machine sensor variables that are considered in predictive maintenance. The air temperature has a positive relationship of a value of 0.88 with the process temperature and a negative relationship of -0.88 with rotational speed and torque. The analysis aids in gaining the insights about the features and extracting the valuable variable interactions impacting machine failure prediction.

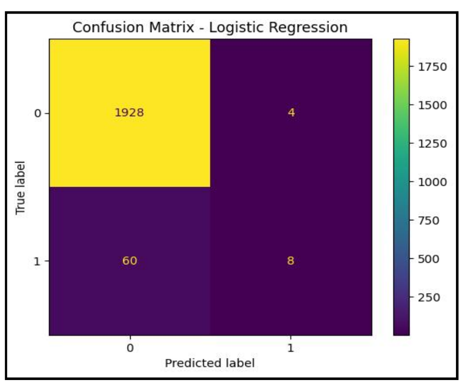

Fig 18: Confusion Matrix of Logistic Regression

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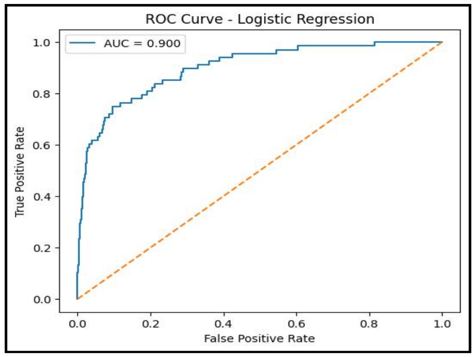

Fig 19: ROC curve for Logistic regression

The confusion matrix indicates that 1928 correct non-failures are predicted, 8 correctly recognized failures, 4 false positives and 60 false negative outcomes. The AUC of the ROC curve is 0.90, which is high in terms of classification. These findings can measure how effective the "Logistic Regression" model is in "predicting machine" breakdown in predictive maintenance dataset.

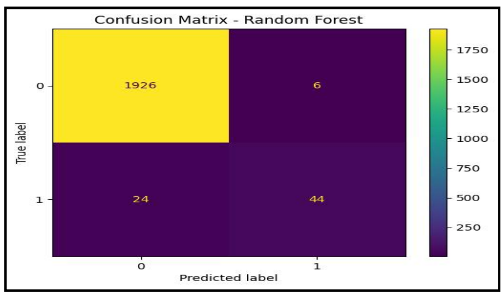

Fig 20: Confusion matrix for Random Forest

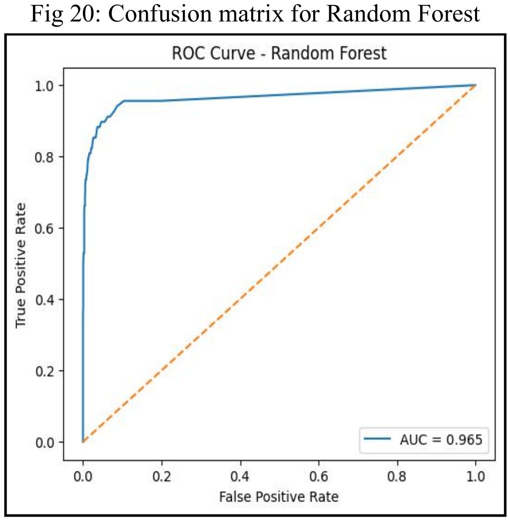

Fig 21: ROC curve for Random Forest

The "confusion matrix" indicates receiving 1926 correctly recognized non-failure cases and 44 correctly recognized machine failures, with 6 false positives and 24 false negatives. The "ROC curve" shows an "AUC" of 0.965, which implies a good predictive behavior. The outcomes of these experiments gauge the efficiency of the "Random Forest" model used in predicting machine failures in the predictive maintenance report.

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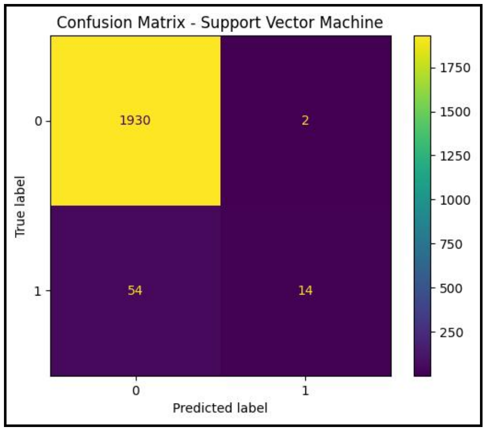

Fig 22: Confusion matrix for SVM

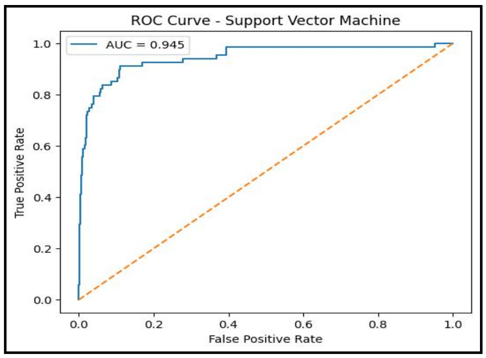

Fig 23: ROC curve for SVM

The "confusion table" indicates that 1930 correct non-failures and 14 correctly failed were obtained, but 2 false positives and 54 false negatives can be obtained. The AUC value on the ROC curve stands at 0.945 that shows good classification. These findings assess the efficiency of the Support Vector Machine model in predicting machine failure in the predictive maintenance dataset.

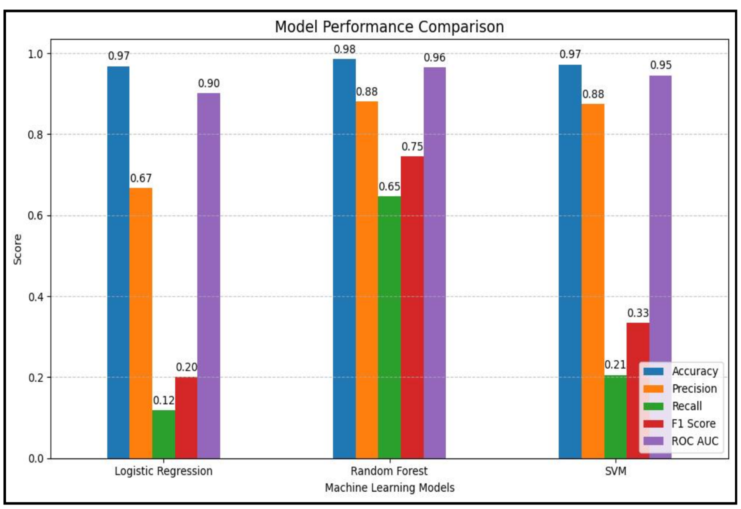

Fig 24: Model Comparison graph

The comparison graph demonstrates the results of the performance of “Logistic Regression”, “Random Forest”, and “SVM models”. “Random Forest” has the most accurate values at 0.98, a recall at 0.65 and ROC AUC of 0.96. This comparison contributes to the involvement of the best “machine learning” model in predictive maintenance in intelligent manufacturing systems.

V. DISCUSSION

The findings indicate that machine learning algorithms can efficiently work with data from the manufacturing sensors to forecast what may happen to the equipment. Logistic Regression has a high overall accuracy but presents poor performance in identifying failure cases because of low recall. The Support Vector Machine model offers high classification accuracy as well but is poor in detecting failure instances on a regular basis. Random Forest is the top model of the three models and ranked high in accuracy, recall, and the ROC-AUC. This demonstrates that ensemble learning models are better able to capture non-linear relationships between variables including temperature, rotational speed, torque, and tool wear in the predictive maintenance dataset (Pundir *et al.* 2022). The data represented in the analysis is synthetic data, not actual industrial sensor historical data. Moreover, there can be a tendency towards the presence of class imbalance between the failure and the non-failure observations, which can affect the model performance in the sphere of the rare failures occurrence identification. Most of the future studies can include larger real-life datasets and sophisticated modelling to enhance predictive precision and extrapolation in the industrial setup.

VI. CONCLUSION

Summary of Findings

This study analyses how machine learning can be used in intelligent manufacturing systems for predictive maintenance. The variables used to forecast machine failure are analyzed using machine sensor data, such as “air temperature”, “process temperature”, “rotational speed”, “torque”, and “tool wear”. Exploratory analysis gives information on the nature of the data such as summary statistics, relationships between features, and class distributions, with machine failures constituting about 3.39 percent of the observations. Three “classification algorithms” (“Logistic Regression”, “Random Forest”, and “Support Vector Machine”) are applied to assess the performance of predictive means.

According to the results, the classification accuracy of all models is high, but their capability to find machine failure is different. The overall accuracy and “ROC AUC” of the “Logistic Regression” are 0.97 and 0.90, respectively, whereas the “Support Vector Machine” model has an “accuracy” of 0.97 and an “ROC AUC” of 0.945. The “Random Forest” model shows the highest success with an accuracy of 0.98, a recall of 0.65, and ROC AUC of 0.965, which means that this Model is more successful in detecting machine failures. These results indicate that the ensemble learning methods are effective in analyzing manufacturing sensor data. The analysis shows that machine learning applications can assist predictive maintenance through understanding the current state of operations and identifying the possible malfunction of equipment in manufacturing facilities.

Future Work

Future studies are expected to include real data sets in industries to enhance the model dependability and workability. More machine learning and deep learning systems ought to be researched to improve predictive and failure detection performance (Peruzzini *et al.* 2024). Developed methods of managing class imbalance must also be implemented to enhance the detection of infrequent failure instances (Raoufi *et al.* 2024). The real-time sensor data streams should also be integrated to contribute to the creation of smart predictive maintenance systems in the smart manufacturing settings.

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