Proactive Fault Prediction in Marine Diesel Engines Using Edge Computing Technology

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Abstract

Modern marine machinery is inherently complex, comprising interconnected systems and subsystems, including the ship management system and the safety and protective systems for the vessel and crew. These subsystems are interconnected and collectively contribute to the ship's operational purpose; their maintenance may be critical to ensuring smooth system operation. Marine diesel engines used to produce the electricity on board, are the primary source of electricity and supply power to all essential and non-essential equipment, if any unplanned breakdown occurs in the machinery it disturb the ship operation and impact of huge financial, environmental and life loss. Increasingly rigorous international regulations regarding ship and crew safety, as well as environmental protection, encourage ship owners to implement the proactive maintenance system to ensure interrupt operation without delay. This paper presents a framework that utilizes real-time auxiliary-engine sensor data ollected from a cargo ship over a one-year monitoring period. Edge-computing hardware was installed aboard the ship, and five machine-learning models—Logistic Regression, Extra Trees, Random Forest, LightGBM, and XGBoost—were developed; the XGBoost model appeared to outperform the other models. The model achieved a reported accuracy of 98.89% following hyperparameter tuning, suggesting strong predictive e performance. This research may offer a scalable, interpretable, and data-driven framework for predictive maintenance in complex marine environment, contributing to the advancement of ship machinery and sustainable asset management.

Keywords: Proactive maintenance, Machine learning model, Edge computing, Ship, Marine equipment, Marine Diesel Engine.

1. Introduction

In 2023, worldwide shipping generated approximately 35.9 million tons of carbon dioxide, as shown in Figure 1; this contribution may have prompted the International Maritime Organization (IMO) to pursue a reduction in ship-related air pollution of at least 40% by 2030[1]. The composition and quantity of emissions from ship machinery may depend substantially on engine condition and the accuracy of combustion-parameter adjustment. According to the 2023 Engine Retrofit Report of the Lloyd's Register, appropriate maintenance technologies may sustain ship operational efficiency and reduce carbon emissions[2]. Appropriate maintenance practices may keep ship machinery in its intended operating condition and reduce downtime, which could otherwise increase repair and replacement costs[3]. Effective maintenance strategies for marine diesel engines may support smooth

operations, reduce disruptions, and optimize fuel efficiency, which could contribute to global supply-chain stability and economic growth [4].

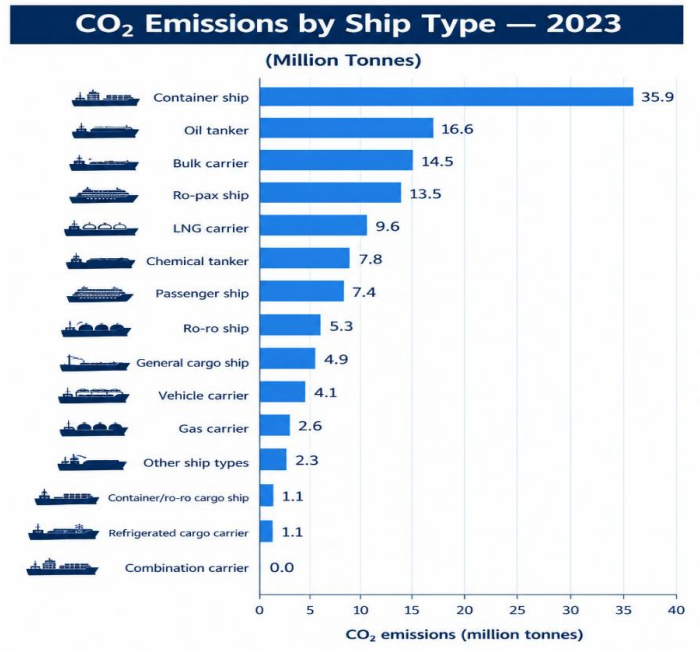


Figure 1. Global Merchant Vessel generated CO2

The maintenance of commercial ships may be essential to operational efficiency and safety at sea. Presently, ship maintenance often relies on preventive (or scheduled) strategies, in which maintenance is performed according to a timetable rather than existing machine conditions; consequently, such strategies may not predict equipment breakdowns [5]. The integration of edge computing with marine diesel engines may constitute a predictive maintenance technique [6]. Predictive maintenance entails the analysis of marine diesel engine sensor data and the deployment of machine-learning models on edge devices to anticipate component failures and schedule preventive repairs, thereby potentially enhancing reliability and extending equipment lifespans [7]. This method may also improve operational efficiency while reducing breakdown costs, energy consumption, and carbon dioxide emissions.

Our research addresses the edge computing and machine learning framework for monitoring auxiliary engine (AE) real-time sensor signals and predictive insights for early fault identification and diagnosis. The main objective of the Edge computing system is to establish minimum latency and real time monitoring by integrating edge node in place of auxiliary engine control module, which may facilitate operational independence from cloud-based technology and ensure continuous internet availability. Additionally, the implementation of various machine learning models—executed on the edge computing node—sought to identify the optimized model that may yield superior prediction accuracy, thereby ostensibly preventing overfitting and maximizing computational efficiency.

2. Literature Review

Generally, maritime operations function continuously—seemingly without interruption—and ship crews are afforded minimal time for the systematic attention of machinery, a constraint that may necessitate automated fault diagnosis. Therefore, the analysis and diagnosis of faults in marine diesel engines appears essential, since these engines constitute the primary source of electricity aboard ship, continuously supplying power to navigation equipment, safety equipment, and propulsion apparatus, among other systems. A wide range of predictive maintenance techniques has been proposed in the literature for fault prediction and diagnosis in marine diesel engines.

Liu et al. measured engine accelerometer readings at different loads. The authors utilized the gated recurrent unit based denoising auto encoder on multidimensional time series data of roller bearings[8]. They found the method suitable for improving the efficiency of rolling bearing by carrying out an online diagnosis while the engine turns. Vera Garcia et al. present an approach to improving four-stroke engine database collection and simulation, using a reliability-centered methodology for a one-dimensional thermodynamic engine model that evaluates feedback during failure[9]. The proposed architecture may provide substantial real-time diagnostic capacity, with ongoing updates incorporating new indicators to address a broad range of potential failures. Baris Yigin et al. developed generative adversarial networks (GANs) for condition monitoring of ship machinery and reported that the model appeared to achieve high accuracy in a real-time shipboard environment[10]. Research has demonstrated that mapping convolutional neural network models onto system-on-chip architectures, such as Xilinx Zynq, may enhance performance for target detection tasks [11]. Collectively, these studies may provide a useful reference for the implementation of edge-computing-based fault prediction.

3. Methodology

This study employs a mixed-method approach that combines quantitative and qualitative methods, which may enhance methodological rigor and practical relevance. The quantitative component comprises real-time sensor data from a diesel engine, including pressure, temperature, and level measurements, as well as alternator parameters; these data are analyzed using machine-learning models, and model performance is assessed with metrics such as area under the curve (AUC) and root mean square error (RMSE). The qualitative component consists of structured interviews with ship's crew and technicians to elucidate operational machine behavior and validate assumptions.

Figure 2 delineates the proposed edge-computing framework for early fault prediction in a marine diesel engine. The edge-computing approach may reduce latency by enabling local operation independent of cloud computing [12]. This study analyzes sensor data from the auxiliary engine of the M.V. African Roadrunner, a bulk carrier built in 2015, registered under IMO number 9691034, and sailing under the Bahamian flag. The 900 samples were collected from the logbook under the supervision of senior ship management and include parameters such as exhaust-gas temperature, fuel pressure, rack position, turbocharger characteristics, and alternator measurements. The dataset also incorporates findings from crew interviews and reports prepared by company technicians. All data are processed on an edge-computing device. A Raspberry Pi 4 with 4 GB of RAM serves as the edge-computing device and is capable of running multiple machine-learning models and generating outputs with minimal latency.

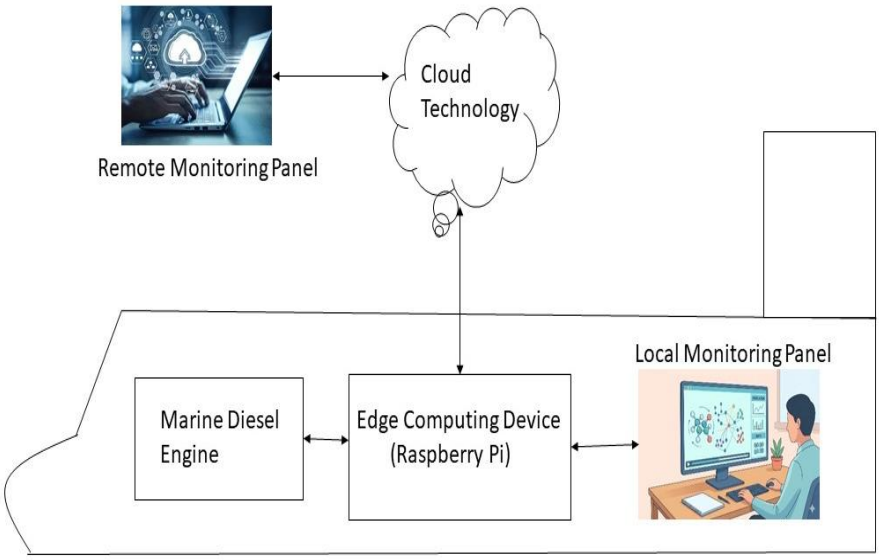


Figure 2. Overview of proposed research methodology

Edge-computing devices connect directly to the auxiliary-engine control-panel data-transmission line through a buffer, which supports model training on incoming data. This work trains five machine-learning models, including Logistic Regression, Extra Trees, Random Forest, LightGBM, and XGBoost. The local monitoring panel assesses fault-prediction accuracy in conjunction with qualitative interview data; it also stores prediction and diagnostic results in a cloud database. Cloud computing may support complex marine-problem analyses because its storage capacity can accommodate larger machine-learning models, while remote stations can monitor fault prediction and diagnosis.

4. Results

The collected dataset undergoes preprocessing, including missing-value identification, data normalization, and exclusion of out-of-range observations; all proposed models are trained and tested on the pre-processed dataset; he model trained on the Anaconda platform runs on a Raspberry Pi 4.Figure 3 presents a comparison of the proposed models' performance under hyperparameter tuning for early fault prediction in the auxiliary engine. The plot suggests that XGBoost outperformed the other models.

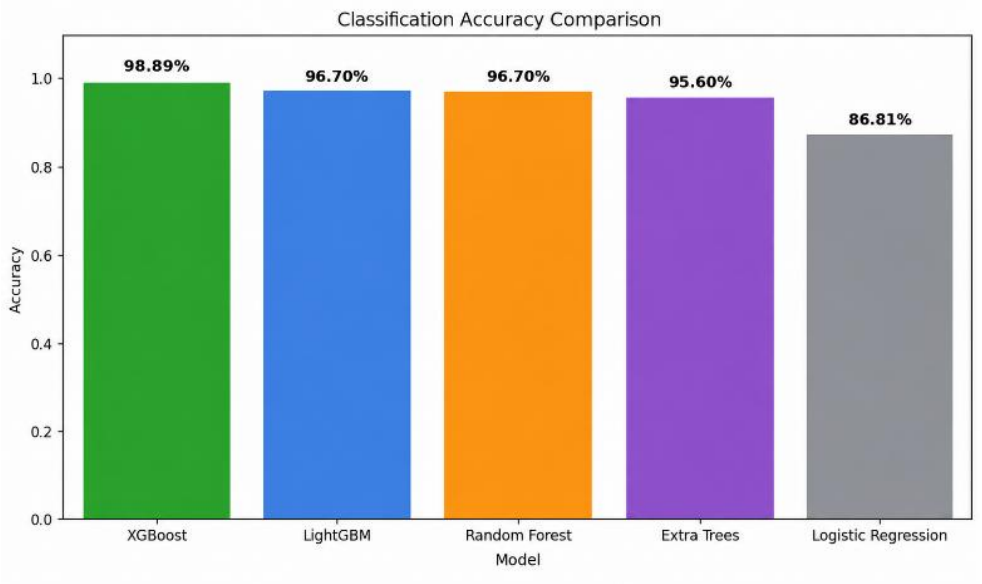
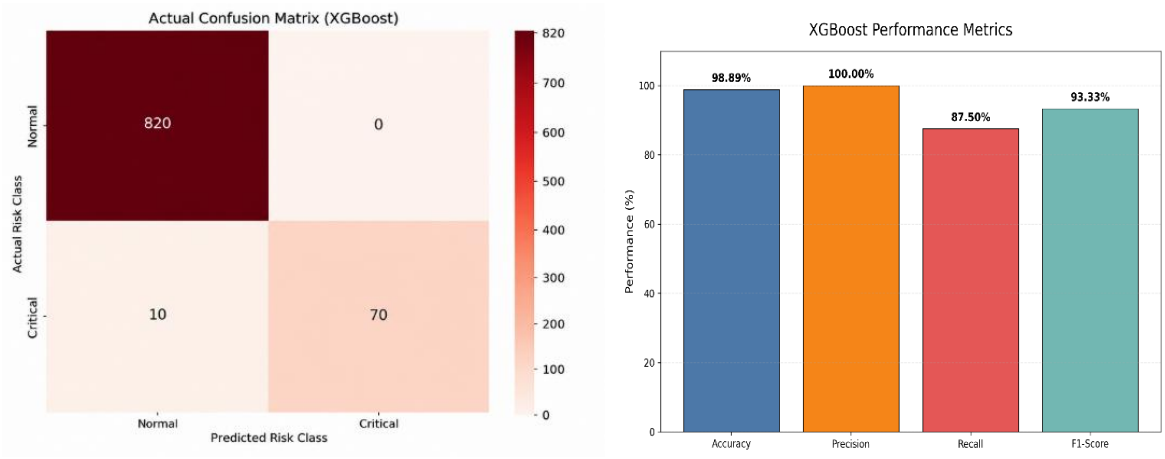


Figure 3. Comparison of accuracy of proposed models

Figure 4(a) presents the confusion matrix for the XGBoost model, from which the performance metrics shown in Figure 4(b) are calculated. The proposed model appears robust in predicting auxiliary-engine faults.



(a) (b)

Figure 4. Confusion matrix of XGBoost model (a) and Performance values of model (b)

The system may also enhance ship safety: automated data analysis could enable operators to identify potential risks more rapidly such as diesel engine failure (Auxiliary Engine), which could lead to serious incident at sea. Additionally, a reduction in manual inspections may lower the risk of human error, thereby contributing to navigational safety.

5. Conclusion

Ship Machinery maintenance is planned through lifecycle management strategies during the design and construction phases, which may be tailored to vessels intended for passenger or cargo transport. Effective planning may extend the operational lifespan of a ship mandated by International Safety Management Code (ISM Code). Components whose renewal would not entail significant

economic or functional loss may be maintained until failure, whereas cargo-handling and safety systems may require maintenance according to operating hours and calendar time. Current ship-maintenance systems appear to assign responsibility to an onboard officer, with jobs scheduled according to operating hours and calendar time and maintenance guided by vessel-specific manufacturer recommendations.

In this experiment, an edge-computing device installed onboard to monitor an auxiliary engine and more than 12 months of sensor-recorded data were used to train five machine-learning models, which were run on Raspberry Pi 4 hardware; the results suggest that XGBoost achieved 98.89% prediction accuracy after hyperparameter tuning and outperformed the other models.

The long-term objective may be the deployment of this edge-computing system to improve prediction accuracy, including fault prediction and automated system diagnosis. This may be enabled by a large, real-time dataset for system training and testing, with edge-computing equipment installed close to the sensors.

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