DEVELOPMENT OF PROACTIVE MAINTENANCE PLAN FOR IDENTIFICATION OF SHIP'S MAIN ENGINE FAILURES

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1. **ABSTRACT:** Ocean shipping is the primary means of transportation for international trade since 90% of traded products are transported over the seas. Accordingly, ensuring that ships operate in an energy-efficient manner is crucial to ensuring that global transportation becomes more efficient, and that financial savings are realized. One of the more potent remedies in this area is achieved by producing the ship's efficient maintenance plan for the engine room. This reduces operating costs while increasing system reliability and operational safety. To achieve this, the proposed research employs a modern maintenance approach, namely the proactive maintenance strategy. A small marine diesel engine is employed in this study, and its operational characteristics are collected to assist in the creation of a condition-based maintenance plan. In addition, machine learning-based models are experimented with, trained, and tested to forecast engine performance using diesel engine data. As a result, applying the suggested model to any engine that is being studied yielded a better maintenance schedule and ensured more effective fault identification with an accuracy of 89.1%.

Nomenclature

Abbreviation	*Meaning*
ML	Machine Learning
AI	Artificial Intelligence
CBM	Condition-Based Maintenance
IoT	Internet of Things
RCM	Reliability-Centred Maintenance
CM	Condition Monitoring
SVM	Support Vector Machine
KNN	K-Nearest Neighbour
MLP	Multi-Layer Perceptron
TP	True Positive
TN	True Negative

FP	False Positive
FN	False Negative

2. INTRODUCTION

The maritime industry is vital to global trade, transportation, and exploration, and it offers priceless opportunities and experiences. In this industry, safety, efficiency, and profitability are all directly impacted by maintenance; thus, its significance cannot be emphasised. Recent technological advancements and their significant contributions to environmental sustainability have proved the promise of ML and AI-based control systems. The vessel may experience negative impacts from any inaccuracies in the output function of the engine control unit, such as increased fuel consumption, reduced manoeuvrability, and in extreme cases, engine failure [1].

It is impossible to exaggerate the significance of maintenance, considering that the maritime and offshore sector is the second largest in the world. Effective maintenance practices are essential for maximising equipment lifespan, ensuring safe operations, and achieving operational efficiency. The maritime industry today employs several maintenance operations to ensure the effective procedure and maximum performance of ships. These concepts include CBM, risk-based maintenance, and corrective maintenance. The maritime environment presents many challenges, including regular use, exposure to seawater, and severe weather. Having ship maintenance not properly performed puts a ship's lifetime and crew safety at risk by increasing structural damage to the ship, and system failures [2].

It is becoming increasingly clear as technology develops how AI algorithms and machine learning could improve the procedure of maritime industry maintenance. These advancements in technology have the potential to improve maintenance decision-making, minimize downtime, and enhance reliability. By analysing engine data from the past and present, it becomes feasible to develop models that can predict and prevent issues. The integration of machine learning and artificial intelligence algorithms into maintenance methods could lead to operational efficiency in the industry. Ultimately this could result in increased profitability and improved performance [3].

Maintenance practices play a role in fostering an eco-sustainable maritime industry. They ensure performance and minimize fuel consumption, which is vital, for efficient goods transportation. Among all the components of a ship, the diesel engine holds significance [4]. Engine maintenance is necessary to guarantee continuous functioning, limit disturbances, and maximise fuel economy. This demonstrates how important it is to keep a strong and operational fleet to support global trade.

The current studies primarily address the challenges and drawbacks associated with maintenance procedures, in the transportation sector. Due to factors such, as weather conditions, stringent regulations, and demanding standards, these procedures often fall short of achieving sustainability, efficiency, and reliability goals set by the industry [5, 6]. This results in higher emissions, downtime, failure rates, and safety hazards [7]. Predicting and preventing malfunctions is the aim of integrating AI and machine learning into maritime systems; yet, a fundamental challenge for both human and machine algorithms is the reliable identification of anomalies [8, 9].

Recently there have been studies focusing on maintenance procedures, in the marine industry. These studies have examined the impact of maintenance approaches, on performance and productivity utilizing a range of research methods. On the other hand, Ingemarsdotter in 2021 [10] explored several difficulties encountered in 2021 when implementing CBM. Having reliable and accurate data collection techniques is one of these difficulties. Additionally, the research results showed that the successful implementation of CBM depends on the availability of skilled personnel who can effectively analyse the data and make informed maintenance decisions.

Machine learning algorithms and predictive analytics are used by the maritime industry to improve maintenance decision-making. These techniques enable fleets to plan maintenance programs based on data collected for predictions, using pattern recognition and historical data analysis to predict future events [11]. Payette and Abdul-Nour [12] carried out a study on the use of machine learning applications for reliable engineering processes in 2023. The studies resulted in a 24% increase in equipment reliability and a 15% reduction in maintenance costs.

Remote monitoring and diagnostic devices were considered a turning point for the maintenance procedures, in the marine industry. These innovative solutions reduce the need for inspections and minimize downtime by offering real-time evaluation of ship systems and components from onshore locations [13]. In 2020, Alshamrani [14] investigated remote monitoring technologies, such as IoT through the use of sensors, connections, and advanced data processing techniques. It has been demonstrated that these techniques can reduce maintenance costs by up to 20% and increase equipment availability by up to 15%.

A maintenance approach known as RCM flags essential ship systems and parts as high priority according to potential failure modes. In 2010, areas that significantly affected performance and safety were researched by Afefy [15] since RCM optimizes maintenance efforts and ensures efficient allocation of resources. It has been established from the findings that the implementation of RCM resulted in a decline in maintenance costs by as much as 30% and a reduction in equipment failures by as much as 25%. Therefore, proper application of RCM requires an understanding of vessel systems, operations, risks and consequences [16]. In addition, the complexity of modern vessels makes it challenging to determine which sections are necessary and when to do maintenance [17].

Fleets can now operate more reliably, safely, and overall more efficiently thanks to the use of real-time analytics and sophisticated data analysis tools, but the complexity of these actions makes it impractical to simply prioritize without considering the relationships between these actions likewise, a planning approach that can quantitatively assess the importance of different actions and the impact on marine engine maintenance in practice is lacking and therefore current research on identifying and prioritizing key actions in marine engine maintenance applications is limited.

Despite significant advances in offshore maintenance techniques, there are still areas that need to be addressed and improved. The optimization of comprehensive maintenance strategies for the specific needs of marine engines and their operating conditions is one such area. Although current methods of maintenance show promising results [18], reviews and new standards are needed to ensure proper implementation. Another problem is the integration of state-of-the-art technology into current comprehensive maintenance strategies [19]. Although several recent ships have started using this technology, it still needs to be operated by larger ships all over the industry. This will require significant consideration of factors such as feasibility, affordability, and compatibility with current policies.

This study aims to implement the proactive maintenance method for marine diesel engines. Standardized experiments that replicate the effects of diesel engine component malfunctions will be conducted, where subsequent temperature changes will be highlighted. Advanced machine learning techniques will next be used to analyse the gathered data and create failure detection prediction models. Our objective is to use these models to predict and stop problems before they happen, which will ultimately increase the marine diesel engine's longevity and dependability.

3. METHODOLOGY

A comprehensive approach is proposed to combine sophisticated machine learning techniques, data analytics, and standardized testing to address the issue. The main goal of this approach is to design a used-for-emergency maintenance specially designed for marine diesel engines. The diagnostic-technical process is shown in Figure 1. This process is repeated periodically after one iteration for continuous monitoring and early failure detection.

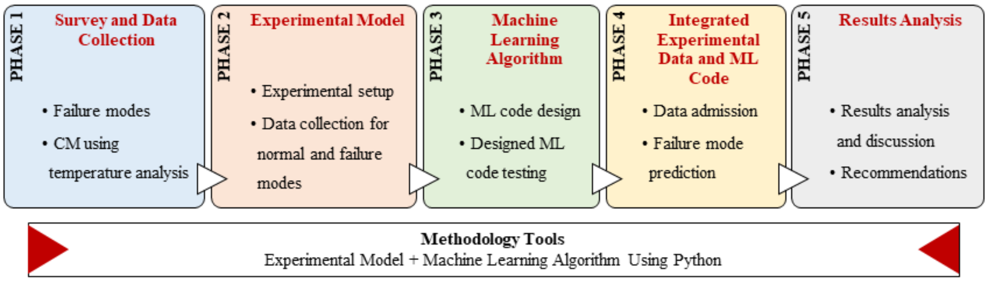

Figure 1: Methodology Layout

The analysis is performed using a temperature sensor mounted on an air-cooled, single-cylinder, 4-stroke diesel engine. This simplifies the temperature data needed for the analysis. The engine specifications are shown in Table 1.

Table 2. Diesel engine specifications

Specification	*Value*
Engine Model Number	186FA
Type	Air-cooled diesel engine
Oil	SAE 15W-40
Displacement	418 cc
Max Power	10 hp
Normal Speed	3000/3600 rpm
Injection Timing	Intake Open: BTDE 13° Intake Close: ATDE 52° Exhaust Open: BBDC 57° Exhaust Close: ABDC 8'30''
Valve Lash	Intake: 0.1 – 0.15 (cold state) Exhaust: 0.1 – 0.15 (cold state)
Fuel	Diesel
Net Weight	48 kg
Gross Weight	55 kg

The experimental design involves simulating the potential faults of a diesel engine and monitoring the resulting temperature changes. To achieve this goal, temperature sensors are attached to the engine cylinder head and exhaust gas. Engine configuration and applications are considered when deciding where to place the sensors; engine manufacturers and industry experts were consulted to determine the best locations to record temperature fluctuations associated with potential breakdowns. The sensors are then carefully coupled to the engine using appropriate mounting and running procedures to ensure accurate and reliable data collection. This method assures proper distribution of sensors on the engine to enable critical tracking and strategic changing of monitored parameters. A dataset is then collected and analysed to easily identify potential problems early and help understand how the engine is behaving.

Continuous recording of temperatures between 60 and 120 seconds could provide a comprehensive understanding of thermodynamics. Advanced machine learning algorithms are used to efficiently process the acquired readings, and Python programming is used train and test those models numerically. This analytical approach saves engine performance and efficiency by improving the ability to detect parameter changes caused by faults or environmental changes. Data collected from experiments were used to train different machine learning models using a 5-fold cross-validation data partitioning scheme. The data collected included patterns for different scenarios identified as 8 classes, with one class representing normal driving performance and the other representing 7 problems requiring urgent attention. Classes are named normal operation, air filter blockage 20%, air filter blockage 40%, air filter blockage 60%, air filter blockage 80%, oil level 25%, oil level 50%, and oil level 75%. The training portion of the data in a single fold was used to train Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Naive Bayes, Decision Tree, Multi-Layer Perceptron (MLP), and AdaBoost models. A comparison of the results achieved will be presented in the following section to choose the best model to implement the machine learning approach to marine diesel engines.

3.1 Evaluation Matrix

The evaluation matrix is calculated for each machine learning model investigated using the following equations [20] to assess the effectiveness of each model:

Eq. (1) is used to calculate the accuracy of each model defining the closeness of the generated results to the actual experimental results.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

Precision describes how close various results of the same quantity are to one another and is calculated for each model using Eq. (2).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

Each model's recall is obtained using Eq. (3) which describes the cases the model predicted correctly.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

The f1-score of each model is calculated using Eq. (4) and it summarizes the precision and recall parameters by obtaining the harmonic mean.

$$\text{f1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

In the previous equations, TP indicates the true positive, TN; true negative, FP; false positive, and FN; false negative. Macro-averaged values of the mentioned matrix were also obtained which considers that all the proposed classes contribute to the final average quantity equally. In addition, weighted-averaged values, which show the contribution of each class to the average quantity depending on its size, were also investigated.

4. RESULTS AND DISCUSSION

4.1 Experimental Results

The engine was operated normally to collect the temperature data, for daily operation with a clean air filter and a full oil sump and use them as the base data for the machine learning model in the case of no failure as recorded in Table 3. The data show an average exhaust gas temperature of 54.4°C and an average cylinder head temperature of 24.8°C.

Table 2. Normal operating temperatures for the diesel engine

Time (minutes)	*Air Filter Blockage (0%)*		*Oil Level (100%)*	
	Exhaust Gas (°C)	*Cylinder Head (°C)*	*Exhaust Gas (°C)*	*Cylinder Head (°C)*
10	53	24	53	24
11	53.2	24.2	53.2	24.1
12	53.3	24.4	53.5	24.2
13	53.6	24.5	53.9	24.5
14	53.7	24.7	54	24.6
15	53.9	24.8	54.3	24.4
16	54	25	54.8	24.7
17	54.9	25.4	55.1	25.1
18	55.7	25.6	55.7	25.2
19	56	25.7	56.1	25.4
20	56.5	25.8	56.4	25.7

Two failure modes were investigated on the single-cylinder engine artificially. The first failure mode was achieved by the blockage of the air intake filter by various percentages and the temperatures were recorded for the exhaust gases as well as the engine's cylinder head as shown in Table 3.

Table 3. Air filter blockage failure results

Time (minutes)	*Air Filter Blockage (20%)*		*Air Filter Blockage (40%)*		*Air Filter Blockage (60%)*		*Air Filter Blockage (80%)*	
	Exhaust Gas (°C)	*Cylinder Head (°C)*	*Exhaust Gas (°C)*	*Cylinder Head (°C)*	*Exhaust Gas (°C)*	*Cylinder Head (°C)*	*Exhaust Gas (°C)*	*Cylinder Head (°C)*
10	65	25.8	73	27.2	77.3	29	80.5	31.1
12	65.7	25.9	73.4	27.3	77.5	29.2	80.7	31.3
14	66.2	25.7	73.5	27.6	77.6	29.3	80.9	31.7

16	67	25.6	73.7	27.8	78	29.6	92	31.9
18	68	25.8	74.3	28.4	78.6	30	96	32.1
20	69	26	75	28.7	80.3	30.1	90	32.3

The second failure mode was achieved by the reduction of the oil level in the sump by various percentages and the temperatures were recorded for the exhaust gases as well as the engine's cylinder head as shown in Table 4.

Table 4. Oil level failure results

Time (minutes)	*Oil Level (75%)*		*Oil Level (50%)*		*Oil Level (25%)*	
	Exhaust Gas (°C)	*Cylinder Head (°C)*	*Exhaust Gas (°C)*	*Cylinder Head (°C)*	*Exhaust Gas (°C)*	*Cylinder Head (°C)*
10	70	24.6	75	26	76.6	26.8
12	70.6	24.8	75.3	26.2	76.8	27
14	70.9	24.9	74.8	26.4	77.1	27.5
16	71.2	25.2	73	26.9	77.3	27.7
18	72.3	25.7	72	27.6	78.2	28.7
20	73	26.3	75.1	28	78.6	29.3

4.2 Machine Learning Results

The machine learning models were implemented using python programming on Google Colaboratory. The main package used was sklearn which provided the libraries for cross validation splits, machine learning models and the evaluation metrics. The dataset collected during the experimentation represented by the two temperature features "Exhaust Gas" and "Cylinder Head" were first analysed using correlation measurements to further understand their relationship with the 8 classes previously introduced. Figure 2 shows that the correlation between the "Exhaust Gas" feature and the "Class" is -0.08, the correlation between the "Cylinder Head" and the "Class" is -0.27 and there is a high correlation between the "Exhaust Gas" and the "Cylinder Head". This makes the "Class" feature challenging to determine directly from the available features.

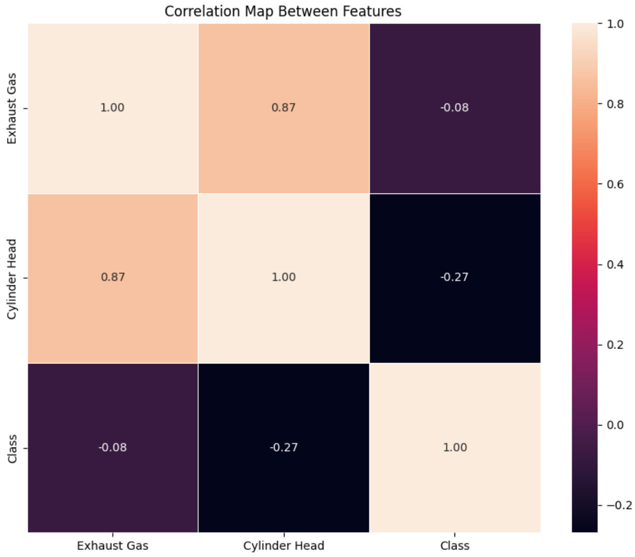

Figure 2: Correlation of Features and Class

Afterwards, the collected data were split using the 5-fold cross-validation scheme. Accordingly, each training split was used to build a model and test with the remaining portion. The average of the testing results for all splits is then presented. The obtained classification results are shown in Table 5 using the various machine learning models previously mentioned.

Table 5. Machine learning model results

Model	*Accuracy*	*Macro Average Precision*	*Macro Average Recall*	*Macro Average f1-score*	*Weighted Average Precision*	*Weighted Average Recall*	*Weighted Average f1-score*
Logistic Regression	0.75	0.6635	0.667	0.643	0.748	0.75	0.733
Random Forest	0.859	0.822	0.813	0.807	0.866	0.859	0.856
SVM	0.688	0.66	0.583	0.597	0.745	0.688	0.698
KNN	0.828	0.835	0.771	0.773	0.877	0.828	0.83
Naive Bayes	0.844	0.803	0.792	0.794	0.852	0.844	0.845
Decision Tree	0.891	0.872	0.854	0.853	0.904	0.891	0.89
MLP	0.406	0.175	0.208	0.17	0.269	0.406	0.305
AdaBoost	0.5	0.282	0.333	0.286	0.462	0.5	0.464

The results showed that the highest accuracy was obtained using the "Decision Tree" model which achieved an accuracy of 0.891 in accurately predicting the engine failure type. The "Decision Tree" model likewise produced the greatest f1-score of 0.853. This demonstrates that, given the collected data, the "Decision Tree" model is the most accurate in forecasting an engine failure as shown in Figure 3.

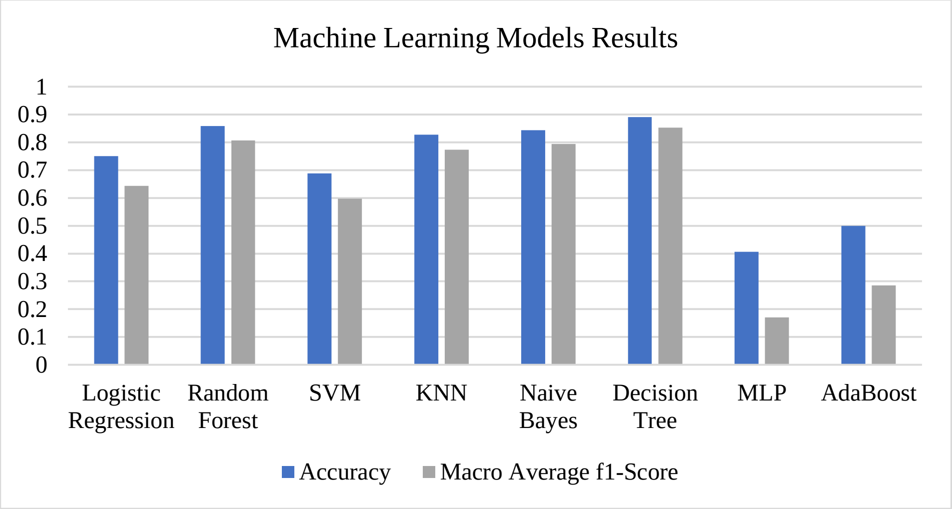

Figure 3: Accuracy and Macro Average Score Results of ML Models

5. CONCLUSION

This research aims to utilize machine learning models to maintain marine diesel engines by predicting system faults before they occur. To achieve this goal an experimental model was created using a single-cylinder, four-stroke, air-cooled diesel engine. During the engine operation, various issues related to the oil level and air filter were deliberately induced to collect data on these failures. This dataset was then used to train and evaluate machine learning models through a 5-fold cross-validation split.

- Multiple machine learning models were examined using the collected data to determine the best one based on accuracy and macro average f1-score.
- The experimental data revealed that with each induced failure there was an increase in exhaust gas and cylinder head temperatures.
- When applied to machine learning models, the results showed that the "Decision Tree" model had both the highest average f1-score among all investigated models and an accuracy of 89.1%.

These findings indicate that this particular machine learning model is the most effective in predicting diesel engine problems based on the readings obtained from the engine contributing to the establishment of proactive maintenance systems on board ships through predicting failures before they occur thus preventing them.
Future research will include the examination of more failure modes as well as a different larger diesel engine to reach closer results for system implementation on ship engines. The machine learning models will be trained based on more parameters such as machine vibration as well as engine load. This will help improve the ML model to predict more failure modes in ships' main engines and thus reduce maintenance cost and machinery downtime.

6. REFERENCES

[1] R. Naradasu, J. Srinathu, and R. Ramakrishnan, "Towards artificial intelligence based diesel engine performance control under varying operating conditions using support vector regression," *THERMAL SCIENCE*, vol. 17, pp. 167-178, 05/01 2013, doi: 10.2298/TSCI120413218N.
[2] A. Saihi, M. Ben-Daya, and R. A. As'ad, "Maintenance and sustainability: a systematic review of modeling-based literature," *Journal of Quality in Maintenance Engineering*, vol. 29, no. 1, pp. 155-187, 2023, doi: 10.1108/JQME-07-2021-0058.
[3] A. Pudar, *Maintenance Reliability in Maritime Industry*. 2023.
[4] I. Lazakis, O. Turan, and S. Judah, *Establishing the Optimum Vessel Maintenance Approach Based on System Reliability and Criticality Analysis*. 2012.
[5] S. Dragos, A. Purcarea, A. Cotorcea, N. Florin, and D. Coșofreț, "Naval maintenance. From corrective maintenance to condition monitoring and IoT. Future trends set by latest IMO amendments and autonomous ships," 09/30 2021.
[6] I. Lazakis, O. Turan, and S. Aksu, *Improving ship maintenance: A criticality and reliability approach*. 2010.
[7] Ç. Karatuğ, Y. Arslanoğlu, and C. G. Soares, "Review of maintenance strategies for ship machinery systems," *Journal of Marine Engineering & Technology*, vol. 22, no. 5, pp. 233-247, 2023/09/03 2023, doi: 10.1080/20464177.2023.2180831.
[8] V. Koilo, "Sustainability issues in maritime transport and main challenges of the shipping industry," *Environmental Economics*, vol. 10, pp. 48-65, 09/03 2019, doi: 10.21511/ee.10(1).2019.04.
[9] G. Sujesh and S. Ramesh, "Modeling and control of diesel engines: A systematic review," *Alexandria Engineering Journal*, vol. 57, no. 4, pp. 4033-4048, 2018/12/01/ 2018, doi: https://doi.org/10.1016/j.aej.2018.02.011.
[10] E. Ingemarsdotter, M. L. Kambanou, E. Jamsin, T. Sakao, and R. Balkenende, "Challenges and solutions in condition-based maintenance implementation - A multiple case study," *Journal of Cleaner Production*, vol. 296, p. 126420, 2021/05/10/ 2021, doi: https://doi.org/10.1016/j.jclepro.2021.126420.
[11] M. Theng and D. Theng, *Machine Learning Algorithms for Predictive Analytics: A Review and New Perspectives*. 2020.
[12] M. Payette and G. Abdul-Nour, "Machine Learning Applications for Reliability Engineering: A Review," *Sustainability*, vol. 15, no. 7, doi: 10.3390/su15076270.
[13] J. Kuschel and F. Ljungberg, "Decentralized Remote Diagnostics: A Study of Diagnostics in the Marine Industry," in *People and Computers XVIII — Design for Life*, London, S. Fincher, P. Markopoulos, D. Moore, and R. Ruddle, Eds., 2005// 2005: Springer London, pp. 211-226.
[14] M. Alshamrani, "IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 8, Part A, pp. 4687-4701, 2022/09/01/ 2022, doi: https://doi.org/10.1016/j.jksuci.2021.06.005.
[15] I. Afefy, "Reliability-Centered Maintenance Methodology and Application: A Case Study," *Engineering*, vol. 02, 01/01 2010, doi: 10.4236/eng.2010.211109.
[16] S. Eriksen, I. Utne, and M. Lützen, "An RCM approach for assessing reliability challenges and maintenance needs of unmanned cargo ships," *Reliability Engineering & System Safety*, vol. 210, p. 107550, 02/01 2021, doi: 10.1016/j.ress.2021.107550.
[17] V. J. Jimenez, N. Bouhmala, and A. H. Gausdal, "Developing a predictive maintenance model for vessel machinery," *Journal of Ocean Engineering and Science*, vol. 5, no. 4, pp. 358-386, 2020/12/01/ 2020, doi: https://doi.org/10.1016/j.joes.2020.03.003.
[18] R. Krishnamurthi, A. Kumar, D. Gopinathan, A. Nayyar, and B. Qureshi, "An Overview of IoT Sensor Data Processing, Fusion, and Analysis Techniques," *Sensors*, vol. 20, no. 21, doi: 10.3390/s20216076.
[19] Z. H. Munim, M. Dushenko, V. J. Jimenez, M. H. Shakil, and M. Imset, "Big data and artificial intelligence in the maritime industry: a bibliometric review and future research directions," *Maritime Policy & Management*, vol. 47, no. 5, pp. 577-597, 2020/07/03 2020, doi: 10.1080/03088839.2020.1788731.
[20] P.-N. Tan, Michael Steinbach, and Vipin Kumar, *Introduction to Data Mining*. Pearson Education India, 2016.