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Real-Time Fault Detection and Classification in Engine Components using Machine Learning

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***Abstract*— The reliability of automotive engines is critical for vehicle performance and safety. This research presents a machine learning-based approach for real-time fault detection and classification in four key engine components: oxygen sensors, spark plugs, turbochargers, and radiators. We employ XGBoost regression for fault prediction and classification models to categorize component failures. A digital twin model of the engine cooling system was developed to enable real-time visualization, monitoring, and performance prediction of critical engine components using live sensor input data. Developing a Remaining Useful Life (RUL) prediction model for oxygen sensors is identified as a promising direction for future work. The dataset is synthesized with threshold values according to real-world sensor readings, ensuring high accuracy and interpretability using explainable AI techniques. Experimental results demonstrate the effectiveness of the proposed methodology in fault identification and performance prediction, improving predictive maintenance strategies.**

***Index Terms*— Machine Learning, Fault Detection, Classification, Engine Components, XGBoost, Predictive Maintenance, Remaining Useful Life (RUL).**

I. Introduction

Modern automotive systems rely on Electronic Control Units (ECUs) for real-time monitoring and optimization of engine performance [1]. The complexity of engine subsystems, such as oxygen sensors, spark plugs, turbochargers, and radiators, demands efficient fault detection mechanisms [2]. Traditional rule-based diagnostics suffer from delays and inaccuracies in predicting failures [3]. Machine learning (ML) offers a data-driven solution by learning from historical performance and real-time sensor readings [4]. This study aims to develop an ML-based fault detection system to classify faults and estimate the remaining useful life of oxygen sensors. Feature selection and interpretability are incorporated using XGBoost [5]. The impact of engine parameters on component failures is analysed to optimize predictive maintenance [6]. Several studies have explored ML in automotive diagnostics, but limited research integrates classification and regression for multiple components [7-9]. The proposed framework bridges this gap by leveraging real-world datasets [10].

II. Objective

Develop a machine learning-based fault detection and classification system for key automotive components, including oxygen sensors, spark plugs, turbochargers, and radiators, using real-time sensor data.

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Implement individual classification models for each component to categorize performance into Low, Medium, and High, enabling early fault detection and predictive maintenance. Leverage XGBoost regression models to analyse the degradation patterns of critical components, providing a data-driven approach for predictive analytics in automotive diagnostics. Establish a mathematical degradation model for oxygen sensors, enabling accurate Remaining Useful Life (RUL) estimation based on real-time sensor data and historical performance trends. Enhance vehicle reliability and operational efficiency by reducing unexpected component failures, ultimately improving engine performance, fuel efficiency, and emissions control. Validate the proposed models using real-world automotive datasets, ensuring robustness, generalizability, and adaptability for real-time deployment in Electronic Control Units (ECUs).

III. METHODOLOGY

The proposed methodology follows these steps:

A. Data Acquisition

- Real-world datasets with 20,000 sensor readings per component were collected.
- Features include oxygen sensor voltage, coolant temperature, air-fuel ratio, exhaust temperature, and sensor age.

B. Preprocessing

- Data normalization, handling missing values, and feature scaling.
- Threshold values set based on empirical studies [11].

C. Fault Detection and Classification

- XGBoost-based fault detection for each component.
- Three classification models for oxygen sensors, spark plugs, and turbochargers.
- Labels categorized as “Normal,” “Degrading,” and “Faulty.”

D. Remaining Useful Life (RUL) Prediction

- Regression model using degradation trends over time.
- Where D(t) is the degradation level and β is the degradation rate.
- D_(failure)represents the failure threshold used to estimate RUL.

IV. DATASET

A. Radiator Performance

Y Variable: Radiator Performance

- Threshold Range: 0.0 to 69.61
- Representation: Operational efficiency in dissipating engine heat (coolant flow, heat exchange, ambient conditions)
- Purpose: Ensures efficient engine temperature regulation, prevents overheating
- Units: Dimensionless metric from heat dissipation factors

Significance: Ensures efficient temperature regulation under varying conditions

X Variables and Thresholds:

- Coolant Temperature: 52.19C – 129.38C
- Coolant Flow Rate: 5.00 – 19.99 L/min
- Ambient Temperature: -9.99C – 44.99C
- Radiator Clogging: 0.02% – 99.99%
- Fan Speed: 500 – 2999 RPM
- Corrosion Level: 0.00% – 99.99%

B. Oxygen Sensor Performance

Y Variable: Oxygen Sensor Performance [%]

- Threshold Range: 0.0 to 49.94
- Representation: Efficiency in maintaining optimal air-fuel ratio (stoichiometric); higher values indicate better emissions control

- Purpose: Reduces emissions and ensures proper combustion; thresholds based on typical performance and failure scenarios
- Units: Percentage

Significance: Ensures efficient combustion, reduced emissions, and optimal fuel usage
X Variables and Thresholds:

- Sensor Voltage: 0.08V – 1.10V
- Air-Fuel Ratio: 12.0 – 18.0
- Exhaust Gas Temperature: 200C – 1000C
- Engine RPM: 500 – 7499
- Fuel Trim: -25% to 25%

C. Spark Plug Performance

Y Variable: Spark Plug Performance

- Threshold Range: 0.0 to 100.0
- Representation: Efficiency in igniting the air-fuel mixture; higher values indicate reliable ignition and better performance
- Purpose: Monitors and predicts ignition issues (e.g., misfires, incomplete combustion)
- Units: Percentage

Significance: Ensures reliable ignition, efficient combustion, and misfire prevention
X Variables and Thresholds:

- Ignition Timing: -5to 50
- Engine RPM: 500 – 7999
- Air-Fuel Ratio: 10.00 – 19.99
- Voltage Supply: 8.00V – 15.00V
- Plug Gap: 0.50mm – 1.99mm

D. Turbocharger Performance

Y Variable: Turbocharger Performance

- Threshold Range: 0.0 to 100.0
- Representation: Operational efficiency in providing compressed air; higher values indicate better performance and fuel efficiency
- Purpose: Detects issues like reduced boost, turbo lag, or mechanical failure
- Units: Percentage

Significance: Ensures optimal power, efficiency, and prevents overheating or mechanical damage
X Variables and Thresholds:

- Boost Pressure: 5.00 PSI – 40.00 PSI
- Exhaust Gas Temperature: 300C – 1200C
- Turbo RPM: 10,010 – 149,992
- Air Intake Restriction: 0.00% – 29.99%
- Turbo Lag: 0.10 – 5.00 seconds

The list of the 4 components and their key features used in this project is mentioned in table 1.

TABLE I. DATASET DESCRIPTION

Component	Number of Samples	Key Features
Oxygen Sensor	220,000	Air-Fuel Ratio, Sensor Age
Spark Plug	220,000	Ignition Timing, Wear Level
Turbocharger	220,000	Boost Pressure, RPM
Radiator	220,000	Coolant Temp, Flow Rate

V. CLASSIFICATION

Classification is a supervised learning technique used to categorize data into predefined classes based on input features. In this project, Random Forest classification model was implemented to predict the performance states of four critical automotive components: Spark Plug, Turbocharger, Radiator, and Oxygen Sensor. The models classify each component's performance into three categories: Low, Medium, and High, enabling predictive maintenance and early fault detection. Each classification model was evaluated using standard performance metrics, including Accuracy, Precision, Recall, and F1-score, to ensure robust predictions. The results for Spark

Plug, Turbocharger, and Radiator classification models are discussed in Section A, with performance comparisons presented in Table 2. The models provide a data-driven approach for fault detection, enhancing vehicle reliability and reducing unexpected failures.
To assess the performance of the classification models, the following metrics were used:

A. Accuracy

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \# \quad (1)$$

Accuracy measures the proportion of correctly classified instances out of the total instances. While useful, it may not be the best metric for imbalanced datasets.

B. Precision

$$\text{Precision} = \frac{TP}{TP + FP} \# \quad (2)$$

Precision calculates the ratio of correctly predicted positive cases (delayed flights) to the total predicted positives, indicating how many of the predicted delays were actually correct.

C. Recall (Sensitivity)

$$\text{Recall} = \frac{TP}{TP + FN} \# \quad (3)$$

Recall measures the model's ability to correctly identify actual delayed flights, ensuring fewer missed delays.

D. F1-Score

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \# \quad (4)$$

The F1-score balances precision and recall, making it a crucial metric for imbalanced datasets.

TABLE II. PERFORMANCE COMPARISON OF DIFFERENT COMPONENTS OF AN ENGINE

Metric	Components			
	Oxygen Sensor	Radiator	Spark Plug	Turbocharger
Precision				
0	0.88	0.82	0.79	0.76
1	0.93	0.87	0.85	0.81
2	-	0.85	0.86	0.82
3	-	-	0.84	0.73
Recall				
0	0.83	0.74	0.79	0.68
1	0.95	0.93	0.86	0.83
2	-	0.36	0.88	0.85
3	-	-	0.78	0.62
F1-Score				
0	0.86	0.78	0.79	0.72
1	0.94	0.90	0.86	0.82
2	-	0.51	0.87	0.83
3	-	-	0.81	0.67
Accuracy				
	0.91	0.86	0.85	0.81

VI. Regression

Regression is a supervised learning technique used to predict continuous values based on input features. In this project, XGBoost regression model was implemented to estimate the degradation trends of four critical automotive components: Spark Plug, Turbocharger, Radiator, and Oxygen Sensor. These models were trained using preprocessed datasets, which include key sensor parameters such as temperature, pressure, RPM, fuel-air ratio, and voltage levels.

Unlike classification, where the objective was to categorize component performance into distinct states, the regression models aimed to predict the degradation levels and remaining useful life (RUL) of each component over time. All regression models were evaluated using standard regression performance metrics, which are explained in Section A. The results of each regression model are presented in Table 3.

Evaluation Metrics

To assess the performance of the regression models, the following metrics were used:

A. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \# \qquad (5)$$

MAE measures the average absolute difference between actual and predicted values, indicating how close the predictions are to the true delay values. Lower MAE values indicate better model performance.

B. Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \# \qquad (6)$$

MSE penalizes larger errors more than MAE by squaring the differences between actual and predicted values. Lower MSE values indicate better accuracy.

C. R-squared (R^2) Score

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \# \qquad (7)$$

The R^2 score measures how well the regression model explains the variance in the target variable. A value closer to 1 indicates a better fit.

TABLE III. Comparison of Different Models on Performance Metrics

Model	MAE	MSE	R2 Score
Oxygen Sensor	1.7317	4.8331	0.9378
Radiator	4.0564	25.4923	0.8472
Spark Plug	4.1484	26.9696	0.9564
Turbocharger	5.7063	51.4046	0.8836

VII. Results and Discussions

Feature Importance Analysis:

- Engine RPM and air-fuel ratio significantly impact sensor performance.
- Turbocharger faults correlated with excessive boost pressure fluctuations.

A. Regression Results

- Oxygen Sensor Model (Fig 1.):
  - The model achieved an MAE of 1.7317, indicating a low average error in prediction.
  - The MSE of 4.8331 suggests a relatively small variance in the prediction errors.
  - With an R^2 Score of 0.9378, the model explains 93.78% of the variance in the oxygen sensor performance, demonstrating high predictive accuracy.
- Radiator Model (Fig 2.):
  - The MAE of 4.0564 reflects a moderate average prediction error.

- The MSE of 25.4923 indicates a higher spread of errors compared to the oxygen sensor model.
- An R^2 Score of 0.8472 shows that 84.72% of the variance in radiator performance is explained, indicating good but less precise predictions than the oxygen sensor model.

➢ Spark Plug Model (Fig 3.):

- The model recorded an MAE of 4.1484, suggesting a moderate average error in predictions.
- The MSE of 26.9696 indicates a slightly higher error variance than the radiator model.
- With an R^2 Score of 0.9564, the model accounts for 95.64% of the variance, indicating excellent predictive performance.

➢ Turbocharger Model (Fig 4.):

- The MAE of 5.7063 reflects the highest average prediction error among the models.
- The MSE of 51.4046 indicates the largest variance in prediction errors, suggesting greater unpredictability.

An R^2 Score of 0.8836 shows that 88.36% of the variance in turbocharger performance is explained, indicating strong but not the best performance among the models.

B. Classification Results

Oxygen Sensor Classification Model (Fig 5.):

➢ Displays a strong linear correlation with predictions closely clustered around the ideal fit line.

➢ Minimal outliers indicate high model accuracy and strong generalization for real-world deployment.

Radiator Classification Model (Fig 6.):

➢ Shows moderate accuracy with a wider spread in predictions, especially at extreme values.

➢ The trend is generally followed, but some inconsistencies and outliers suggest scope for tuning.

Spark Plug Classification Model (Fig 7.)

➢ Demonstrates a well-calibrated and accurate prediction pattern with tight clustering.

➢ Low outlier density and consistent performance across all ranges highlight model reliability.

Turbocharger Classification Model (Fig 8.)

➢ Captures the overall trend, but with noticeable scatter and prediction error.

➢ Outliers and deviations indicate a need for enhanced feature engineering or hyperparameter tuning.

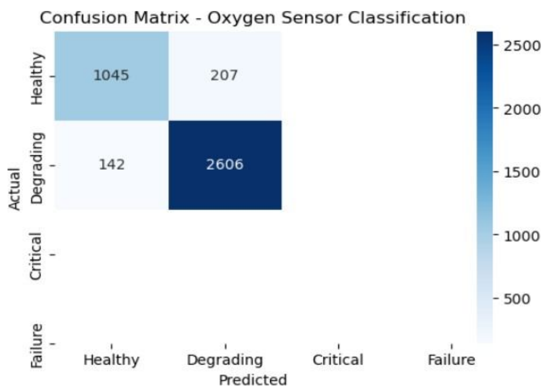

Fig. 1. Confusion Matrix - Oxygen Sensor Classification

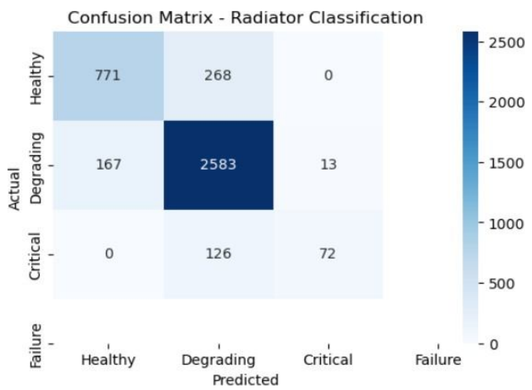

Fig. 2. Confusion Matrix - Radiator Classification

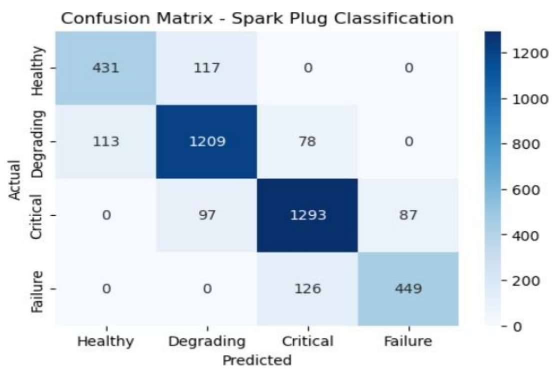

Fig. 3. Confusion Matrix - Spark Plug Classification

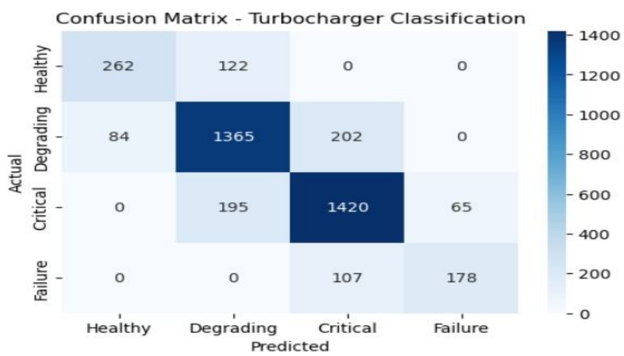

Fig. 4. Confusion Matrix - Turbocharger Classification

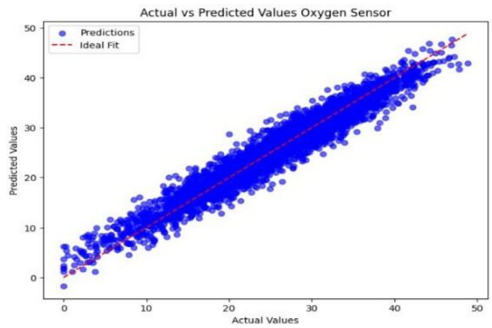

Fig. 5. Oxygen Sensor Performance

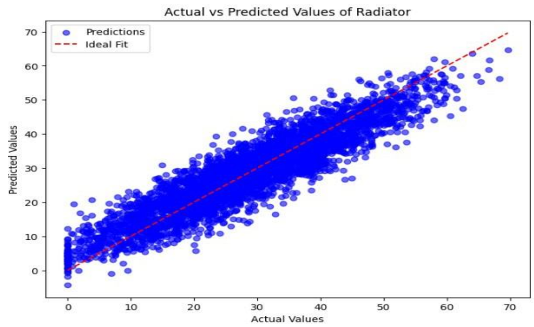

Fig. 6. Radiator Performance

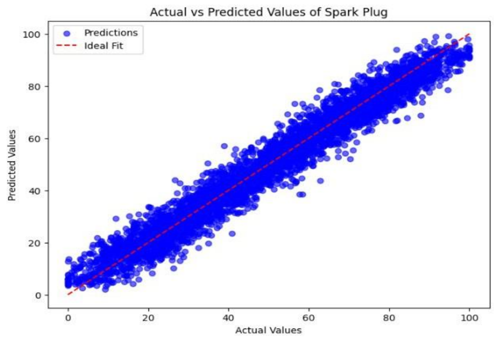

Fig. 7. Spark plug Performance

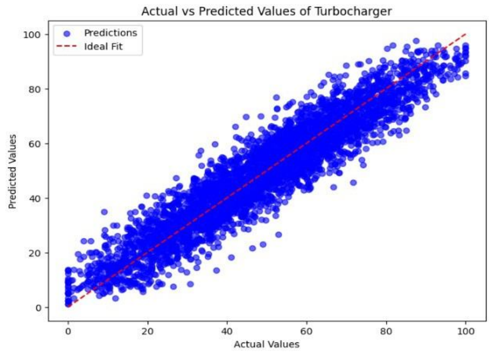

Fig. 8. Turbocharger Performance

VIII. CONCLUSION

This research successfully implements a machine learning-based classification and regression models for real-time fault detection in Oxygen Sensor, Spark Plug, Turbocharger, and Radiator performance. The Random Forest classifier demonstrated high accuracy in categorizing performance states into Low, Medium, and High, enabling predictive maintenance. Feature importance analysis using XGBoost identified key influencing parameters for each component, improving the interpretability and the predictive performance of the model. The implementation of the digital twin model provided an effective platform for simulating the thermal and functional behavior of engine components, supporting proactive diagnostics and performance analysis. Additionally, developing an oxygen sensor degradation model to accurately estimate Remaining Useful Life (RUL) is identified as a valuable future extension, which could help ensure timely replacements and improved maintenance planning. The results validate the effectiveness of data-driven approaches in automotive diagnostics. Future work will focus on real-time deployment in vehicle ECUs and enhancing model robustness using machine learning techniques.

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