

Toward Fully Digitalized Vessel Operations: Architecture, Technologies, and Operational Transformation

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Abstract

Maritime digitalization is growing and has thus generated a demand for intelligent monitoring of vessels that can make them more efficient, safe and predictive. The research presented in this paper introduces a digital vessel framework that combines synthetic operational data production with AI models and Digital Twin technology. A set of 5,000 records representing variables such as engine performance, fuel usage, temperature, vibration, navigation, and energy characteristics, is developed to simulate conditions on board a vessel. Various machine learning models are used for condition classification, anomaly detection, and sequential analysis, such as Random Forest, Isolation Forest, and LSTM. The Random Forest classifier reached 99.60% accuracy on the synthetic test dataset, whereas the LSTM generalized poorly (47.19% validation accuracy). This result should not be interpreted as representative of real-vessel deployment performance. A digital-twin prototype visualization dashboard is created to model vessel health. The method presented is designed as a tool to test digital vessel technologies in a simulation environment and serves as a precursor to integration at an operational level on real vessels.

Keywords: Digital Vessel, Digital Twin, Maritime IoT, Predictive Maintenance, Artificial Intelligence, Machine Learning, Vessel Monitoring System

I. INTRODUCTION

Background

Maritime transport plays a key role in international trade and transit, and accounts for a significant share of global transportation. Traditional vessels still operate as standalone systems, with operational information for propulsion, navigation, safety, and machinery systems remaining largely onboard with only limited communication to shore-based facilities [1]. Recent advances in digital technologies are transforming ships into connected cyber-physical systems by embedding and interfacing Industrial Internet of Things (IoT), advanced communication networks, Artificial Intelligence (AI), and Digital Twin (DT) technologies [2][3]. A fully digitalized vessel architecture integrates all physical assets, sensing systems, data processing, communication capabilities, and intelligent applications to create better operational awareness and decision support [4]. These advancements in maritime digitalization highlight the increasing significance of integrated control platforms, predictive analysis tools, and digital twins to ensure real-time monitoring, maintenance optimization, and enhanced operational efficiency.

Problem Statement

While digital ship technology has progressed significantly, there are challenges in implementing these technologies, including limited amounts of operational ship data, complex integration of disparate shipboard systems, and testing intelligent algorithms in real operating environments [5]. Legacy equipment integrated with existing systems uses different communication protocols, making data integration a significant challenge [6][7]. Additionally, the continuous operation data for the development and evaluation of AI monitoring and predictive maintenance systems is often confidential and missing, while academic research relies heavily on such data. A simulation-based approach, with synthetic vessel data, is essential to develop and validate digital vessel technologies in a controlled research environment.

Aim and Objectives

The project's aim is to build a digital vessel framework using Python for synthesizing sensor data, performing analysis using artificial intelligence, and modeling a simulation-based digital-twin prototype of a vessel.

Main objectives are:

II. LITERATURE REVIEW

- To create a synthetic dataset describing the operational characteristics of the vessel's operating parameters like engine conditions, fuel usage, temperature, vibration, and navigation status.
- To adopt data processing and analysis methods for anomalies based on artificial intelligence to carry out Predictive Maintenance.
- To develop a simplified digital-twin prototype to simulate real-time vessel conditions.
- To test the effectiveness of the proposed framework by analyzing and visualizing its performance.

Research Contribution

The research has developed a software-based framework that can be reproduced and used to study digital vessel operations without the need for confidential ship data. The main idea is to seamlessly combine synthetic IoT data generation, machine learning for condition monitoring, and digital-twin prototype visualization within a common architecture. This study illustrates an implementation path for shifting from information generation to intelligent operational monitoring using a digital vessel approach rather than a purely conceptual one. The suggested framework paves the way for further investigation into maritime digital transformation, offering a platform for incorporating real-time data from ships, cloud-based systems, and advanced technologies for autonomous navigation.

Hybrid Communication Infrastructure

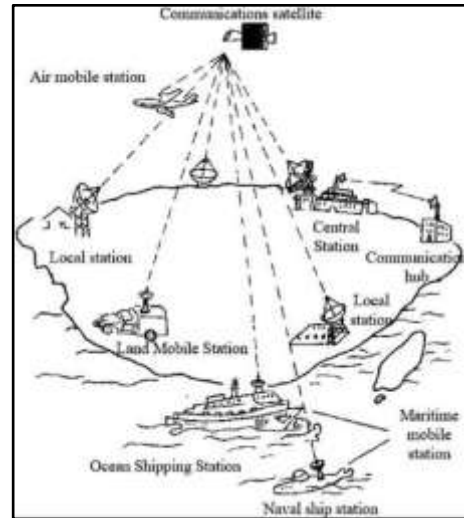


Fig. 1. Hybrid Communication Infrastructure

Maritime communication system development has shifted from traditional satellite-based communication systems to advanced hybrid communication systems. Previous communication systems on vessels primarily relied on Geostationary-Satellite Communication (GEOSAT) systems, which cover vast areas but have disadvantages in terms of latency and bandwidth [8]. Recently, satellite communication systems combining GEO, MEO, and LEO satellites with terrestrial networks have been developed to ensure reliable data transmission and increase system reliability [9][10]. Hybrid satellite-terrestrial communications enable vessels to be monitored daily and remotely, and also facilitate operational information exchange between the ship and shore facilities. Edge computing further enhances system efficiency by enabling data processing at the edge when network connections are unavailable.

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Smart Sensing and Data Integration

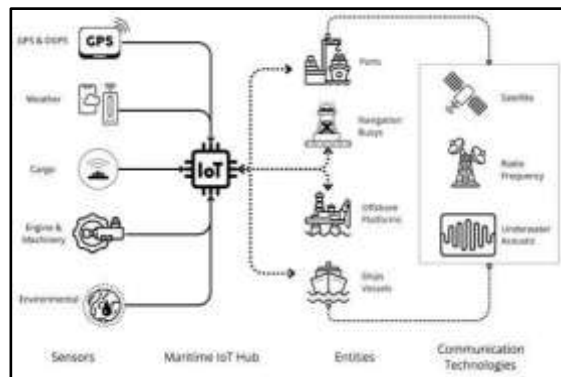


Fig. 2. Smart Sensing IOT Technology

Smart sensing technologies provide essential data acquisition capabilities needed to support digital vessel operations. Contemporary vessel monitoring systems combine IoT sensors, field instruments, and condition monitoring equipment to gather data from vessel systems such as propulsion, machinery, cargo, navigation, and environmental systems [11]. The high-resolution sensor data can analyze the health of the equipment, the conditions in which it's operating, and the safety of those around it all in one [12]. Shipboard environments, however, involve multiple equipment manufacturers and communication protocols that hinder data interoperability and integration [13][14]. To derive useful operational insights from the myriad, different sensor data, data loggers, edge computing platforms, and sophisticated processing routines are therefore necessary.

Integrated Control and Monitoring Systems

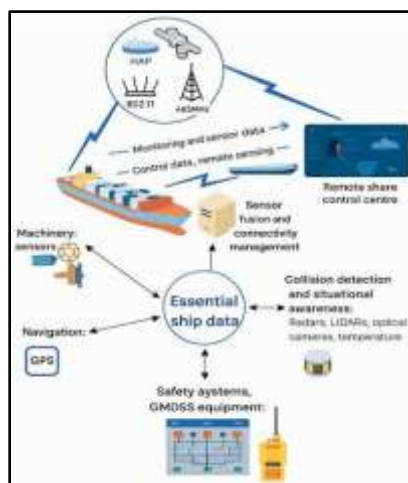


Fig. 3. Integrated Control and Monitoring Systems

Integrated control and monitoring systems represent a significant step toward ship digitization, replacing standalone shipboard systems with a unified control and monitoring system. Traditional vessels have limited information sharing and visibility due to separate systems for navigation, propulsion, cargo management, and vessel safety monitoring [15]. Digital vessel concepts create centralized environments for monitoring and multi-view visualization and analysis of various operational parameters. These environments provide real-time data feeds on engine performance, fuel usage, energy efficiency, and navigation conditions, along with safety alerts and maintenance recommendations [16]. Effective implementation of integrated monitoring requires the ability to synchronously manage data and create a shared data architecture that links vessel subsystem data.

Digital Twin and Operational Intelligence

By modeling vessels in virtual form with ongoing operating parameters, digital twin technology is an important aspect of enabling intelligent maritime operations. Digital models have been successfully used in preliminary applications for equipment condition assessment and performance prediction. Recent advancements in digital twin applications have extended to predictive maintenance, voyage optimization, risk assessment, and operational decision support [17][18]. A vessel digital-twin prototype can simulate equipment behavior, analyze different operating scenarios, and provide information to support proactive maintenance scheduling [19]. However, much remains to be done in terms of data availability, measurement accuracy, system integration, and standardization of digital twin frameworks.

Research Gap

While maritime connectivity, sensing technologies, integrated monitoring systems, and digital twin applications have seen significant advances, the full digital vessel approach remains difficult to implement. Existing solutions generally focus on particular technological aspects and do not propose an integrated experimental environment. Public maritime datasets are available; however, publicly accessible datasets containing comprehensive, high-resolution onboard machinery, propulsion, auxiliary-system, and condition-monitoring data remain limited, making it challenging to evaluate the performance of AI and predictive maintenance tools. Therefore, a Python-based simulation framework using synthetic vessel

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IV. PROPOSED METHODOLOGY

data provides a controlled and reproducible platform to investigate digital vessel operations, AI-based analysis, and the implementation of a digital-twin prototype before actual deployment.

III. SYSTEM ARCHITECTURE OF A DIGITAL VESSEL



Fig. 4. Architecture of a Fully Digitalized Vessel Ecosystem

The proposed digital vessel architecture features five layers, providing intelligent monitoring, analysis, and decision-making capabilities. The Physical Layer comprises the core assets of the vessel's structure, including engines, propulsion systems, cargo handling systems, navigation systems, power systems, and safety systems [19]. The Sensing Layer gathers and processes operational information received from various sources such as engine sensors, equipment sensors, navigation sensors, and environmental sensors in real-time. The Data Layer handles data storage and processing as well as integration, adopting edge and cloud-based computing strategies [20]. The Communication Layer supports secure transmission of data across satellites (GEO/MEO/LEO), terrestrial networks, and network management solutions [21][22]. The Application Layer offers monitoring dashboards, performance analysis, predictive maintenance, and decision support tools to provide intelligence. These layers communicate with shore-based fleet operations to enable monitoring, technical support, analytics, and management activities within an integrated cyber-physical digital vessel environment.

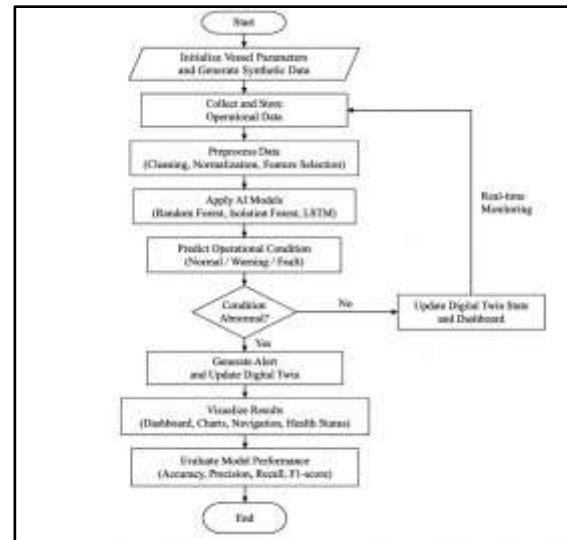


Fig. 5. Flow Diagram

The proposed methodology involves developing a framework for digital simulation of a vessel using Python, providing synthetic operational data, data preprocessing algorithms and techniques, AI-based predictive algorithms, and a simulation-based digital-twin model. The methodology is based on the digital vessel architecture, whereby vessel data acquisition, processing, smart analysis, and operation monitoring verification are simulated.

Vessel Data Generation

Simulated operational conditions for a synthetic vessel are created in a synthetic dataset using Python tools and procedures. A total of 5,000 records are generated, each representing an operational observation for a vessel during a particular time period. Key data available on this dataset includes engine RPM, engine load, fuel consumption, exhaust temperature, lubrication oil pressure, coolant temperature, vibration level, vessel speed, latitude, longitude, heading, wind speed, wave height, power consumption and operational status. The dataset generated consists of the normal and abnormal operating conditions, which will help in the predictive maintenance analyses.

Data Processing and Integration

The obtained dataset is first split into training and testing sets using an 80:20 ratio, where 80 percent of the data is used for training models and 20 percent is reserved for testing and evaluating model performance. This split is performed before any

preprocessing to prevent data leakage. Data quality checking is then performed on the training data to detect missing values, duplicated data, and inconsistent data. Feature extraction based on operational relevance follows to select the required parameters. Standard scaling is applied to numerical variables, with scaling parameters fitted on the training data only and then applied to the test data. This ensures that no information from the test set is used during model training.

AI Model Development

An AI-based predictive analysis model is developed using the processed vessel dataset to predict and diagnose abnormal operating conditions. Three machine learning techniques are considered: Random Forest for classification-based fault prediction, Isolation Forest for anomaly detection, and LSTM networks for analyzing sequential patterns of vessel operation.

Random Forest Model

Multiple decision trees are used for classification of vessel operational conditions using Random Forest [23]. The final prediction is determined by majority voting:

$$\hat{Y} = \text{Mode}\{T_1(X), T_2(X), \dots, T_n(X)\}$$

where:

- T_n represents an individual decision tree and $\hat{Y}$ represents the predicted vessel condition.

Isolation Forest Model

To identify abnormal vessel behavior, the anomaly score of operational observations is calculated using the Isolation Forest technique [24]. The formula for the anomaly score is given as:

$$S(x, n) = 2^{-\frac{E(h(x))}{c(n)}}$$

where:

- $E(h(x))$ represents the average path length of sample isolation
- $c(n)$ represents the normalization factor based on sample size.

LSTM Model

LSTM is used for analyzing time-series vessel data by learning sequential relationships between operational parameters [25]. Unlike a simple RNN, the LSTM uses gate mechanisms (input, forget, and output gates) to control information flow. The gate equations are: the input gate $i_t = \text{sigmoid}(W_{xi} * x_t + W_{hi} * h_{t-1} + b_i)$, the forget gate $f_t = \text{sigmoid}(W_{xf} * x_t + W_{hf} * h_{t-1} + b_f)$, the output gate $o_t = \text{sigmoid}(W_{xo} * x_t + W_{ho} * h_{t-1} + b_o)$, and the cell state update $c_t = f_t * c_{t-1} + i_t * \tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c)$. The hidden state is then:

$$h_t = o_t \odot \tanh(c_t)$$

where:

- h_t represents the current hidden state, computed from the output gate o_t and the cell state c_t
- x_t represents input sensor data at time t
- W_x and W_h represent the input and recurrent weight matrices of each gate, and b represents the bias

The models are based on operational characteristics like temperature, vibration, fuel consumption and engine characteristics that were used to classify a vessel as normal, warning and fault.

Digital Twin Modelling

A simplified simulation-based digital-twin prototype is developed in Python to represent a virtual vessel's operational state. The digital-twin prototype integrates data from various sensor types, AI predictions, and equipment health indicators to continually update the vessel's state [26].

The vessel digital state is defined as:

$$DT_t = f(X_t, A_t, M_t)$$

where:

- DT_t = digital twin state at time t
- X_t = sensor data input
- A_t = AI prediction output
- M_t = vessel operational model

The digital twin continuously updates its condition:

$$DT_{t+1} = DT_t + \Delta X_t$$

where ΔX_t represents the change in vessel operational parameters.

The model embodies relevant states of the vessels such as the condition of the engine, energy performance, navigation status and condition of maintenance.

Performance Evaluation

Established evaluation metrics for machine learning models and the digital-twin prototype are used to evaluate performance. Overall prediction correctness is measured by accuracy, and the reliability of fault predictions is measured by precision. The model's ability to detect actual abnormal cases is assessed by recall, and the F1-Score provides a balanced measure between recall and precision. Scalability would require additional evaluation of computational performance as dataset size, sensor count, and model complexity increase. Based on the results, the effectiveness of the proposed digital vessel monitoring framework is analyzed.

V. PROJECT MANAGEMENT FRAMEWORK FOR DIGITAL TRANSFORMATION AND COMMISSIONING

Digital Transformation Planning and Requirement Analysis

The first steps in the proposed digital transformation process involve defining the requirements for the vessel, its onboard systems, communications, and data availability. In this phase, goals, necessary digital technologies, system architecture, and implementation approach would be established. Evaluation of propulsion systems, navigation equipment, monitoring systems, sensors, and communication networks would ensure compatibility with the proposed digital vessel structure [27].

System Development and Integration Management

During the development phase, integration of vessel subsystems, data acquisition platforms, artificial intelligence models and digital twins' components will be in focus. Proposed project activities would include software development, database management, sensor data integration, dashboard construction, and testing of communication interfaces [28]. A structured management approach would enable coordination of system implementation across hardware, software, and personnel to ensure optimal execution.

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Testing, Validation and Commissioning Process

Commissioning would be a process that validates the digital vessel system performance and reliability prior to deployment. Functional testing would include data collection for AI-based prediction, updating the digital-twin prototype, and visualization. System validation would be conducted using simulated operational scenarios to test fault detection, monitoring accuracy, and response performance under various vessel conditions [29].

Operational Deployment and Continuous Improvement

Once successfully commissioned, the digital vessel framework would be used for operational monitoring and decision support. System updates, performance assessment, cybersecurity management, and integration of new intelligent technologies would be continuous improvement activities [30]. The framework could be implemented and adapted to support long-term digital transformation, enabling efficient vessel operation, condition-based maintenance, and data-driven maritime management.

VI. PROJECT IMPLEMENTATION AND OPERATIONAL TRANSFORMATION

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START
1. Initialize digital vessel
environment
2. Generate vessel operational
data
    - Engine parameters
    - Navigation data
    - Environmental data
3. Preprocess collected data
    - Remove missing values
    - Normalize parameters
    - Extract important features
4. Develop AI monitoring models
model
    - Train fault prediction
behavior
5. Update Digital Twin Model
    - Receive real-time data
    - Update vessel state
    - Simulate abnormal
conditions
6. Generate operational dashboard
    - Display engine status
    - Monitor navigation

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- Analyze energy consumption
 - Provide maintenance alerts
7. Evaluate system performance
- Calculate accuracy
 - Validate prediction results
 - Improve operational decisions
- END

The proposed digital vessel framework is implemented using Python-based synthetic data generation, data preprocessing, machine learning models, and digital-twin prototype simulation. The system integrates vessel information such as engine performance, navigation status, energy consumption, and equipment condition. Abnormal conditions are detected by AI-based analysis, and the vessel operational condition is updated continuously by the digital-twin prototype for intelligent monitoring.



Fig. 6. Integrated Control System Dashboard (conceptual integration)

The dashboard provides simulated real-time visualization of vessel operations through engine monitoring, navigation overview, weather information, safety alerts, energy analysis, and condition-based maintenance functions. It integrates data feeds into a single interface, enabling operators to evaluate vessel performance, identify risks, and make data-driven operational decisions.

VII. RESULT AND DISCUSSION

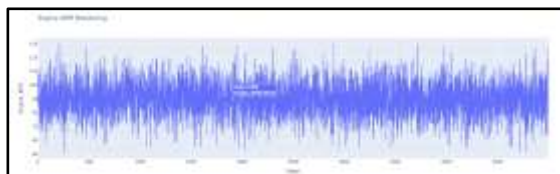


Fig. 7. Engine RPM Monitoring Analysis

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The Engine RPM monitoring plot shows variations in the propulsion system's operational speed during the simulated vessel operation. The RPM values fluctuate within the normal operating range, indicating dynamic engine behavior under varying conditions. This visualization enables continuous monitoring of engine performance and identification of abnormal rotational patterns.

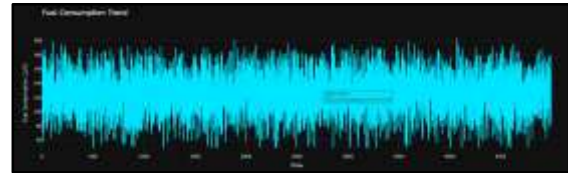


Fig. 8. Fuel Consumption Trend Analysis

The fuel consumption trend shows variations in fuel consumption during the simulated operation period. The graph illustrates continuous changes in engine load and condition. Fuel consumption monitoring enables assessment of energy efficiency, optimization of fuel usage, and provides data insights for sustainable vessel operation.

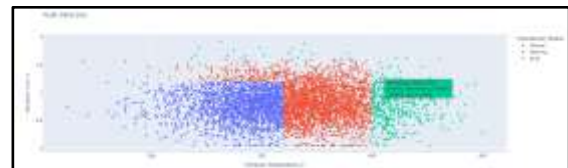


Fig. 9. Fault Detection Analysis

The fault detection visualization shows the relationship between exhaust temperature and vibration levels across various operational states. Classification labels are applied to distinguish normal, warning, and fault conditions. This analysis demonstrates the monitoring system's ability to identify abnormal equipment behavior based on sensor characteristics.



Fig. 10. Vessel Navigation Tracking Analysis

The navigation tracking visualization shows vessel movements on the water. Vessels are displayed in a geographical coordinate system with their operational status classified by color. Various operating states are shown along the simulated voyage path. The figure illustrates how navigation data is integrated with

vessel condition monitoring to provide enhanced situational awareness and decision support.

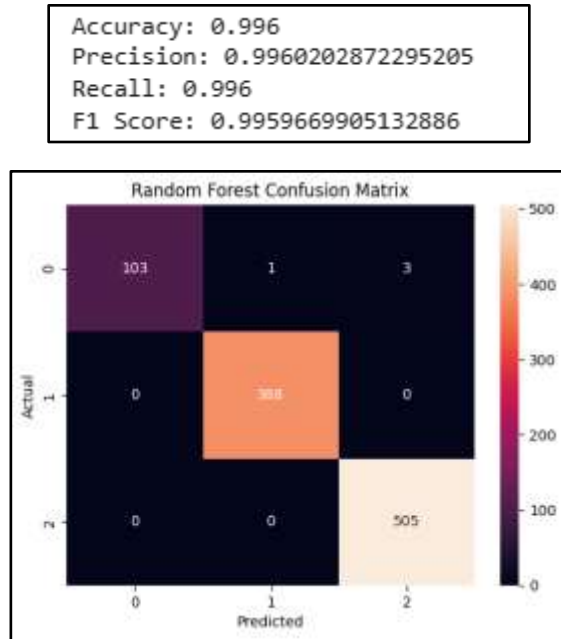


Fig. 11. Random Forest Evaluation

The Random Forest confusion matrix shows classification performance under vessel operational conditions on the synthetic test dataset. The model achieved 99.6% classification accuracy on the synthetic test dataset with low classification errors. This result should not be interpreted as representative of real-vessel deployment performance. The matrix shows successful identification of normal, warning, and fault states on the synthetic dataset, demonstrating the effectiveness of machine learning-based condition monitoring under simulated conditions.

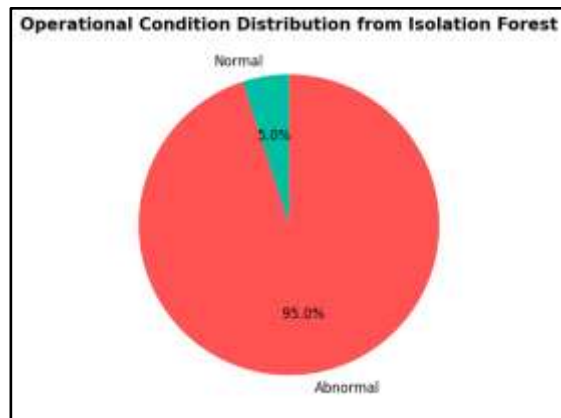


Fig. 12. Isolation Forest Anomaly Detection Analysis

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The Isolation Forest visualization depicts the distribution of normal and abnormal vessel conditions. The model classified 4,750 samples as anomalous and 250 as normal, yielding a high anomaly ratio. This result likely reflects the contamination parameter setting in the Isolation Forest configuration, which was tuned to maximize sensitivity to potential fault conditions in the synthetic dataset. The high anomaly rate should be interpreted as an exploratory finding rather than a definitive classification, as the threshold selection significantly influences the detected anomaly proportion. The outcome suggests the potential of unsupervised anomaly detection to identify possible equipment issues without requiring extensive failure data, though further calibration of detection thresholds is needed to achieve a more balanced classification suitable for operational use.



Fig. 13. LSTM Model Training Performance Analysis

This visualization shows the LSTM's learning behavior across 20 training epochs. As the model is optimized, training accuracy gradually increases while loss decreases. However, the validation performance indicates limited generalization, with a validation accuracy of 47.19% that is only modestly above the 33% expected from random guessing across three classes. This suggests that the LSTM model requires further tuning, more representative sequential data, and additional feature engineering. The LSTM results should not be interpreted as successful generalization.

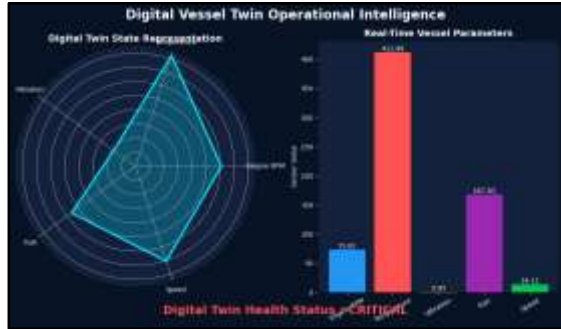


Fig. 14. Digital Twin Operational Intelligence Analysis

The digital-twin prototype visualization provides a virtual representation of vessel operations based on RPM, temperature, vibration, fuel usage, and speed inputs. Radar and bar charts are used for simulated real-time condition representation within the simulation environment. The generated health status indicates a critical condition, supporting condition-based maintenance and operational decision-making.

Discussion

TABLE I. Random Forest Model Statistics

Parameter	Details
Model	Random Forest Classifier
Purpose	Vessel condition classification
Accuracy (%)	99.6
Precision (%)	99.60
Recall (%)	99.6
F1-score (%)	99.59

TABLE II. LSTM Model Statistics

Parameter	Value
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Training accuracy	60.57%
Validation accuracy	47.19%
Validation loss	0.9884

The proposed digital vessel framework was developed to enable integrated use of synthesized sensor data, AI-based analysis, and digital-twin prototype visualization for maritime operational monitoring in a simulation environment. The Random Forest model obtained 99.6% accuracy, 99.60% precision, 99.6% recall, and a 99.59% F1-score on the synthetic test dataset. These results demonstrate strong performance under simulated conditions but should not be interpreted as representative of real-vessel deployment performance. The Isolation Forest model identified anomalous operating patterns, with 250 records classified as normal from the generated dataset. The high anomaly ratio reflects the sensitivity-tuned contamination parameter and should be further calibrated for operational use. The visualization results demonstrated the framework's capability for monitoring engine parameters, fuel consumption, navigation status, fault conditions, and digital-twin health representation within the simulation environment. The integrated dashboard provided a comprehensive operational picture, enabling data-driven decisions and condition-based maintenance within the digital vessel simulation framework.

VIII. CHALLENGES AND FUTURE WORK

- The developed framework is a simulation-based environment, and further research is required to validate it under real operating conditions on vessels and to integrate it with onboard hardware systems.
- Optimization is required for the AI models to handle more complex scenarios, such as simultaneous multiple equipment failures and variable sea conditions.

Future research will emphasize integrating real-time ship sensor data, cloud-based communication systems, and advanced AI methods to maximize digital vessel capabilities. The digital-twin prototype can be enhanced by incorporating real-time updating mechanisms, autonomous decision support systems, and improved fault prediction algorithms. Future development will focus on implementing cybersecurity measures, integrating with current ship

control systems, and testing practical applications in collaboration with the maritime industry.

IX. CONCLUSION

This study developed an intelligent maritime monitoring framework composed of two core components: a simulation-based digital-twin prototype and AI-based analysis using synthetic digitized data. The proposed system enabled machine learning-based condition analysis for ships and visualization of the operating environment within a simulation context. The Random Forest model showed strong classification performance on the synthetic test dataset, whereas the LSTM model exhibited limited validation performance. Both anomaly detection and digital-twin representation are integral components for condition-based maintenance applications. The final dashboard integrated engine monitoring, navigation tracking, energy analysis, safety assessments, and maintenance functions. The study demonstrates the feasibility of the proposed architecture and the performance of the evaluated models under synthetic simulation conditions. Further validation using operational vessel data is required before the approach can be considered representative of real-world deployment.

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