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AN ADVANCED AI-BASED SYSTEM FOR INTELLIGENT BRIDGE ALARM MONITORING ON MARITIME VESSELS

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Effective alarm monitoring systems are crucial within the maritime sector to ensure safety and operational continuity. Artificial intelligence is one of the most popular fields nowadays and is often used for machine learning applications. Utilizing AI-based anomaly detection and predictive analytics to analyze real-time alarm data from the ship's sensor level, the proposed system enhances situational awareness and reduces false alarms. Therefore, machine learning models are trained on hundreds of thousands of historical alarm patterns to detect potential faults and improve response times. The automated clustering tool provides a classification of maritime alarm scenarios, and a simulated framework that mimics these alerts showcases the system's ability to focus on essential alerts rather than nonsensical ones. Training them on data until October 2024 allows the ground-truth knowledge to be explicitly built, accounting for recent advancements and findings in the field of maritime processes. Experimental results demonstrate significant improvements in alarm classification accuracy and early detection, enabling data-driven decision-making in the marine domain.

1. INTRODUCTION

Big data and the Internet of Things are making significant inroads in the maritime sector, complemented by advanced technologies such as machine learning and artificial intelligence, which are emerging as key drivers in the ongoing transformation of the marine industry into a genuinely value-centric ecosystem that enhances safety, efficiency, and operational resilience. One of the biggest challenges in marine operations is the effective monitoring and management of shipboard alarm systems. With many sensors onboard, warnings are necessary to protect the personnel, cargo, and vessels. Traditional alarm monitoring systems suffer from high false alarm rates, slow response times, and a limited ability to forecast future failures. Elaborate maritime operations, alarming systems that create bulk quantities of data, identifying anomalies, and providing business insights are leading to an increasing number of alarm management systems.

In this paper, we propose an alarm monitoring framework for armed forces vessels that incorporates artificial intelligence and dynamic machine learning, executed through Python-based simulations. The proposed model examines AI and ML methodologies that can enhance alert classification, minimize false positives, and facilitate preemptive decision-making. Thus, such a system, with its ability to handle real-time data processing and predictive analytics through the combination of these features, can also become capable of preventive measures as well as recovery, consequently improving productivity in the maritime process, ranging from alarms to monitoring.

In this paper, we aim to design and deploy experimental AI-based monitoring dashboards for maritime ship alarms using Python simulations, which will demonstrate the productivity, performance improvement, and predictive analytical performance of AI-based shipping fleet management in real-time.

These various objectives involve: Construct a simulation environment in python programming to simulate real alarms with signal data and alarms to make the detection robust; Develop AI/ML algorithms to detect and classify alerts into critical and non-critical while minimizing the false positives, use the predictive technique to identify the alert that is most likely to create a problem before it happens to prevent mission critical incidents, Report the ability of such AI/ML algorithms on evaluation metric: accuracy, response times, and reliability on marine alarm data; And prove the applicability of such an application to improve marine safety and logistics decision making. The paper aims to achieve this goal by enabling the industry to progress toward intelligent maritime systems, demonstrating the significance of AI and machine learning in today's shipboard systems.

By combining real-time data processing and predictive analytics for maritime alarm management, the system facilitates the effective and efficient prevention, detection, analysis, recovery, and feedback processes.

The management and prevention, detection, analysis, recovery, and feedback processes of maritime alarms can be efficient and effective with a system that combines real-time data processing and predictive analytics.

The objective of this paper is to design and deploy an experimental AI-based monitoring dashboard above the alarms in maritime ships using Python simulations to demonstrate productivity, performance improvement, and Predictive analytical capabilities.

In more detail, the goals of these papers are: create a Python-based simulation framework that mimics real-world maritime alarm situations, considering both sensor data and alarm triggers; Utilize AI and ML algorithms to classify alarms, distinguish between critical and non-critical alerts, and minimize false positives; employ predictive analytics to identify possible failures and anomalies before they become critical issues; assess the performance of the system through the analysis of accuracy, response times, and reliability in the detection of maritime alarms; demonstrate the potential applicability of AI in the surveillance of naval alarms to improve marine safety and decision-making.

Thus, this paper aims to achieve this goal by supporting the development of intelligent maritime systems as a new paradigm, emphasizing the importance of artificial intelligence and machine learning in state-of-the-art shipboard systems.

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2. RELATED WORK

AI (artificial intelligence) and ML (machine learning) technologies are being increasingly utilized in the maritime industry to address alarm management issues and enhance operational efficiency. These technologies have revolutionized conventional approaches by integrating smart technologies that enhance security, reduce alarm fatigue, and facilitate predictive maintenance [1–10].

Challenges in alarm management. Alarm systems are a necessity onboard that help to protect the crew, cargo, and the vessel itself. On the flip side, the problem of false alarms remains ubiquitous, with as little as 2% of maritime activation alerts being due to the activation of other beacons, such as emergency position-indicating radio beacons (EPIRBs) or personal locator beacons (PLBs). That problem fosters alarm fatigue, wherein crew members silence or ignore alerts, thereby delaying prompt action and jeopardizing safety. Additionally, due to the complexity of maritime operations, high-frequency alarm handling systems must be established. An alarming frequency (>20,000 alarms/day/ship) is expected in the engine rooms of a ship [5–8]. With the recognition of these limitations, context-aware alarm systems designed to distinguish between life-critical and non-life-critical conditions are now viewed as a promising solution to these challenges [9-12].

Single-label alarm classification with AI and ML. AI and ML have become transformative tools in sorting out alarms and handling false positives [13]. They include algorithms trained on sensor data, so that we can examine queries and identify patterns, detect outliers, pinpoint real risks, and automate our decisions. For example, using AI for anomaly detection can reduce false alarm rates, as contextual input and behavior patterns can help differentiate bad actors from the overall regular pattern or behavior, which is crucial for ML/AI-based systems. Smart alarm management systems can dynamically filter alarms based on changing operational conditions, allowing operators to focus on what matters while eliminating unnecessary noise.

Predictive maintenance and analytics. AI-based predictive maintenance systems are transforming the level of safety and efficiency that the maritime industry requires. These automated systems continuously check onboard sensors for hundreds of parameters, ranging from engine performance to vibration and fuel-air ratio, to detect the earliest signs of impending failure in advance of the actual event. Predictive algorithms set targets for equipment reliability and downtime, improving KPIs by preventing major failures and their associated costs. However, predictive analytics also evolved on board with the use of machine learning-based solutions, which predict errors in advance, thereby helping to accelerate the decision-making process in such scenarios. Such techniques aim to contribute to the desired outcome of the experimental system proposed in this work, which considers predictive information as part of alarm management.

Python-based simulation frameworks. Another area of interest towards maritime applications is the implementation of Python-based frameworks for outputting real-time or simulated data processing. A classic example of this is how Python's SimPy library has been effectively utilized to model and simulate complex systems in myriad real-world scenarios. These mechanisms provide a reasonable basis for applying AI and ML algorithms to simulate maritime environments through testing alarm classification, failure detection, and response optimization. The most interesting aspect is that AI within these platforms enables researchers to evaluate system performance through well-defined experiments, extracting information on precision, reliability, and extensibility [2,3].

Digital transformation in the maritime sector. The maritime industry is gradually ushering in a new era of monitoring and control, where land-based and shipboard processes are being digitized like never before. The focus of maritime ecosystems digital transformation initiatives includes the utilization of frontier technologies such as AI & the IoT in enhancing operational safety, efficiency, and decision making across the complete value chain of maritime operations. This generates a crucial enabler for such change in intelligent alert systems, which are consistent with broader market trends such as smart shipping and automated decision-making frameworks. Such aversion is particularly relevant in a context where the complexity of maritime operations is increasing and human errors are inevitable, thereby increasing the crew's trust in technology on board.

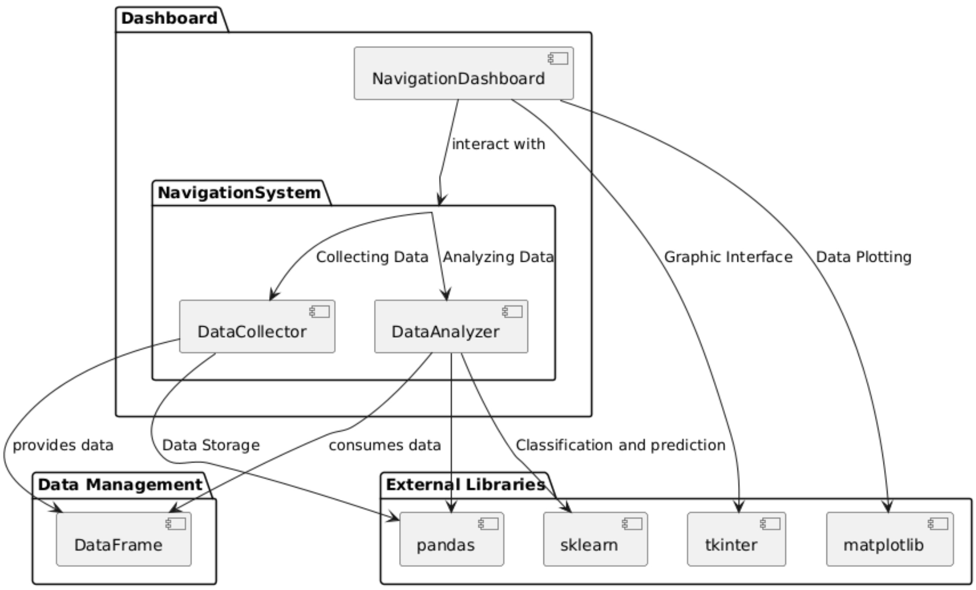


Fig. 1 – System architecture of the AI-based intelligent bridge alarm monitoring system for maritime vessels.

3. **SYSTEM DESIGN AND IMPLEMENTATION**

3.1. SYSTEM ARCHITECTURE

The proposed system (see Fig. 1) is represented as a modular framework where real-time data acquisition, machine learning-based alarm stratification, and predictive analytics are all synchronized and methodically interwoven. As shown in the unified diagram, the architecture is organized into several fundamental elements, including the dashboard Interface, which contains the system features housed under a single flag of a Dashboard that serves as a user-facing interface. It is composed of two main modules that constitute two core components, *NavigationDashboard,* which is responsible for real-time visualization of alarm data and machine learning findings. It contains implementations of methods to train and display results for random forest, gradient boosting, SVM, and logistic regression models, as well as the *Navigation System*, which serves as the core processing unit, interfacing with data collection and data analysis components. It enables alarm processing by executing real-time data streams. The second layer, the data collection and processing layer, where the *DataCollector* module collects real-time data from onboard sensors (*e.g.*, timestamp, ship name, latitude, longitude, speed, heading, radar alerts, GPS accuracy, true heading). Expectation-based alarm classification and predictive modeling are built on this data. The system also defines a *calculate_distance()* function for geospatial tracking and anomaly detection based on vessel movement.

The DataAnalyzer module, used for alarm classification and predictive modeling, is the third component: an AI-based data analysis module. It applies multiple AI approaches, including supervised alarm classification models such as random forest, gradient boosting, and SVM; a Predictive model to avoid failures before they become critical; and logistic regression to estimate the alarm's degree of severity. We have external libraries and dependencies also, where the system uses external libraries such as Panda library – for processing and manipulating structured data, Sklearn library which provides machine learning models for alarm categorization, *tkinter* framework – a simple python application to plot real time data and to adjust alarms, and *matplotlib* – visualization of live alarm trends and predictive analytics.

Architectural overview. The functional flow is detailed using a structured workflow from which the following approach is described:

- *Data collection* where sensor data is continuously collected by the *DataCollector* module.
- *Real-time data analysis*. Once the data has been collected, it needs to be processed in real-time, allowing AI algorithms to classify alarms as critical or non-critical. Analytics through dashboard visualization enables alarm predictions to be better visualized through the embedded *NavigationDashboard*, thereby improving situational awareness upon analysis [7].
- *Predictive analytics:* The system analyzes historical patterns alongside predictive ML models to predict system failures in advance for preemptive remediation.

Therefore, the proposed work utilizes AI and ML-based approaches to enhance the classification of alerts, reduce false positives, and facilitate proactive decision-making. The servlet demonstrates the effectiveness and reliability of maritime alarm management through the integration of real-time data processing and predictive analytics.

3.2. DATA COLLECTION AND SIMULATION

The *Data Collection and Simulation* module (see Fig. 2) is a critical component of the AI-based Intelligent Bridge Alarm Monitoring System, designed to replicate real-world maritime alarm scenarios. This section outlines the Python-based simulation framework, the data sources used, and the process for generating a synthetic dataset to create a realistic testing environment for machine learning models.

1. PYTHON-BASED SIMULATION FRAMEWORK FOR MARITIME ALARM DATA

A Python-based simulation framework has been developed to establish an experimental setup for alarm monitoring and receive training on data until October 2023. This framework generates and processes synthetic maritime alarm data that mimics real-world conditions in an operational environment. It has been well defined by(1) provides real-time data streams, which consists in) mimicking onboard sensors that will trigger alarm signals at different interval range, logging navigational errors, engine failures and safety hazards; (2) customizable alarm triggers that represents the framework which allows the user to able to input alarms provided that it falls to the interval range–critical warning and informational alarms respectively; (3) noise and uncertainty, where in random noise and variability are introduced to increase robustness and mimic a false alarm, sensor fault or environmental perturbation (*e.g.*, turbulent sea states, GPS drift. They keep a close eye on the simulation framework to see if it is effectively integrated with the data processing pipelines responsible for organizing the incoming data and conditioning it for analysis.

All data processing pipelines that format the incoming data and prepare it for further analysis are integrated into the simulation framework. By doing so, the machine learning models receive formatted and relevant information.

2. DATA SOURCES AND PREPROCESSING

The system extracts information from various maritime sources, including onboard sensors, simulative ship navigation systems, radar alarms, GPS accuracy, engine efficiency, fuel economy; a historical maritime database (the visual data of the marine alliance of alarm networking maturity); and environmental weather data (the information on wave height, wind speed, and visibility conditions were included for improving the alarm prediction efficiency).

The preprocessing steps are as follows: *data cleaning* - this step helps remove inconsistencies, null entries, and duplicate records to improve data quality. *Feature engineering*, which explained the process of aggregating features that can denote an abnormal vessel motion, that is, heading change, and even sensor activity (see Fig. 2). *Normalization and standardization* represent the process of rescaling numerical features, which will ensure the machine learning models perform well across diverse data distributions.

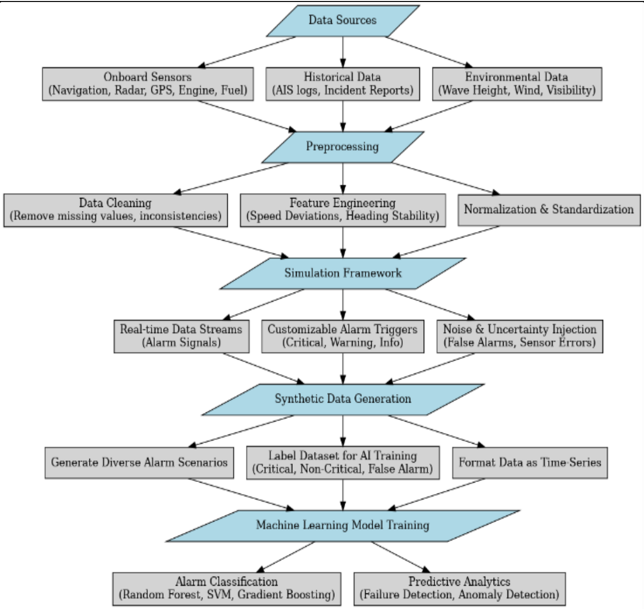


Fig. 2 - The process of data collection and simulation model.

3. SYNTHETIC DATASET GENERATION

A synthetic dataset for training AI models to be effective, considering that real-world maritime alarm datasets are limited due to their inability to be shared publicly. The dataset aims to contain all alarm scenarios essential for modeling both nominal conditions, false alarm conditions, and critical/clearing conditions. The supervised learning pipeline is then applied to those alarm events that have a clear status as necessary, non-critical, or false positive (labeled data). Finally, the time series data format that is responsible for the alarm patterns should be modeled over time. This ensures you are catching both predictive trends and early warning capabilities.

It implements stochastic modeling, along with rule-based sporadic injections of anomalies, to create realistic data samples that closely capture benign alarms in the maritime domain.

Importance of data collection and simulation. The simulation framework, implemented in Python, provides a robust testbed for designing and evaluating algorithm functions for alarm monitoring in a nautical environment. Moving to synthetic and real-world data, the system guarantees the following: improving the scenarios and quality of AI models for operating in various environments onboard ships. *High-quality training data is* used to significantly improve the precision of alarm classifications and decrease false positives. *Predictive capability* that uses a proactive decision-making approach through the early detection of potential failures

Such a technique ensures that the system has effectiveness and reliability and can most certainly be deployed in practical maritime operations.

3.3. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING METHODOLOGY

The system is used in marine alarm monitoring with machine learning. The system employs machine learning classification and anomaly detection models, such as the supervised learning for alarm classification (see Fig. 3), where it is random forest (RF), and the support vector machines (SVM) (see Fig. 4) for detecting alarm classes and regular or non-alarm classes based on sensor data patterns. Neural Networks and tendency to learn complex interactions among features and ability to generalize over time, and unsupervised learning for anomaly detection (see Fig. 3), which is composed of autoencoders and isolation Forest for unusual alarm patterns detection to identify possible faults before they occur. In this regard, we perform K-Means Clustering to cluster similar alarm patterns and subsequently identify outlier alarms. Such models may help distinguish real threats from false alerts, thereby improving situational awareness and operational efficiency.

Training and testing approach. The AI/ML models are trained on a synthetic maritime alarm dataset generation through Python-based simulation, data splitting represented 70% of the dataset for training; 20% for validation; 10% for testing; cross validation represented by K-fold cross-validation (k=5) to escape overfitting (i.e., overtraining) to improve model generalization; and that the performance metrics are based on accuracy, precision, recall, F1-score for classification model- and mean squared error (MSE) and anomaly score thresholds are adopted for anomaly detection models.

Feature engineering and model selection. Feature engineering is performed on sensor data based on raw features, utilizing sensor readings (temperature, pressure, vibrations, fuel levels, *etc.*), alarm time, and frequency. Time-based features that examine trends in alarm frequency over time (hourly, daily, weekly) are also considered derived features. We also have the statistical attributes (mean, standard deviation, and percentiles of sensor values). Additionally, contextual features are employed, such as alarm correlation with the environmental conditions (weather, location).

Principal component analysis (PCA) is used to minimize less critical information by reducing dimensionality. In contrast, SHAP (SHapley Additive exPlanations) analysis is used to identify the significant features contributing to the classification of alarms.

The system improves efficiency in maritime alarm monitoring as well as accuracy by optimizing model selection through HP (grid search and Bayesian optimization).

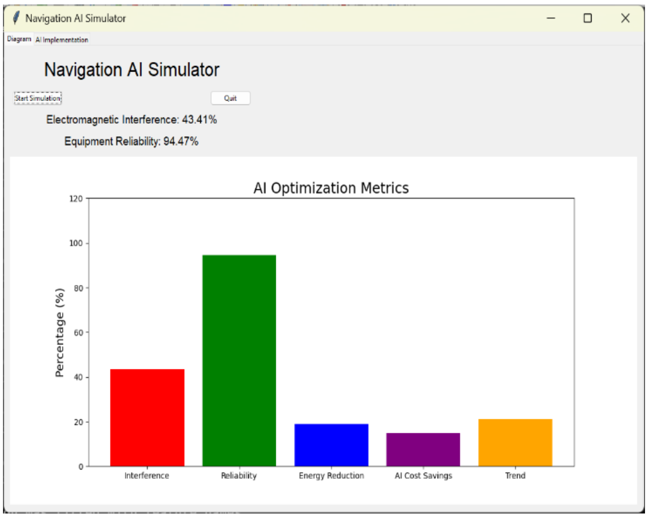
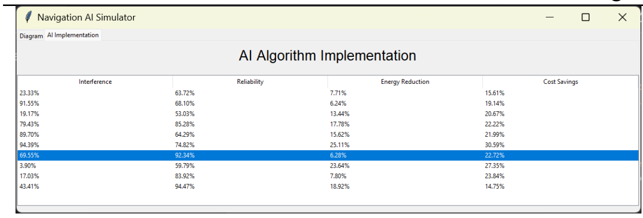


Fig. 3 – Predictive model for interference of collected electrical signals, for establishing degree of confidence, for energy prediction, reducing maintenance costs using AI, and estimating future trends.



Navigation AI Simulator

Diagram AI Implementation

AI Algorithm Implementation

Interference	Reliability	Energy Reduction	Cost Savings
23.33%	63.72%	7.71%	15.61%
91.55%	68.10%	6.24%	19.14%
19.17%	53.03%	13.44%	20.67%
79.43%	85.28%	17.78%	22.22%
89.70%	64.29%	15.62%	21.99%
94.39%	74.82%	25.11%	30.59%
69.55%	92.34%	6.28%	22.72%
3.90%	59.79%	23.64%	27.35%
17.03%	83.92%	7.80%	23.84%
43.41%	94.47%	18.92%	14.75%

Fig. 4 – Data resulting from training using artificial intelligence-based algorithms, such as random forest.

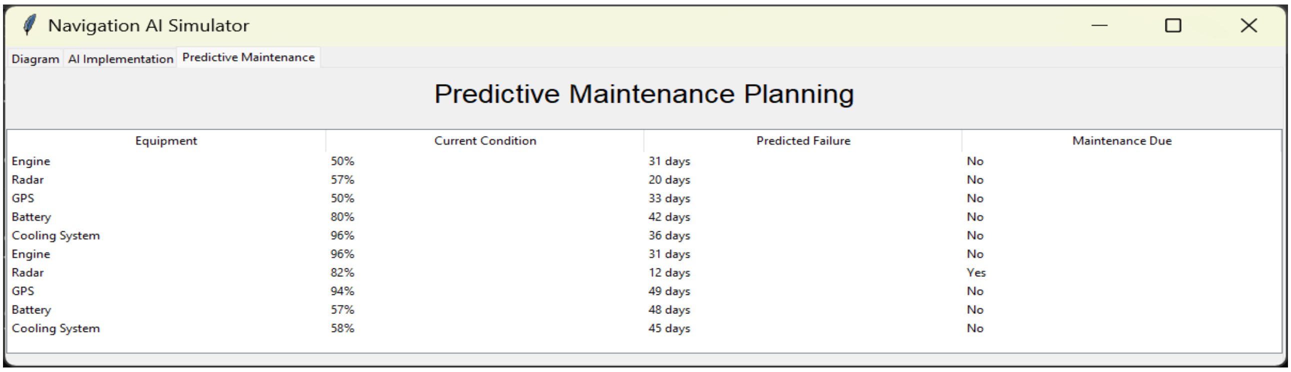
On timed system alarm detection and timeliness usage on maritime vessels. The method employs an enhanced feature selection method that begins with PCA. This dimensionality reduction helps retain the relevant features with minimal redundancy, empowering the AI model to better process warnings without being overwhelmed by excess complexity. This entails the application of SHAP (SHapley Additive exPlanations) analysis, which is essential for discerning the key variables that dictate alert classification. As a result, it integrates a system that ensures model alerts are consistently recognized, even as you train them, while providing clear explanations of its decisions to be human-understandable and trusted.

In addition to optimizing the rank of the essential features, the system is externally optimized for its predictive ability. Optimizing the AI model → Focus on road performance: An optimized AI model with the best performance can be achieved by applying hyperparameter tuning techniques. Grid Search is a systematic approach that systematically explores parameter combinations to find alternatives within the training data, ensuring that all possible options are evaluated. In contrast, Bayesian Optimization utilizes intelligent machines to guide the prediction of which combinations would yield the most benefits. This combination of methods provides a highly efficient marine alarm monitoring system that reduces false alarms and enhances the real-time detection of emergency alerts. Such advanced methods improve the speed and reliability of alarm detection while maintaining transparency throughout the entire process, making it a crucial instrument for maritime safety and on-board decision-making.

4. EXPERIMENTAL RESULTS AND EVALUATION

4.1. PERFORMANCE METRICS

Performance analysis of the system is crucial from a success perspective, which is implemented by comparing the proposed system with various metrics, including accuracy, precision, recall, and F1 score, for alert classification. These metrics provide a holistic measure of how well the machine learning models can discriminate between critical and less critical alerts while maintaining control over both false positives and false negatives. In addition, the proposed AI approach demonstrates the following performance (see Fig. 5), highlighting improvements in detection accuracy and response efficiency when compared to standard alarm monitoring systems.



Navigation AI Simulator

Diagram AI Implementation Predictive Maintenance

Predictive Maintenance Planning

Equipment	Current Condition	Predicted Failure	Maintenance Due
Engine	50%	31 days	No
Radar	57%	20 days	No
GPS	50%	33 days	No
Battery	80%	42 days	No
Cooling System	96%	36 days	No
Engine	96%	31 days	No
Radar	82%	12 days	Yes
GPS	94%	49 days	No
Battery	57%	48 days	No
Cooling System	58%	45 days	No

Fig. 5 – The predictive model for maintenance planning

4.2. CASE STUDIES AND SIMULATIONS

The algorithm is validated on simulated maritime alarm systems, producing high-value alarms and anomalies from on-time sensor data input by the alarm system.

Finally, example cases demonstrated instances of detected alarm waves, highlighting cases where the models successfully identified abnormal alarm patterns, thereby preventing potential system crashes. The critical alarm identification improved response times as an HMI in visualizations, enabling quicker decisions with less impact on operators. "Test results also further validate that the SYS 634 could improve maritime safety by enabling intelligence-driven, data-centric alarm management.

Ultimately, in all aspects of evaluation, the AI-driven solution that utilizes this algorithm demonstrates superior performance and more accurate and capable classifications compared to the classical solution. The higher F1 score further substantiates the precision-recall balance, rendering the AI tool a better reporting instrument for HR. The Peace Palace in The Hague, Netherlands, serves as a hub for international law. Still, it also serves as a reminder that machine learning techniques can be applied to monitor alarms in the sea, potentially improving safety and decision-making in operational settings.

4.3. DISCUSSION

The experimental results demonstrated that AI and ML algorithms can enhance marine alarm monitoring by significantly reducing the number of false positive alarms and improving the delivery of alarms to the human operator. The results indicate that the algorithm has performed satisfactorily for various alarm types and in predicting future breakdowns, leading to improved decision-making and cost reduction. This will enhance marine safety by eliminating false alarms during ship operations, allowing the crew to focus on genuine threats. Artificial Intelligence-based solutions, in addition to innovative ship technology, are part of a more significant shift that requires sophisticated data analytics to enable efficient and proactive maritime operations.

5. **CONCLUSION**

In this study, a new experimental operational framework built on AI and machine learning techniques is proposed to track alarms in marine vessels, thereby enhancing alarm management systems and increasing the overall safety of maritime systems. AI-driven categorization and anomaly detection models are utilized to keep responses efficient by minimizing false positives while prioritizing key alerts. Interpreted in Python, this framework provides an estimate of the system's performance in terms of its ability to distinguish actual positive threats from false alarms, thereby providing evidence of its usefulness in the preventive decision-making phase of marine system operation. The findings demonstrate that integrating AI and ML into an alert monitoring system can significantly enhance the reliability of marine safety systems, concurrent with the sector's digitalization. The approach, however, has some limitations, despite yielding positive results.

Moreover, the integration of currently sailed passage data can create the foundation for further revision in the accuracy and robustness of the models in future work. Finally, by providing support for alarm response as well, we can lighten the cognitive workload of the crew and allow them to perform their job more safely, thereby ensuring the ship sails more safely.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Bogdan Asalomia: conceptualization, methodology, software development, writing – original draft, data curation, formal analysis, supervision.
Gheorghe Samoilescu: investigation, validation, resources, writing, review & editing, project administration.
Marius Iulian Mihailescu: data analysis, machine learning implementation, visualization, writing, review & editing, experimentation, performance evaluation.

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