26 AUGUST 2024

ANALYSIS AND RECOMMENDATIONS FOR PREDICTIVE MAINTENANCE

DETECTING THE ANOMALOUS ACTIVITY OF A SHIP'S ENGINE

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EXECUTIVE SUMMARY

Our analysis of ship engine data has revealed significant patterns in engine behaviour that can be used to predict and prevent anomalies. The most critical parameters for monitoring are engine RPM, lubrication oil temperature, fuel pressure, and coolant pressure. By focusing on these key indicators, we can implement a robust predictive maintenance strategy to reduce downtime, increase safety, and optimise fuel consumption.

OVERVIEW OF METHODS AND RESULTS

Three methods were employed for anomaly detection in the ship engine data:

1. Interquartile Range (IQR)

2. One-class Support Vector Machine (SVM)

3. Isolation Forest

ANOMALY DETECTION RESULTS

Method	Anomalies Detected	Percentage
IQR	422	2.16%
One-class SVM	780	4.0%
Isolation Forest	780	4.0%

Both One-class SVM and Isolation Forest detected a higher percentage of anomalies compared to the IQR method. This suggests that these machine learning approaches may be more sensitive to subtle patterns in the data.

KEY FEATURE COMBINATIONS AND INSIGHTS

INTER-QUARTILE-RANGE (IQR) METHOD

The IQR method identified key feature combinations for anomalies, with the top three being:

1. Fuel pressure - lub oil temp (143 occurrences)

2. Coolant pressure - lub oil temp (107 occurrences)

3. Engine rpm - lub oil temp (68 occurrences)

Image 1

Scatter Plots of Key Feature Pairs for IQR

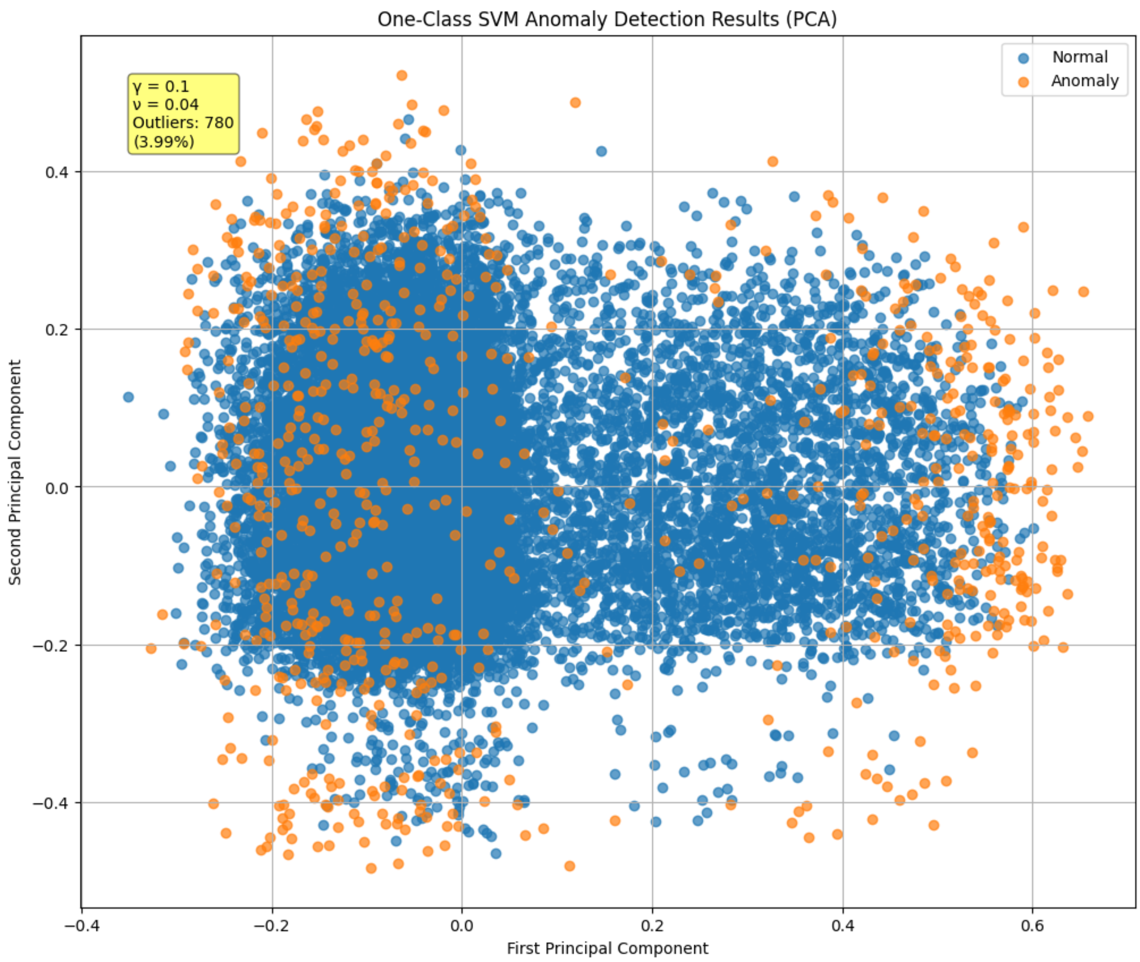
INSIGHTS

Lubrication oil temperature is involved in the top three anomaly combinations, indicating it's a critical factor in engine health. Fuel pressure, coolant pressure, and engine RPM also frequently appear in anomalous combinations.

Image 1 visualises these key feature pairs, showing distinct patterns of anomalies, particularly at high engine RPM values combined with extreme values of other parameters. For instance, the 'Engine rpm vs lub oil temp' plot shows a cluster of anomalies at high RPM and high oil temperatures, indicating a potential overheating issue during high-speed operations.

ONE-CLASS SUPPORT VECTOR MACHINE (SVM) AND ISOLATION FOREST INSIGHTS

Image 2



One-class SVM PCA Scatter Plot

Both methods identified similar key feature pairs, with engine RPM consistently being the most important feature. The One-class SVM method, visualised using PCA in *Image 2*, shows anomalies distributed around the periphery of normal data points, effectively identifying unusual combinations of engine parameters.

Both methods identified similar key feature pairs:

1. Engine rpm vs lub oil temp
2. Engine rpm vs Fuel pressure
3. Engine rpm vs Coolant pressure
4. Engine rpm vs Coolant temp
5. Engine rpm vs Lub oil pressure
6. Fuel pressure vs lub oil temp

Image 3

Scatter Plot of Key Feature Pairs One-class SVM

Image 3 presents scatter plots of key feature pairs for the One-class SVM method, detecting a more nuanced set of anomalies across a broader range of operating conditions compared to the IQR results.

INSIGHTS

- Engine RPM is consistently the most important feature, appearing in the top 5 feature pairs for both methods. Lubrication oil temperature and fuel pressure are also significant in detecting anomalies.

- The consistency across methods reinforces the importance of these feature relationships in identifying engine anomalies.

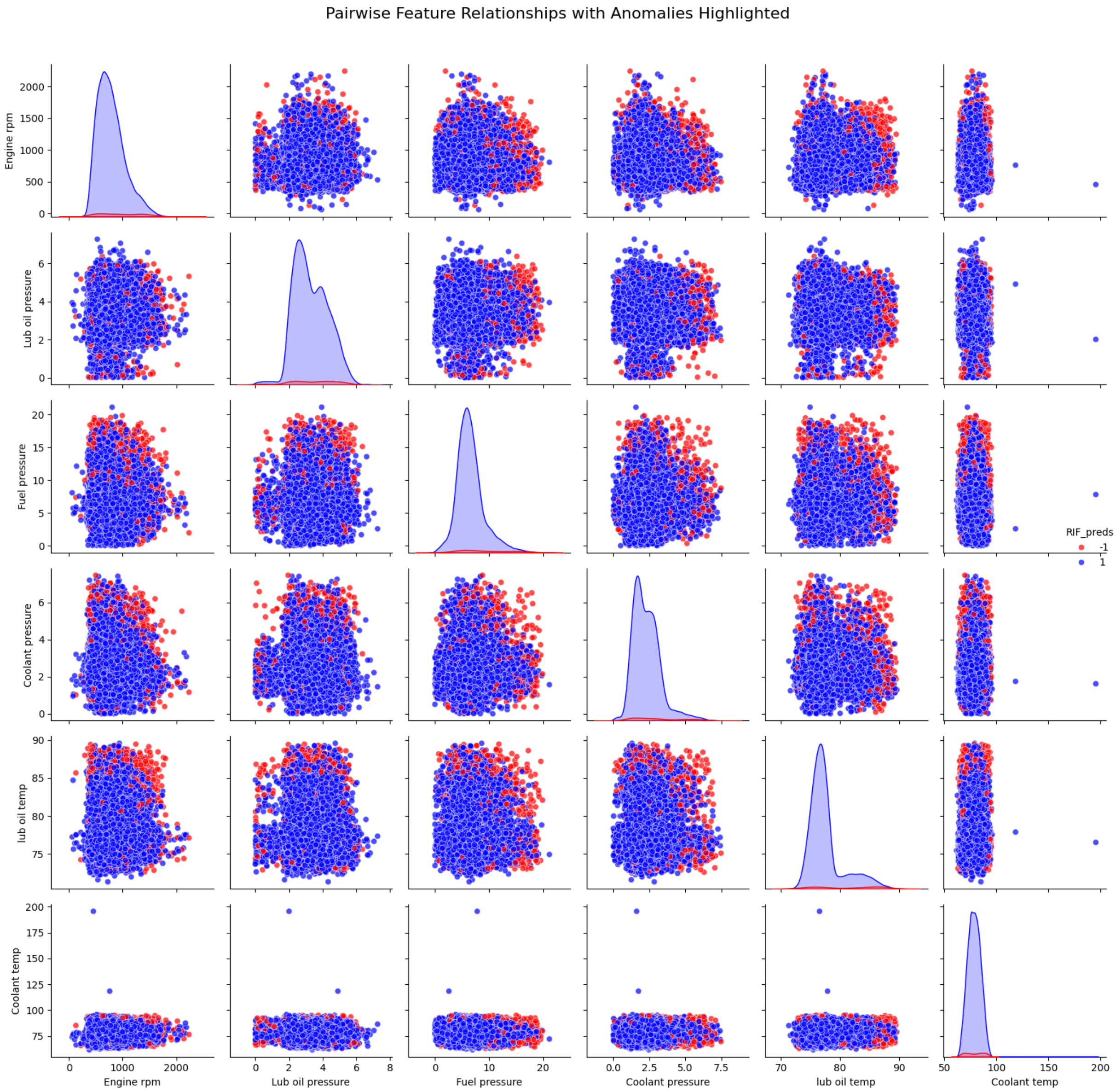
- The Isolation Forest method also detected 780 anomalies (4.0% of the data), providing a consistent anomaly rate with the One-class SVM method.

- Notably, the Isolation Forrest method appears particularly sensitive to unusual combinations of engine RPM with other parameters, as evidenced by the distinct patterns in the first row of plots. The 'lub oil temp' column also shows a high concentration of anomalies, reinforcing the importance of this parameter in detecting unusual engine behaviour.

Image 4

Scatter Plot of Key Feature Pairs Isolation Forrest

Image 5



Pairwise Feature Relationships with Anomalies Highlighted (Isolation Forrest)

The Isolation Forest method (*Image 4* and 5) provides a comprehensive view of pairwise feature relationships. Key insights include:

1. Engine RPM: Anomalies are concentrated at very low and very high RPMs.

2. Lubrication Oil Pressure: Anomalies are more prevalent at lower oil pressures.

3. Fuel Pressure: Anomalies appear more frequently at higher fuel pressures.

4. Coolant Pressure: Anomalies are detected at both low and high pressures.

5. Lubrication Oil Temperature: A high concentration of anomalies is observed at elevated temperatures.

6. Coolant Temperature: Anomalies are primarily clustered at higher temperatures.

The Isolation Forest method effectively identifies complex, multi-dimensional anomalies that may not be apparent when examining single parameters in isolation.

RECOMMENDATIONS

Based on the analysis, we recommend the following actions to improve engine maintenance and reduce downtime:

1. **Prioritise Monitoring:** Implement real-time monitoring systems focusing on engine RPM, lubrication oil temperature, fuel pressure, and coolant pressure. Set up alerts for significant deviations from normal ranges.

2. **Establish Thresholds:** Use the IQR method results to set initial thresholds for each parameter, refining them over time based on actual maintenance needs and false positive rates.

3. **Implement Advanced Anomaly Detection:** Deploy a combination of One-class SVM and Isolation Forest models for real-time anomaly detection, potentially catching more subtle issues.

4. **Predictive Maintenance Schedule:** Use anomaly detection results to schedule preventive maintenance, focusing on lubrication, fuel, and cooling systems.

5. **Regular Model Updating:** Continuously collect data on actual engine problems and maintenance actions to retrain and improve the models.

6. **Human-in-the-Loop System:** Implement a system where detected anomalies are reviewed by experienced engineers before triggering maintenance actions.

7. **Cost-Benefit Analysis:** Conduct a thorough analysis of the predictive maintenance system, estimating cost savings from reduced downtime and prevented major failures.

BUSINESS IMPACT

Implementing these recommendations is expected to yield significant benefits:

1. Reduced Downtime: Catch potential issues early, improving overall fleet efficiency.

2. Cost Savings: Prevent major engine failures, saving on costly repairs and replacements.

3. Improved Safety: Enhance the safety of crew and cargo through early detection of engine issues.

4. Optimised Fuel Consumption: Maintain engines at peak performance for better fuel efficiency.

5. Enhanced Customer Satisfaction: Ensure fewer delays in deliveries, potentially increasing business.

6. Data-Driven Decision Making: Use valuable data for informed fleet management and maintenance strategies.

7. Competitive Advantage: Set the company apart in the shipping industry with advanced predictive maintenance.

By adopting these data-driven approaches to engine maintenance, the company can expect significant improvements in operational efficiency, cost savings, and overall fleet performance.