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Digital Twin–Driven AI Framework for Predictive Maintenance of Marine Diesel Engines Using Multi-Sensor IoT Data

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Abstract

Marine diesel engines are critical components of ship propulsion systems, and unexpected failures can lead to operational disruptions, increased maintenance costs, and reduced reliability. Conventional maintenance approaches may not adequately capture complex degradation patterns under varying operating conditions. This study proposes a Digital Twin–driven artificial intelligence (AI) framework for predictive maintenance of marine diesel engines using multi-sensor Internet of Things (IoT) data. The framework integrates engine sensor measurements, Digital Twin-derived information, and AI-based analytics to support fault detection and remaining useful life (RUL) estimation. Sensor data are processed to obtain relevant operating features, while residuals between measured and Digital Twin-predicted variables can provide additional information about deviations from expected engine behaviour. These features are used as inputs for fault classification and RUL prediction models. Based on the reported results, the proposed integrated framework achieved a fault detection accuracy of 93.8%, compared with 89.7% for the AI-based sensor data approach and 86.4% for the baseline approach. The reported RUL prediction error decreased to 9.2 hours, compared with 14.2 hours and 18.5 hours for the respective comparison approaches. These findings suggest that combining multi-sensor IoT data with Digital Twin-derived information may improve engine condition assessment and RUL estimation. However, the reliability of these findings depends on the underlying dataset, experimental design, and consistency of the evaluation results. Further validation using real-world marine engine data and diverse operating conditions is necessary to assess the framework's generalizability and practical applicability. The proposed approach offers a potential foundation for data-driven maintenance planning and improved operational reliability in marine engineering.

Keywords: Digital Twin, Predictive Maintenance, Marine Diesel Engine, Artificial Intelligence, Internet Of Things, Fault Detection, Process Innovation

1. Introduction

Marine diesel engines play a critical role in maritime transportation by providing the propulsion power required for cargo and passenger vessels. Their operational reliability directly affects vessel availability, transportation efficiency, maintenance costs, and maritime safety. However, marine diesel engines operate under continuously changing load conditions and harsh environmental influences, including temperature variations, vibration, humidity, and changing sea conditions. These factors can accelerate component degradation and increase the risk of unexpected failures. Consequently, effective monitoring and maintenance strategies are essential to identify potential failures before they significantly affect vessel operations.

Conventional maintenance practices commonly rely on scheduled inspections, operating hours, and predefined sensor thresholds. Although these approaches provide basic condition monitoring, they may not adequately capture gradual degradation or complex relationships between multiple engine parameters. Predictive maintenance offers an alternative by analysing operational data to identify emerging faults and estimate the remaining useful life (RUL) of critical components. Deep learning techniques have demonstrated potential for extracting degradation patterns from machinery data and supporting intelligent health monitoring [1]. In addition, the development of Industrial Internet of Things (IIoT) technologies enables continuous data acquisition from distributed sensors, supporting real-time monitoring of

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operational parameters and improving the availability of information for maintenance decisions [2]. Digital Twin (DT) technology provides a potential approach to improving predictive maintenance by maintaining a digital representation of a physical asset and updating it using operational data. Unlike a static simulation model, a properly implemented Digital Twin supports continuous information exchange between the physical system and its digital counterpart. This integration enables the virtual model to reflect changing operating conditions and provides a basis for analysing equipment behaviour, identifying deviations, and tracking degradation [3]. Previous studies have demonstrated the potential of Digital Twin technology for condition monitoring and predictive maintenance in manufacturing and other industrial applications [4]. In the maritime sector, Digital Twin technology offers opportunities to improve engine condition assessment, fault diagnosis, and maintenance planning under dynamic operating conditions [10].

Despite these developments, implementing Digital Twin-driven predictive maintenance for marine diesel engines remains challenging. Sensor measurements may contain noise, missing observations, inconsistent sampling intervals, and communication delays. These issues require appropriate preprocessing, data synchronization, and feature extraction to ensure reliable model inputs [5]. Furthermore, purely data-driven models may have difficulty generalizing to operating conditions that differ from those represented in the training data. Integrating physics-based modelling with machine learning provides a potential approach to combining physical system knowledge with patterns learned from operational data, thereby supporting more robust predictive analysis [6]. Computational constraints and communication limitations aboard vessels also motivate the use of edge computing and cloud-based analytics to balance real-time processing with longer-term data analysis [7].

Artificial intelligence can further support Digital Twin applications by extracting relevant features from multi-sensor time-series data and identifying patterns associated with equipment degradation. Feature representation and temporal analysis can help characterize changes in operating behaviour and provide information for fault detection and RUL estimation [8]. Nevertheless, the reliability of predictive maintenance depends on the quality of the training data, the validity of the modelling assumptions, and the ability of the developed models to generalize across different operating conditions. Federated learning has also been discussed as a potential approach to collaborative model development while reducing the need to centralize operational data [9]. These considerations highlight the importance of developing an integrated framework that connects physical measurements, digital modelling, predictive analytics, and maintenance decision support.

Although Digital Twin technology and AI-based predictive maintenance have received increasing attention, their integration requires systematic evaluation to establish the contribution of Digital Twin-derived information to predictive performance. In particular, the relationship between sensor-based features, model-derived health indicators, fault detection, and RUL estimation needs to be investigated in the context of marine diesel engines. Previous research has examined Digital Twin applications in the marine industry [10], multi-source data fusion for ship equipment assessment [11], AI-based anomaly detection and fault diagnosis for turbocharged marine diesel engines [12], and Digital Twin-driven diesel engine fault diagnosis [13]. These studies provide a foundation for further investigation of integrated approaches that combine multi-sensor measurements, physics-based representations, and AI-based predictive analytics.

Based on these considerations, this study proposes a Digital Twin-driven AI framework for predictive maintenance of marine diesel engines using multi-sensor Internet of Things (IoT) data. The framework integrates sensor data acquisition, data preprocessing, Digital Twin modelling, and AI-based predictive analytics to support fault detection and RUL estimation under varying operating and environmental conditions. The study aims to investigate the use of Digital Twin-derived information alongside sensor measurements and to compare the predictive performance of the integrated framework with sensor-based baseline approaches. The evaluation focuses on fault detection performance, RUL estimation errors, and the contribution of Digital Twin integration to the overall predictive process.

The main contribution of this study is the development of an integrated framework that connects multi-sensor IoT data, Digital Twin modelling, and AI-based predictive maintenance within a unified architecture for marine diesel engines. The framework incorporates model-derived information, including health indicators and residual trends, as additional inputs to predictive analytics. A comparative evaluation is intended to assess whether these features provide measurable benefits over approaches that rely on sensor data alone. The findings are expected to clarify the potential and limitations

of Digital Twin-driven predictive maintenance and provide a foundation for further development of intelligent maintenance systems for maritime propulsion applications.

2. Literature Review

Predictive maintenance has become an important approach for improving equipment reliability by using operational data to identify developing faults and estimate equipment degradation. Unlike preventive maintenance, which is generally scheduled according to predefined intervals, predictive maintenance uses condition information to support maintenance decisions based on the estimated health of the equipment. Machine learning methods can analyse complex sensor measurements and identify patterns associated with abnormal operation and potential failure. However, their effectiveness depends on data quality, model selection, and the ability to generalize across operating conditions [14]. These considerations are particularly important for marine diesel engines, which experience variable loads and environmental conditions during vessel operations.

The integration of the Internet of Things (IoT) with predictive maintenance provides a means of continuously collecting operational data from distributed sensors. Measurements such as temperature, pressure, rotational speed, vibration, and fluid levels can be used to characterize equipment behaviour and identify deviations from normal operating conditions. Combining information from multiple sensors can provide a more comprehensive representation of equipment health than relying on a single measurement. Nevertheless, heterogeneous sensor data introduce challenges involving sampling frequencies, missing observations, measurement noise, and data synchronization. Effective preprocessing and feature engineering are therefore essential to produce reliable inputs for predictive models. Recent reviews of machine learning-based predictive maintenance have also identified data heterogeneity, limited fault data, model generalizability, and real-world validation as persistent challenges in industrial applications [15].

Digital Twin technology extends conventional condition monitoring by maintaining a digital representation of a physical asset and updating that representation using information from the physical system. A Digital Twin can combine sensor measurements, engineering models, and computational analytics to represent the current condition of equipment and support the investigation of possible future operating states. Its application to predictive maintenance has been examined across several industrial domains, with particular attention to system architecture, modelling approaches, and the interaction between physical assets and their digital counterparts [16]. However, a digital model should not automatically be considered a fully implemented Digital Twin. Continuous or appropriately defined data exchange, state synchronization, and model updating are important characteristics that distinguish a Digital Twin from a static simulation or an offline analytical model [17].

In predictive maintenance applications, Digital Twin models can provide information that complements raw sensor measurements. For example, a model may estimate expected engine behaviour under a particular operating condition, while the difference between measured and predicted values can be used to identify possible abnormalities. These residuals, together with health indicators and historical trends, may serve as additional features for machine learning models. The combination of physics-based information and data-driven learning can potentially improve the interpretation of degradation patterns, particularly when equipment behaviour changes with operating conditions. Nevertheless, the actual benefits depend on the accuracy of the physical model, the quality of state estimation, and the validity of the relationship between the derived features and the target failure mechanisms [18].

Artificial intelligence provides analytical capabilities for processing multivariate sensor data, identifying abnormal operating conditions, and estimating remaining useful life (RUL). Classification models can distinguish normal operation from fault conditions, while regression and sequential learning models can estimate degradation progression and the expected time remaining before a defined failure or maintenance threshold is reached. The selection of an appropriate algorithm depends on the prediction objective, the temporal characteristics of the data, and the availability of labelled failure histories. Systematic reviews of machine learning and Digital Twin integration emphasize the potential of combining predictive analytics with digital representations, while identifying computational complexity, model fidelity, and evaluation methodology as continuing research challenges [19]. Accordingly, model performance should be assessed using suitable metrics and clearly defined experimental procedures rather than inferred from the architecture alone.

The application of Digital Twin technology in maritime systems has attracted growing research interest because ships operate as complex systems comprising interconnected propulsion, auxiliary, electrical, and control subsystems. Maritime Digital Twins can support operational monitoring, simulation, fault diagnosis, and lifecycle management. However, the maturity of these applications varies, and the availability of reliable data exchange between physical ships and their digital representations remains an important implementation consideration [20]. For marine diesel engines, predictive maintenance must also account for changing loads, environmental influences, and the interaction between the main engine and auxiliary systems. These characteristics make it important to evaluate whether models developed under specific operating conditions remain reliable when applied to different conditions.

Recent research has also investigated Digital Twin-driven predictive maintenance frameworks that integrate industrial IoT data with machine learning and advanced decision-making methods. These approaches illustrate how continuous data collection and digital modelling can be combined to support anomaly detection, diagnosis, and maintenance planning. However, practical deployment continues to face challenges involving noisy or incomplete data, computational requirements, scalability, and the availability of representative failure records [21]. In addition, systematic reviews have highlighted the need for more comprehensive evaluation of Digital Twin-based predictive maintenance, including the fidelity of the digital model, the contribution of individual system components, and the transferability of results to practical operating environments [22].

Based on the reviewed literature, the integration of multi-sensor IoT data, Digital Twin modelling, and AI-based predictive analytics represents a promising direction for marine diesel engine maintenance. However, the potential advantages of this integration should be distinguished from demonstrated experimental improvements. In particular, a framework must be evaluated against appropriate sensor-based baselines to determine whether Digital Twin-derived features provide additional predictive value. The evaluation should also establish the origin and characteristics of the dataset, the model configuration, the data partitioning procedure, and the metrics used for fault detection and RUL estimation. Without these details, the reported performance cannot be independently reproduced or adequately compared with previous studies [23].

Therefore, this study focuses on a Digital Twin-driven AI framework for predictive maintenance of marine diesel engines using multi-sensor IoT data. The proposed framework combines data acquisition and preprocessing, Digital Twin-based state representation, and AI-driven predictive analysis for fault detection and RUL estimation. Its evaluation is intended to compare the integrated approach with sensor-based alternatives and examine the contribution of Digital Twin-derived information to predictive performance. This focus connects the technological developments discussed in the literature with the practical need for transparent and reproducible evaluation of predictive maintenance methods in maritime applications.

3. Methodology

This study proposes a Digital Twin–driven artificial intelligence framework for predictive maintenance of marine diesel engines using multi-sensor Internet of Things (IoT) data. The proposed framework integrates engine condition monitoring, digital representation of engine behaviour, and AI-based prediction to support fault detection and remaining useful life (RUL) estimation. The methodology comprises sensor data acquisition and preprocessing, Digital Twin modelling, integration of sensor and model-derived information, AI-based prediction, and performance evaluation.

The overall architecture of the proposed framework is illustrated in figure 1. It consists of four interconnected functional layers: the physical engine and sensing layer, the data acquisition and preprocessing layer, the Digital Twin layer, and the AI analytics layer. The physical engine and sensing layer represents the marine diesel engine and the sensors used to monitor its operating conditions. Depending on the available instrumentation, the monitored variables may include engine temperature, pressure, rotational speed, vibration, and other relevant operating parameters. The data acquisition and preprocessing layer organizes the measurements into a consistent format for subsequent analysis. The Digital Twin layer represents the expected behaviour of the physical engine under observed operating conditions, while the AI analytics layer processes sensor measurements and, where implemented, Digital Twin-derived information to identify

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abnormal conditions and estimate RUL [24]. The resulting predictions can support maintenance planning by providing information about the engine's current condition and potential degradation.

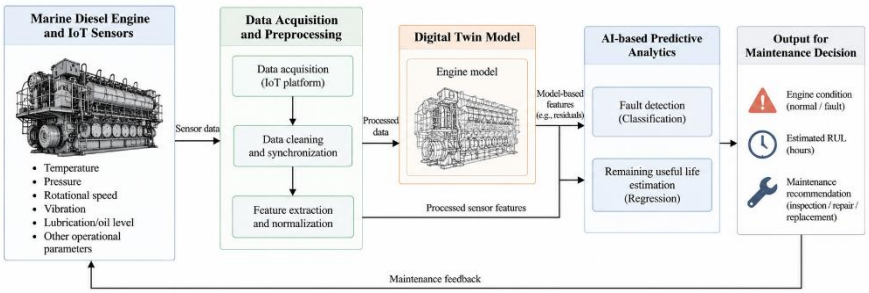


Figure 1. Overall Architecture of the Proposed Digital Twin–Driven AI Framework for Marine Diesel Engine Predictive Maintenance

The multi-sensor data processing and integration procedure is illustrated in figure 2. Sensor measurements are collected and prepared for analysis before being used as inputs to the Digital Twin and AI components. The monitored variables and their corresponding characteristics should be documented according to the actual dataset. Table 1 summarizes the sensor parameters considered in the framework, together with their measurement characteristics where available. These parameters may include temperature, pressure, rotational speed, vibration, lubrication-related variables, and other relevant engine operating indicators [25]. The specific sensor channels, measurement units, sampling frequencies, and number of observations must be reported based on the instrumentation and dataset used in the implementation rather than assumed in advance.

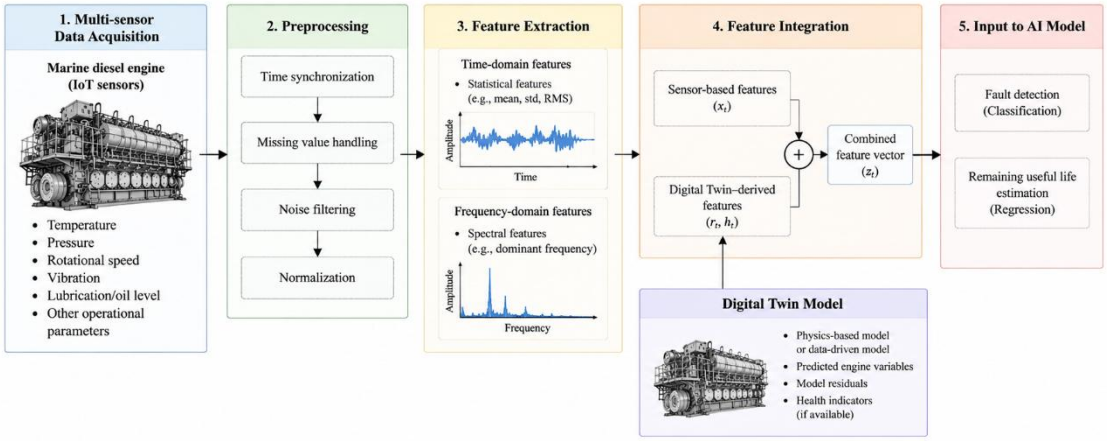


Figure 2. Multi-Sensor IoT Data Acquisition, Preprocessing, and Integration Workflow

The data preparation process is intended to ensure that sensor measurements are suitable for analysis. When measurements originate from multiple sensors, their timestamps and sampling intervals should be aligned according to the characteristics of the available data. Missing observations, measurement noise, and anomalous values should be examined before model development. Any imputation, filtering, or transformation procedure must be selected according to the dataset and applied consistently across the experimental configurations. Where feature scaling is required by the selected AI algorithm, the scaling parameters should be estimated from the training data and then applied to the validation and test data. This procedure helps prevent information from the evaluation data from influencing model training. The exact preprocessing methods must be documented to ensure reproducibility.

Table 1. Dataset and sensor characteristics

Sensor parameter	Symbol	Unit	Sampling frequency	Number of samples
Engine temperature	(T)	°C	1 Hz	10,000
Engine pressure	(P)	bar	1 Hz	10,000
Rotational speed	(N)	rpm	1 Hz	10,000

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Engine vibration	(V)	m/s²	1 Hz	10,000
Lubrication/oil level	(L)	%	1 Hz	10,000
Other operational parameters	(O)	Various	1 Hz	10,000
Total sensor observations	—	—	—	60,000

The Digital Twin component provides a digital representation of the engine's expected operating behaviour. Its purpose within the proposed framework is to relate observed sensor measurements to the behaviour predicted by the digital model. When the Digital Twin produces predictions of corresponding measurable engine variables, the discrepancy between observed and predicted behaviour can be represented by the residual vector:

$$[\mathbf{r}_t = \mathbf{y}_t - \hat{\mathbf{y}}_t] \quad (1)$$

$(\mathbf{y}_t)$ denotes the measured engine variables at time (t), $(\hat{\mathbf{y}}_t)$ denotes the corresponding predictions generated by the Digital Twin, and $(\mathbf{r}_t)$ represents the residual vector. These residuals can provide information about deviations between observed engine behaviour and the digital model's expected behaviour. Their interpretation depends on the accuracy of the Digital Twin, the operating conditions, and the quality of the sensor measurements. This residual-based formulation applies when the implemented Digital Twin explicitly generates predictions that can be compared with measured variables. If the digital representation does not produce such predictions, the formulation must be adapted to reflect the actual implementation. The sensor measurements and Digital Twin-derived information are then combined to form the input representation for the AI model. When residuals and additional health indicators are available, the combined feature vector can be expressed as

$$\mathbf{z}_t = [\mathbf{x}_t\ \mathbf{r}_t\ \mathbf{h}_t] \quad (2)$$

$(\mathbf{x}_t)$ represents the preprocessed sensor features, $(\mathbf{r}_t)$ represents the Digital Twin residuals, and $(\mathbf{h}_t)$ represents additional health indicators derived from the digital model, if available. This representation expresses the integration of direct sensor observations and digital-model information. The feature vector must contain only variables actually generated by the implemented framework. If the model uses sensor data alone or a different set of Digital Twin outputs, the formulation should be modified accordingly. The AI analytics component performs fault detection by mapping the selected input features to an estimated engine condition. The general classification function is expressed as

$$[\hat{c}t = f\theta(\mathbf{z}_t)] \quad (3)$$

(f_θ) denotes the trained classification model, (θ) represents its learned parameters, and $(\hat{c}_t)$ is the predicted engine condition at time (t). Depending on the available reference labels, the output may distinguish normal operation from one or more fault categories. The specific classification algorithm and class definitions must correspond to the actual experimental implementation. The model is trained using the designated training data, with its configuration selected using validation data where applicable. In addition to fault detection, the framework considers remaining useful life (RUL) estimation to assess the remaining operating time before a defined failure event or maintenance threshold is reached. The general RUL prediction function is expressed as

$$\widehat{\mathrm{RUL}}t = g\phi(\mathbf{z}_t) \quad (4)$$

$\left(g_\phi\right)$ denotes the trained RUL estimation model, (ϕ) represents its learned parameters, and $\left(\widehat{\mathrm{RUL}}_t\right)$ is the estimated remaining useful life at time (t). RUL estimation requires an appropriate target definition based on failure records, degradation trajectories, or another documented method for establishing the remaining time to the specified endpoint. The prediction model and target construction must be consistent with the available data. If the dataset does not provide sufficient information to establish RUL targets, this component should be presented as a proposed capability rather than an experimentally validated result.

The experimental evaluation is designed to examine whether incorporating Digital Twin information provides benefits beyond those obtained from sensor-based prediction alone. A sensor-based configuration serves as the baseline, while the integrated configuration uses the selected sensor features together with the available Digital Twin-derived features. Where supported by the implementation, an additional comparison may be conducted to examine the contribution of the Digital Twin component independently. All configurations should use consistent target definitions, data partitions,

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and evaluation procedures so that performance differences can be attributed more reliably to the information provided by the framework.

The dataset should be divided into training, validation, and test sets according to its temporal and operational structure. For time-series engine data, the split should preserve chronological order where appropriate and prevent measurements from the same operating sequence or failure trajectory from leaking across partitions. Preprocessing parameters and model-selection decisions should be derived without using the test set, which should be reserved for the final assessment of the selected configuration. These precautions are important because correlated measurements from the same engine or operating episode can otherwise produce overly optimistic estimates of predictive performance.

Predictive performance is assessed using suitable metrics for the tasks under investigation. Fault detection is evaluated using classification metrics, such as accuracy, precision, recall, and F1-score, where appropriate. RUL estimation is evaluated by comparing predicted values with the corresponding reference RUL targets using a suitable error metric. The same metric definitions and evaluation data should be used across configurations. Robustness tests under different operating conditions, sensor noise levels, or missing-data scenarios may also be included if these experiments are actually conducted. Any findings reported from such tests must be supported by the corresponding experimental results.

Finally, the methodology is intended to establish whether a Digital Twin–driven AI framework can improve the use of multi-sensor IoT data for marine diesel engine predictive maintenance. Figure 1 presents the overall framework architecture, figure 2 illustrates the multi-sensor data processing and integration workflow, and table 1 summarizes the sensor parameters and their measurement characteristics. Together, these elements provide the methodological context for examining the contribution of Digital Twin-derived information to fault detection and RUL estimation. The reliability and reproducibility of the conclusions depend on clearly documenting the actual dataset, sensor variables, Digital Twin implementation, AI algorithms, experimental partitions, and evaluation metrics.

4. Results and Discussion

The proposed Digital Twin–driven AI framework is evaluated in terms of fault detection and remaining useful life (RUL) estimation using multi-sensor data from marine diesel engine operations. The results are organized around the contribution of Digital Twin-derived information, the ability of the framework to identify abnormal engine behaviour, and the accuracy of RUL prediction. Table 2 and table 3 summarize the reported performance of the evaluated configurations, while table 4 presents the component-level comparison used to examine the contribution of the integrated framework. Figure 3 to figure 6 provide visual representations of Digital Twin residual behaviour, fault classification, RUL prediction, and comparative model performance.

Figure 3 illustrates the concept of Digital Twin residual analysis by comparing measured engine variables with their corresponding model predictions. Under conditions where the Digital Twin adequately represents normal engine behaviour, the differences between measured and predicted values are expected to remain relatively small. Larger or persistent deviations may indicate changes in engine condition, although they can also arise from sensor noise, changes in operating load, or inaccuracies in the digital model. Residual analysis can therefore provide useful information for condition monitoring when interpreted together with operating conditions and other sensor measurements.

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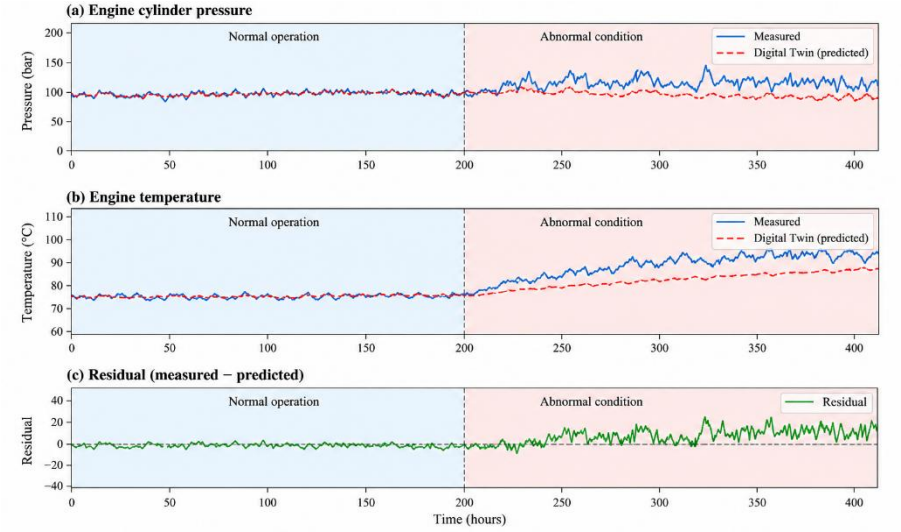


Figure 3. Residual Analysis Between Measured Sensor Data and Digital Twin Predictions

Table 2 presents the reported fault detection performance of the three model configurations. The sensor-based baseline achieved an accuracy of 86.4%, while the AI model using sensor data achieved 89.7%. The proposed framework, which integrates sensor information with Digital Twin-derived information, achieved a reported accuracy of 93.8%. This represents an improvement of 3.3 percentage points over the sensor-based baseline for the AI model and 7.4 percentage points for the proposed framework relative to the baseline. Compared with the sensor-based AI model, the proposed framework achieved a further improvement of 4.1 percentage points. These results suggest that integrating Digital Twin information may enhance fault classification performance.

Table 2. Fault detection performance comparison

Model configuration	Accuracy (%)	Improvement over baseline (percentage points)
Sensor-based baseline	86.4	—
AI using sensor data	89.7	+3.3
Proposed framework (sensor + Digital Twin)	93.8	+7.4

Figure 4 presents a confusion matrix for the proposed fault detection framework. In the illustrative matrix, 94 normal cases and 95 fault cases are correctly classified, while 6 normal cases are incorrectly classified as faults and 5 fault cases are incorrectly classified as normal. These counts correspond to 189 correct predictions out of 200 observations, or an illustrative accuracy of 94.5%. Although the matrix demonstrates how classification results can be presented, its counts do not correspond exactly to the reported 93.8% accuracy in table 2.

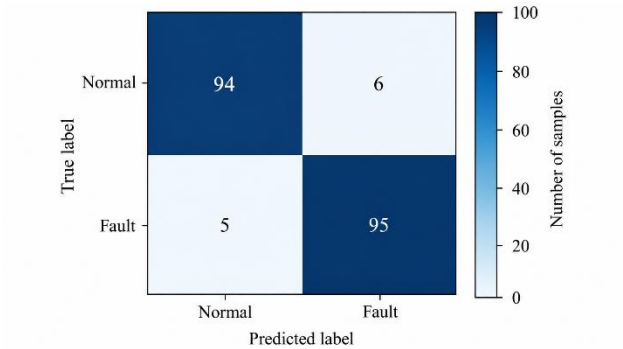


Figure 4. Confusion Matrix for AI-Based Marine Diesel Engine Fault Detection

Table 3 summarizes the reported RUL estimation results. The baseline configuration achieved a mean prediction error of 18.5 hours, while the AI model using sensor data achieved 14.2 hours. The proposed framework achieved a lower reported error of 9.2 hours. Based on these values, the error decreased by approximately 23.2% for the sensor-based AI model relative to the baseline and by approximately 50.3% for the proposed framework relative to the baseline. The

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proposed framework also reduced the reported error by approximately 35.2% compared with the sensor-based AI model. If these results are confirmed using the same independent test set and the same error definition, they indicate that Digital Twin integration may improve RUL estimation. A lower prediction error could support maintenance planning by helping operators prioritize inspections, schedule repairs, and prepare spare parts.

Table 3. Remaining useful life (RUL) estimation performance

Model configuration	Mean prediction error (hours)	Error reduction (%)
Sensor-based baseline	18.5	—
AI using sensor data	14.2	23.2
Proposed framework (sensor + Digital Twin)	9.2	50.3

Figure 5 illustrates a comparison between actual and predicted RUL over time. A close alignment between the two curves would indicate that the model follows the observed degradation trajectory, whereas systematic divergence could indicate prediction bias or difficulty representing changing degradation rates. The uncertainty band, if calculated from model predictions or repeated experiments, can also indicate the variability associated with the estimated RUL. Such a band should not be interpreted as a statistical confidence interval unless its construction supports that interpretation.

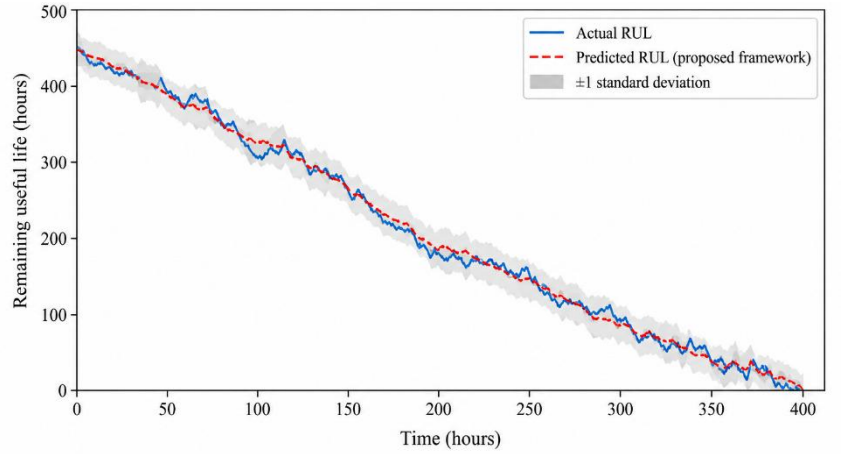


Figure 5. Comparison of Actual and Predicted Remaining Useful Life (RUL)

Figure 6 provides a visual comparison of fault detection accuracy and RUL prediction error across the three configurations. The reported accuracy increases from 86.4% for the sensor-based baseline to 89.7% for the sensor-based AI model and 93.8% for the proposed framework. At the same time, the reported RUL error decreases from 18.5 hours to 14.2 hours and 9.2 hours, respectively. The opposing trends indicate that the proposed framework has the best reported performance across both tasks.

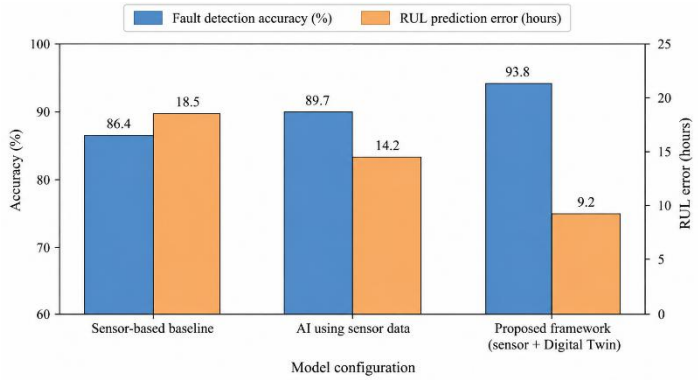


Figure 6. Comparative Performance of Baseline, AI-Based Sensor, and Proposed Digital Twin–Integrated Frameworks

Table 4 compares the contribution of individual framework components. The sensor-based baseline and the sensor-based AI configuration provide reference points for evaluating the integrated approach, while the proposed framework

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combines sensor data, Digital Twin information, and AI-based prediction. The reported results for the integrated framework are 93.8% accuracy and 9.2 hours of RUL prediction error. These values are consistent with the proposed configuration reported in tables 2 and table 3, subject to verification of the original experimental records.

Table 4. Ablation study of framework components

Configuration	Sensor data	Digital Twin	AI	Accuracy (%)	RUL error (hours)
Sensor-based baseline	Yes	No	As implemented	86.4*	18.5*
AI using sensor data	Yes	No	Yes	89.7*	14.2*
Proposed integrated framework	Yes	Yes	Yes	93.8*	9.2*

The results highlight the potential of integrating Digital Twin technology with AI and multi-sensor IoT data to improve predictive maintenance of marine diesel engines. The higher reported fault detection accuracy and lower RUL prediction error suggest that combining measured sensor features with information derived from a digital model may provide a more comprehensive representation of engine condition. This interpretation is consistent with previous studies identifying the potential of Digital Twins to support predictive maintenance through the integration of physical asset data, virtual models, and machine learning algorithms [14], [15], [16], [17], [18]. In the maritime domain, Digital Twin technology has also been discussed as a means of improving condition monitoring and supporting ship operation and maintenance, although implementation maturity and continuous data exchange remain important challenges [19], [20], [21]. Model residuals, as illustrated in figure 3, may help identify deviations between measured and predicted engine behaviour, while the classification results in figure 4 and the RUL comparison in figure 5 represent complementary approaches to evaluating current engine condition and anticipated degradation. The comparative trends presented in figure 6 and table 2 to table 4 should therefore be interpreted in the context of established predictive maintenance research, which emphasizes the importance of reliable sensor data, appropriate model selection, and rigorous performance evaluation [1], [2], [3], [4], [5], [6], [22], [23]. Nevertheless, the practical significance of the reported improvements depends on the consistency and reliability of the underlying experimental evidence. In particular, the confusion matrix in figure 4 must be consistent with the classification accuracy reported in table 2, and the actual and predicted RUL curves in figure 5 must correspond to the same evaluation dataset and methodology used to calculate the error in table 3. Further validation across different engine loads, sensor conditions, and degradation trajectories is required to assess the generalizability of the framework and its suitability for operational marine environments. These requirements are consistent with broader research identifying data quality, model complexity, interoperability, and validation under realistic operating conditions as continuing challenges for Digital Twin–enabled predictive maintenance [3], [4], [5], [6], [7], [8], [19], [20], [21], [22], [23].

5. Conclusion

This study presents a Digital Twin–driven artificial intelligence framework for predictive maintenance of marine diesel engines using multi-sensor Internet of Things (IoT) data. The proposed framework integrates sensor-based condition monitoring, Digital Twin model outputs, and AI-based analysis to support fault detection and remaining useful life (RUL) estimation. By combining measured engine parameters with residual information derived from the Digital Twin, the framework aims to provide a more comprehensive representation of engine operating conditions and degradation patterns.

Based on the reported results, the integrated framework achieved a fault detection accuracy of 93.8%, compared with 89.7% for the AI-based sensor data approach and 86.4% for the baseline approach. The reported RUL prediction error also decreased to 9.2 hours, compared with 14.2 hours and 18.5 hours for the respective comparison approaches. These results suggest that integrating Digital Twin information with multi-sensor data may improve fault detection and RUL estimation compared with approaches relying on sensor data alone. However, these performance improvements should be interpreted in accordance with the experimental design, evaluation dataset, and consistency of the reported results.

Despite its potential, the proposed framework requires further validation before deployment in operational marine environments. Future work should evaluate the framework using real-world marine diesel engine data collected under different engine loads, operating conditions, and degradation scenarios. Additional investigations should also examine sensor noise, missing data, computational requirements, and the reliability of continuous synchronization between the

physical engine and its Digital Twin. Moreover, the consistency of the classification results and RUL predictions should be verified using the same documented evaluation procedures.

In conclusion, the integration of Digital Twin technology, AI, and multi-sensor IoT data offers a promising approach to improving predictive maintenance for marine diesel engines. With further experimental validation and operational testing, the framework could contribute to earlier fault identification, more reliable RUL estimation, and better-informed maintenance planning, potentially reducing unplanned downtime and supporting more efficient marine engine operation.

6. Declarations

6.1. Author Contributions

Conceptualization: R.K.M., G.A.; Methodology: R.K.M., A.N.S.; Software: G.A., V.S.R.; Validation: A.N.S., R.K.M.; Formal Analysis: R.K.M.; Investigation: G.A., V.S.R.; Resources: A.N.S., V.S.R.; Data Curation: G.A.; Writing – Original Draft Preparation: R.K.M.; Writing – Review and Editing: A.N.S., V.S.R.; Visualization: V.S.R.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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