MAJOR PROJECT PROGRESS REPORT

PREDICTIVE MAINTENANCE IN INTERNAL COMBUSTION ENGINES

Submitted in partial fulfilment of the requirement for the award of the degree

of

BACHELOR OF TECHNOLOGY

Under the supervision of
Dr. Subhash Singh

Submitted to
Department of Mechanical and Automation Engineering

Indira Gandhi Delhi Technical University for Women
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CERTIFICATE

It is certified that the work contained in the Project entitled ‘Predictive Maintenance in Internal Combustion Engine’ by Prgya Jha, Sadaf Khan, Akriti Varshney and Shivanshi Jha has been carried out under my supervision and this work has not been submitted elsewhere for a degree.

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CERTIFICATE

This is to certify that the work presented in this B.Tech. Project titled ***"Predictive Maintenance in Internal Combustion Engine"*** is an authentic record of my own work under the supervision of "***Subhash Singh, Assistant Professor",*** "***Department of Mechanical and Automation"***.

It is submitted in partial fulfilment of the requirements for the award of the **Bachelor of Technology in Mechanical and Automation**, **Indira Gandhi Delhi Technical University for Women.**

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DECLARATION OF ORIGINAL WORK

We are Pragya Jha, Sadaf Khan, Akriti Varshney, Shivanshi Jha students of B.Tech. (MAE), hereby declare that the project titled “Predictive Maintenance in Internal Combustion Engine” which is submitted by us for the partial fulfilment of the requirement for the award of the degree of B. Tech. is original, free from plagiarism and not copied from any source without proper citation. This work has not previously formed the basis for the award of any degree, diploma, fellowship or any other similar titles or recognition. In case plagiarism is detected at any stage, we shall be solely responsible for it.

Place: Delhi

Date: 19/02/24

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ABSTRACT

IC engines, commonly known as Internal combustion engines, have been the driving force behind various industries like manufacturing, construction, and transportation. They've played a significant role in shaping the modern world. However, with the world's growing focus on being environmentally friendly and improving operational efficiency, IC engines need to adapt and modernize beyond the traditional ways they've operated for decades. This is where the significance of IoT in the engine industry becomes evident. Our report emphasizes the use of IoT in IC engines to improve their performance, emissions, reliability, and maintenance. IoT devices and sensors can collect and analyse data from the engine and its environment. IoT can also help to detect and prevent faults and failures, predict and diagnose problems, and coordinate the operation of multiple engines in a network.

The main goal of this research is to use cutting-edge machine learning algorithms to create a predictive maintenance system for IC engines. The system schedules maintenance tasks in advance by using real-time data from engine sensors to anticipate possible problems. To evaluate the engine's health, important metrics like engine RPM, coolant pressure, fuel pressure, lubricant oil temperature, and coolant temperature are tracked and evaluated.

This study supports the larger industry trends towards Industry 4.0 and the incorporation of intelligent technologies for engines that run more sustainably and efficiently. The results have ramifications for a number of industries where IC engines are essential to daily operations, such as manufacturing, transportation, and energy production.

CHAPTER 1

INTRODUCTION

1. Overview on IC Engines

For almost a century, IC engines have been a cornerstone of contemporary transportation and power generation. These engines are essential in transforming fuel into mechanical energy via combustion within the engine.

Few applications are; IC engines power the majority of vehicles, motorcycles, and light trucks. Jet engines are a subset of IC engines used in the aerospace industry and it also powers many electricity producers. IC engines have played a significant role in defining modern transportation and electricity generation.

2. Predictive Maintenance in IC Engines

Predictive maintenance in IC engines overcomes significant issues associated with old reactive approaches. Predictive maintenance in IC engines is critical for modern enterprises that want to increase efficiency, cut costs, and embrace sustainable practices. Organizations may unlock the full potential of their IC engines by shifting from reactive to proactive maintenance procedures, assuring reliable and optimum performance in the face of changing operating difficulties.

Internal Combustion (IC) engine predictive maintenance is a game-changing strategy that uses advanced technologies to anticipate and avoid possible problems, reducing downtime and optimising engine performance. The Internet of Things (IoT) plays a critical role in predictive maintenance by enabling real-time data collecting from various sensors strategically integrated within operating assets. These sensors continuously monitor crucial parameters, allowing for the collection of extensive data. Machine learning algorithms analyse this data to detect patterns, abnormalities, and potential flaws, allowing predictive analytics to make timely decisions.

With the introduction of predictive maintenance technology, the world of internal combustion (IC) engines has seen a dramatic development in recent years.

The transition to predictive maintenance is a paradigm shift, embracing the possibilities of the Internet of Things (IoT), enhanced sensors, data analytics, and machine learning. Predictive maintenance shifts the focus from treating what is broken to anticipating and preventing prospective problems by utilising real-time data from sensors strategically placed within the engine.

The condition of an engine is determined by evaluating different indicators that collectively indicate its health, performance, and possible difficulties. Visual Inspection, Oil analysis, Compression Test, Leak down test, Coolant system check, Exhaust smoke, Sound of engine, Service record, Sensor readings, Fluid examination, Driveability.

CHAPTER 2

LITERATURE REVIEW

R. Mobley, (1990), An introduction to predictive analysis

Helps process, maintenance and reliability managers and engineers to develop and implement a comprehensive maintenance management. The aim is to maximize the engine performance and efficiency to get improved power output.

Maintenance and reliability best practices (2019) Spectransys private limited

This paper has focused on the maintenance and management issues around the engineering of the diesel-based combustion ignition engine. And alongside include the economical and psychological aspects as well.

Data Analysis and Acquisition systems for internal combustion engines, (2012) by Umesh Kantute

The book consists of testing an internal combustion engine with measurements of various parameters using a computer. For this the data is acquired from the internal combustion engine and sent to the computer after required conditioning. The data acquisition system increases efficiency of measurement and lowers the cost for tests.

Introduction to sensors in internal combustion engines, (2019) by Shantanu Bhattacharya, Avinash Kumar Agarwal, Om Prakash, Shailendra Singh

Indispensable guide to a subject which draws on many areas of engineering: thermodynamics and combustion, fluid mechanics and heat transfer mechanics, stress analysis, materials science, electronics, and computing.

Automotive sensors, (2009), edited by John Turner and Joe Watson

Sensors are the eyes, ears, and more, of the modern engineered product or system. This book offers a review of sensors and their associated controls systems found in the automotive vehicle. It shows readers to find data and guidance on: automotive telematics.

Advanced motion control and sensing for intelligent vehicles by Fei- Yue Wang

The paper includes detailed discussions of vehicle dynamics and ground-vehicle interactions are provided for the modelling, simulation, and control of vehicles. It includes an extensive review of past and current research achievements in the intelligent vehicle motion control and sensory field, and the book provides a careful assessment of future developments.

CHAPTER 3

Predictive Maintenance with IoT

3.1. What is predictive maintenance?

In the Internet of Things (IoT), predictive maintenance is the process of estimating when machinery or equipment is likely to break by utilizing data gathered from linked devices. The objective is to minimize downtime, maximize equipment lifespan, and lower total maintenance costs by carrying out maintenance tasks exactly in time. It is an effective strategy that uses information from networked devices to predict and stop equipment failures.

3.2. How can IoT be used for predictive maintenance?

Sensor Deployment: Put sensors on the devices you wish to keep an eye on. Numerous data kinds, including temperature, vibration, pressure, humidity, and more, can be gathered by these sensors. Make sure these sensors have Internet of Things connectivity so they can send data across the network.

Data Collection: Real-time data is continuously collected by sensors from the device under observation. For processing, the gathered data might be routed to an edge computing device or a centralized cloud-based platform.

Data Analysis and Processing: Analyse the gathered data using data processing methods, machine learning, and advanced analytics. Determine any trends, patterns, or anomalies that might point to possible problems or suggest when maintenance is due.

Condition Monitoring: Utilizing the data analysis, keep an eye on the equipment's state in real time. Determine the performance measures at baseline and make comparisons.: Put sensors on the devices you wish to keep an eye on. Numerous data kinds, including temperature, vibration, pressure, humidity, and more, can be gathered by these sensors. Make sure these sensors have Internet of Things connectivity so they can send data across the network.

Predictive Modelling: Create predictive models that can estimate the equipment's remaining useful life or indicate when a failure is most likely to happen. Prediction accuracy can be increased by using historical data to train machine learning algorithms.

Alerts and Notifications: Install an alert system that will notify operators or maintenance staff, when possible, problems are detected by the predictive models. Notifications can be delivered by text message, email, or computerized maintenance management system integration (CMMS).

Maintenance Planning: Make better use of the information gathered from predictive maintenance when organizing maintenance tasks. Plan maintenance activities for times when output is low or the equipment is not in use.

Reduced Downtime and Cost Savings: Organizations can minimize unplanned downtime and lower maintenance costs by addressing potential issues before they become failures. When maintenance tasks are determined by the actual state of the equipment rather than by predetermined schedules, they become more focused and effective.

Continuous Improvement: Refine and update predictive models on a regular basis in response to feedback and new data. Make use of the knowledge obtained from predictive maintenance to raise the general performance and dependability of your equipment.

CHAPTER 4

Engine Condition Prediction using Machine Learning

The "Engine Condition Prediction using Machine Learning" project is a comprehensive exploration of leveraging advanced machine learning techniques to predict and assess the condition of internal combustion engines. The project integrates state-of-the-art technologies, including machine learning algorithms and data from IoT-enabled sensors, to develop a robust system for real-time engine health monitoring and predictive maintenance.

4.1 Dataset Collection

The "engine_data.csv" is a comprehensive collection of parameters associated with internal combustion engines. This dataset is curated for the purpose of predicting the engine's condition based on key operational parameters. The dataset includes six features and one target variable, providing a valuable resource for developing machine learning models to assess and predict the health of internal combustion engines.

The parameters used in the dataset: -

- Engine RPM:

Engine RPM (Revolutions Per Minute) represents the rotational speed of the engine's crankshaft. It is a crucial parameter influencing the overall performance and efficiency of the engine.

- Lube Oil Pressure:

Lubricating oil pressure measures the pressure of the oil circulating within the engine. Maintaining optimal oil pressure is essential for proper lubrication and prevention of engine wear.

- Fuel Pressure:

Fuel pressure indicates the pressure of the fuel supplied to the engine. It is a critical factor in ensuring the proper combustion of fuel within the engine cylinders.

- Coolant Pressure:

Coolant pressure measures the pressure of the engine coolant, which plays a key role in regulating the engine temperature. Proper cooling is essential for preventing overheating.

- Lube Oil Temperature:

Lubricating oil temperature represents the temperature of the engine's lubricating oil. Monitoring this parameter is crucial for preventing excessive friction and wear within the engine components.

- Coolant Temperature:

Coolant temperature indicates the temperature of the engine coolant. Maintaining the right coolant temperature is vital for preventing both overheating and excessive cooling.

- Engine Condition (Target Variable):

Engine Condition is the target variable, indicating the overall health and condition of the internal combustion engine. It is a binary variable, where 1 represents a good engine condition, and 0 represents a condition that may require attention or maintenance.

Acknowledgments: We acknowledge the source of the dataset https://www.kaggle.com/datasets/parvmodi/automotive-vehicles-engine-health-dataset/data , for providing this valuable collection of engine parameters. This dataset serves as a foundation for research and development in the field of engine health monitoring and diagnostics.

4.2 Libraries and Modules imported

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

     from sklearn.preprocessing import StandardScaler

     from sklearn.linear_model import LogisticRegression
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.svm import SVC
     from xgboost import XGBClassifier


     from sklearn.model_selection import train_test_split, GridSearchCV
     from sklearn.metrics import classification_report, confusion_matrix
     from sklearn.metrics import accuracy_score
```

Figure 4.1 Libraries and modules imported

- NumPy (np):

NumPy is a powerful library for numerical and mathematical operations in Python, providing support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions.

- Pandas (pd):

Pandas is a data manipulation and analysis library in Python, offering data structures like DataFrame for efficient handling and manipulation of structured data.

- Seaborn (sns):

Seaborn is a data visualization library based on Matplotlib that provides an aesthetically pleasing and informative statistical graphics, enhancing the visualization of complex datasets.

- Matplotlib.pyplot (plt):

Matplotlib is a comprehensive 2D plotting library in Python, and pyplot is a module within Matplotlib that provides a MATLAB-like interface for creating static, animated, and interactive plots.

- StandardScaler from sklearn.preprocessing:

StandardScaler is a preprocessing technique in scikit-learn that standardizes features by removing the mean and scaling to unit variance, ensuring that the features have a consistent scale.

- LogisticRegression from sklearn.linear_model:

Logistic Regression is a linear model used for binary classification that predicts the probability of an instance belonging to a particular class.

- RandomForestClassifier from sklearn.ensemble:

RandomForestClassifier is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of the classes for classification tasks.

- SVC (Support Vector Classifier) from sklearn.svm:

Support Vector Classifier is a machine learning model that performs classification tasks by finding the hyperplane that best separates the data into different classes.

- XGBClassifier from xgboost:

XGBClassifier is an implementation of the gradient boosting algorithm provided by the XGBoost library, designed for efficient and scalable machine learning tasks, particularly in tree-based models.

- train_test_split from sklearn.model_selection:

train_test_split is a function in scikit-learn used for splitting a dataset into training and testing sets, facilitating the evaluation of machine learning models.

- GridSearchCV from sklearn.model_selection:

GridSearchCV is a module in scikit-learn that performs an exhaustive search over a specified parameter grid to find the best hyperparameters for a given machine learning model.

- classification_report and confusion_matrix from sklearn.metrics:

classification_report and confusion_matrix are functions in scikit-learn used for evaluating the performance of a classification model by providing key metrics such as precision, recall, F1-score, and confusion matrix.

- accuracy_score from sklearn.metrics:

accuracy_score is a function in scikit-learn that calculates the accuracy of a classification model by comparing the predicted labels to the true labels.

4.3 Exploratory Data Analysis

- Fig 4.2: First five rows of the dataset

```
[4] engine_df = pd.read_csv("engine_data.csv")
    engine_df.head()
```

	Engine rpm	Lub oil pressure	Fuel pressure	Coolant pressure	lub oil temp	Coolant temp	Engine Condition
0	700	2.493592	11.790927	3.178981	84.144163	81.632187	1
1	876	2.941606	16.193866	2.464504	77.640934	82.445724	0
2	520	2.961746	6.553147	1.064347	77.752266	79.645777	1
3	473	3.707835	19.510172	3.727455	74.129907	71.774629	1
4	619	5.672919	15.738871	2.052251	78.396989	87.000225	0

- Fig 4.3: Data Type of each parameter

```
engine_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19535 entries, 0 to 19534
Data columns (total 7 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Engine rpm        19535 non-null  int64
 1   Lub oil pressure  19535 non-null  float64
 2   Fuel pressure     19535 non-null  float64
 3   Coolant pressure  19535 non-null  float64
 4   lub oil temp      19535 non-null  float64
 5   Coolant temp      19535 non-null  float64
 6   Engine Condition  19535 non-null  int64
dtypes: float64(5), int64(2)
memory usage: 1.0 MB
```

The fields, “Engine rpm” and “Engine Condition” are integer data type, while others are float data type.

- Check for total number of null values, duplicates and the count of each target variable

```
[7] engine_df.isnull().sum()

Engine rpm          0
Lub oil pressure    0
Fuel pressure       0
Coolant pressure    0
lub oil temp        0
Coolant temp        0
Engine Condition    0
dtype: int64
```

```
[8] engine_df.duplicated().sum()

0
```

```
[9] engine_df["Engine Condition"].value_counts()

1    12317
0     7218
Name: Engine Condition, dtype: int64
```

Figure 4.4 Check for null values

The dataframe has no missing values, no duplicate rows. The number of rows with “1” as target variable are 12317 and number of rows with “0” as target variable are 7218.

Inference - Need for data balancing.

4.4 Class Balancing

Class balancing is an important consideration in machine learning, especially when dealing with imbalanced datasets where one class significantly outnumbers the other. Imbalanced datasets can lead to biased models that perform poorly on the minority class and give less accurate results.

```
1    12317
0     7218
Name: Engine Condition, dtype: int64
```

Fig4.5: Before class balancing

```
Class distribution after SMOTE:
1    9869
0    9869
Name: Engine Condition, dtype: int64
```

Figure 4.6: After class balancing

4.5 Visualizing the Distribution of all the Attributes

- **Heatmap**

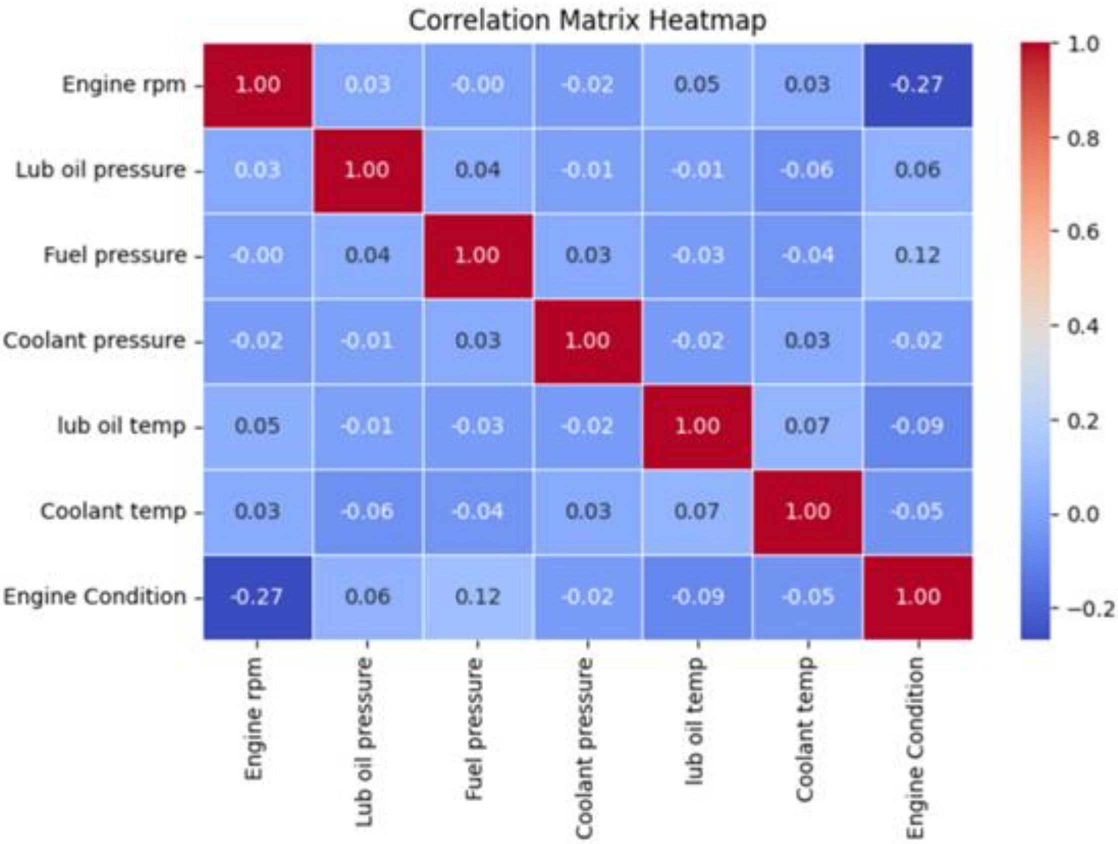

Figure 4.7 Heat map

- **Correlation values**

```
Engine Condition    1.000000
Fuel pressure       0.116259
Lub oil pressure    0.060904
Coolant pressure   -0.024054
Coolant temp       -0.046326
lub oil temp       -0.093635
Engine rpm         -0.268201
Name: Engine Condition, dtype: float64
```

Figure 4.8 Correlation Values

- **Observations from the heatmap and correlation values**

1. Engine rpm: Higher engine rpm is correlated with lower engine condition, according to a moderately negative correlation between engine rpm and engine condition.
2. Lub oil pressure: The data indicates a weak positive correlation between "lub oil pressure" and engine condition, indicating a slight positive correlation between higher lub oil pressure and improved engine condition.
3. Fuel pressure: The variable "fuel pressure" exhibits a weak positive correlation with engine condition, suggesting that there may be a slight relationship between improved engine condition and higher fuel pressure.
4. Coolant pressure: The engine condition and "coolant pressure" show a weak negative correlation, indicating that slightly lower engine condition may be linked to higher coolant pressure.
5. Lub oil temp: Higher lub oil temperature may be associated with slightly lower engine condition because "lub oil temp" has a weak negative correlation with engine condition.
6. Coolant temp: The engine condition and "coolant temp" have a weak negative correlation, suggesting that a higher coolant temperature could be linked to a slightly lower engine condition.

4.6 Standardization of Data

The process of converting numerical features in a dataset to a common scale is known as data standardisation, also known as feature scaling. This guarantees the equal contribution of each feature to the training of the model.

```
engine_df_standardized.head()
```

	Engine rpm	Lub oil pressure	Fuel pressure	Coolant pressure	lub oil temp	Coolant temp	Engine Condition
0	-0.340948	-0.793040	1.859980	0.814018	2.089663	0.516347	1
1	0.316739	-0.354506	3.454699	0.124605	-0.000799	0.647423	0
2	-1.013583	-0.334792	-0.037114	-1.226434	0.034988	0.196298	1
3	-1.189216	0.395510	4.655845	1.343252	-1.129418	-1.071894	1
4	-0.643634	2.319014	3.289902	-0.273186	0.242235	1.381240	0

Figure 4.9: Standardization of data

4.7 Model Selection and Building

	Model	Train Accuracy	Test Accuracy
0	Logistic Regression	0.662401	0.644228
1	Random Forest Classifier	1.000000	0.635270
2	Support Vector Classifier	0.647428	0.634758
3	XGBoost Classifier	0.858587	0.640389

Figure 4.10: Model selection and building

- **Logistic Regression**

Description: Logistic Regression is a linear classification algorithm suitable for binary classification tasks. It models the probability that an instance belongs to a particular class.

Train Accuracy: 66.24%

Test Accuracy: 64.42

Summary: Logistic Regression demonstrates moderate accuracy, with a slightly better performance on the training set.

- **Random Forest Classifier:**

Description: Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes. It is known for its high flexibility and robustness.

Train Accuracy: 100.00%

Test Accuracy: 63.53%

Summary: The Random Forest Classifier achieves perfect accuracy on the training set, but there might be overfitting, as the test accuracy is slightly lower.

- **Support Vector Classifier (SVC):**

Description: Support Vector Classifier is a machine learning algorithm for classification and regression tasks. It aims to find the hyperplane that best separates different classes in the feature space.

Train Accuracy: 64.74%

Test Accuracy: 63.48%

Summary: SVC shows moderate accuracy, with similar performance on both training and testing sets.

- **XGBoost Classifier:**

  Description: XGBoost is an optimized gradient boosting algorithm known for its speed and performance. It builds a series of decision trees and combines their predictions.

  Train Accuracy: 85.86%

  Test Accuracy: 64.04%

  Summary: XGBoost exhibits high accuracy on the training set, indicating good model fitting, and reasonable accuracy on the test set.

- **Inference:**

  We select XGBoost model because of high accuracy compared to other models. We save the model using pickle library

Chapter 5

Engine Condition Prediction: User Interface Application

The "Engine Condition Prediction" Streamlit application is designed to predict the condition of an internal combustion engine based on user-input parameters. The underlying machine learning model, an XGBoost Classifier, has been trained on the dataset, and users can input specific engine metrics to receive a prediction regarding the engine's condition.

- **Technologies:**

The application is built using Streamlit, a Python library for creating web applications with minimal code.

- **Usage:**

1. **Enter Input:** Input fields are provided for users to enter engine parameters.

2. **Prediction:** Clicking the "Predict Engine Condition" button triggers the model to make a prediction.

3. **Diagnosis Output:** The application displays a diagnostic message indicating whether the engine is in good condition or not.

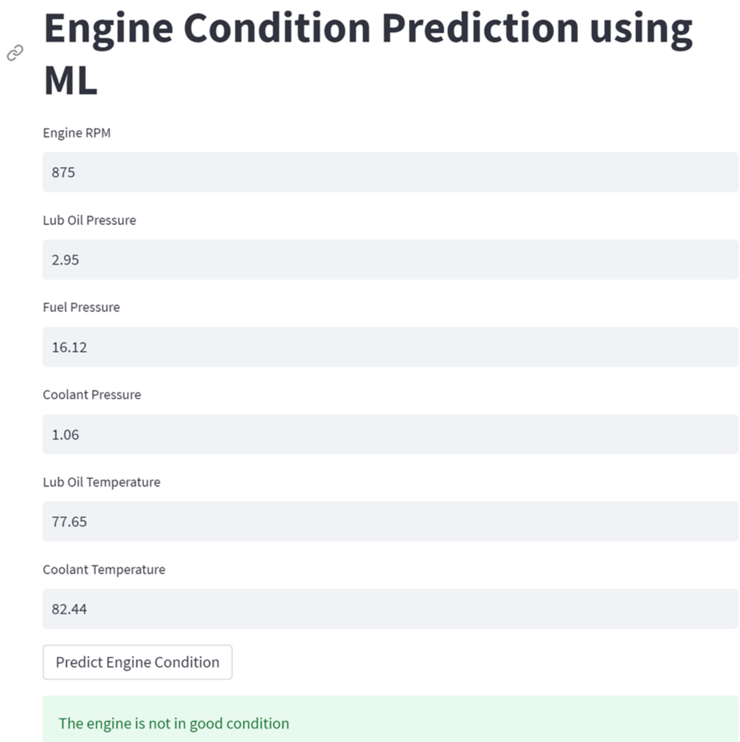

Figure 5.1: Engine condition prediction using ML Application

CHAPTER 6

Benefits of Predictive Maintenance in IC Engines

Why is it important to predict whether the engine is in good or not in good condition?

1.Environmental Impact:

Predictive maintenance can result in optimized engine performance, which can lower emissions and fuel consumption. This promotes an eco-friendly operation by being in line with environmental regulations and sustainability goals.

2.Cost saving:

Predictive analytics-based proactive maintenance scheduling lowers the risk of significant malfunctions, breakdowns, and related expenses. It assists in avoiding costly emergency repairs as well as the expenses related to unplanned downtime.

3.Data Driven Decision Making:

To make accurate predictions, predictive maintenance uses machine learning models and data analytics. More precise decisions can be made about maintenance plans, resource allocation, and equipment replacement thanks to this data-driven methodology.

4.Reduced Downtime:

Predictive maintenance reduces unscheduled downtime by anticipating potential problems before they arise. This guarantees that IC engines run for extended periods of time, which raises overall productivity

5.Extended Equipment Lifespan:

Predictive maintenance helps avoid the cumulative damage that can happen if problems are neglected by taking care of them when they are still in their early stages. As a result, the IC engine's vital parts have a longer lifespan and require fewer replacements earlier than necessary.

6.Improved Safety:

By lowering the possibility of unplanned malfunctions or accidents, predictive maintenance improves safety. Ensuring a safer operating environment for personnel and equipment is facilitated by routine monitoring and early identification of potential issues.

7. Increased Operational Efficiency:

The continuous monitoring and analysis of IC engine performance enable operators to optimize engine settings and parameters for better efficiency. This can result in improved fuel efficiency, reduced emissions, and overall enhanced operational performance.

8.Optimize Maintenance Schedules:

It is possible to schedule maintenance tasks more precisely thanks to predictive maintenance. Maintaining equipment can be done when it is actually needed, maximizing resource utilization and lowering unnecessary maintenance costs, as opposed to depending on usage- or fixed-time schedules.

9.Customised Maintenance Plans:

Predictive maintenance makes it possible to tailor maintenance schedules to the unique circumstances and usage habits of individual IC engines as opposed to using a maintenance strategy that is universally applicable. By taking a focused approach, maintenance efforts are more effective.

10.Real time Monitoring and Control:

Real-time monitoring features are a common feature of predictive maintenance systems, allowing operators to quickly adapt engine operation in response to new problems. By being proactive, possible issues are lessened in their impact.

CHAPTER 7

Potential Enhancements

1. **Feature Engineering**: We are exploring additional features that may contribute to better prediction accuracy. This could involve extracting more relevant information from the existing features or incorporating new sensor data.
2. **Model Selection:** We are experimenting with different machine learning models to find the one that best fits your data. Besides Random Forest, we tried other algorithms such as Gradient Boosting, Support Vector Machines, or Neural Networks.
3. **Cross-Validation:** We can implement cross-validation techniques to assess the generalization performance of our model more reliably. Cross-validation helps estimate how well your model will perform on unseen data.
4. **Feedback Collection:** Add feedback mechanisms to collect user feedback and suggestions for improving the app. Analyse user feedback to prioritize feature requests and enhancements for future iterations.

CHAPTER 8

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