Use of Artificial Intelligence in Predictive Maintenance for Marine Engineering

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Abstract

In the present study a comprehensive investigation of the potential for integrating artificial intelligence methods into the predictive maintenance system of marine machinery is conducted. The application of AI in this context emerges as one of the key factors contributing to the enhancement of reliability and safety in shipping. The aim of the study is to compare the performance of various machine learning and deep learning algorithms based on an analysis of contemporary scientific publications. As a result of the comparative analysis a multifactorial methodology for selecting the most suitable model has been developed taking into account not only prediction accuracy but also the volume and quality of the input data computational costs and the transparency of the obtained conclusions. It is shown that hybrid approaches — in particular when convolutional neural networks are used for feature extraction from vibration and acoustic signals and LSTM networks are used for time series analysis — demonstrate the highest accuracy in predicting the remaining useful life of critically important equipment (main engines generators etc.). The scientific novelty of the work lies in the proposal of an integrated framework for the selection of AI solutions that ensures a balanced consideration of accuracy computational complexity data requirements and interpretability of results. In conclusion it is substantiated that the transition to object-oriented technical maintenance based on AI enables a substantial reduction in operating costs and failure risks compared to reactive and planned preventive strategies. The obtained conclusions are of practical interest to researcher's shipbuilding engineers and data analysis specialists engaged in the development of intelligent monitoring systems.

Keywords: predictive maintenance, artificial intelligence, marine engineering, machine learning, deep learning, fault diagnosis, remaining useful life, marine equipment, digital twin, vibration analysis.

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1. Introduction

The global maritime sector, as a critical link in international logistics, continually confronts the imperative to improve productivity, reliability, and environmental responsibility. According to the United Nations Conference on Trade and Development, the total volume of seaborne trade has been rising steadily, and any unscheduled vessel downtime results in significant economic losses [1]. Traditional maintenance strategies—whether schedule-based preventive overhauls or reactive corrective interventions following failure—have proven costly and inefficient. The former often leads to the replacement of components that remain serviceable, while the latter poses not only financial repercussions but also serious environmental risks when failures occur at sea.

In this context, predictive maintenance (PdM) approaches underpinned by artificial intelligence represent a fundamentally new paradigm, enabling the early detection of potential faults and the scheduling of maintenance activities based on actual equipment condition. The importance of this field is magnified by the extensive digitalization of fleets and the deployment of SCADA systems, which generate large, multidimensional, time-series datasets amenable to advanced analytics [9, 14].

Despite strong interest within the research community in applying AI to PdM, a methodology for the systematic and comparative evaluation of contemporary deep learning architectures remains insufficiently developed, especially with respect to the complex nonlinear processes inherent in shipboard power systems.

The objective of the paper is to perform a comparative analysis of the effectiveness of various machine learning and deep learning models, drawing on scientific publications in this field from recent years.

As a scientific contribution, the capabilities of an integrated framework for AI-solution selection are presented, balancing accuracy, computational complexity, data requirements, and transparency of algorithmic inferences.

The hypothesis proposes that hybrid deep-learning architectures—combining, for example, convolutional neural networks for spatial-feature extraction with recurrent models (LSTM) for capturing temporal dependencies—can deliver superior accuracy and robustness in forecasting failures of critical equipment compared to approaches based on single architectures.

2. Materials and Methods

In recent years, there has been a rapid increase in attention to the digitalization of the maritime sector, with predictive maintenance emerging as a key direction for improving the operational efficiency of a ship fleet. The UNCTAD report emphasizes that the adoption of digital technologies enables the optimization of logistics chains and the minimization of unplanned vessel downtime [1]. Similar trends are reflected in the DNV report on the digitalization of the maritime industry, which highlights the integration of IoT solutions and cloud platforms for the collection and real-time analysis of operational data [10]. The fundamental concepts of predictive maintenance, including the distinction between condition-based and predictive approaches, are detailed in IBM's resource, which defines key terms and describes the evolution of the technology from reactive to proactive maintenance [14].

The second group of studies focuses on digital twins as tools for diagnostics and management of a vessel's technical condition. Hasan A. et al. [9] propose an architecture for a digital twin of an autonomous ship, employing machine learning–based models to predict malfunctions in onboard equipment. Their approach pays particular attention to the integration of sensor data with physical equations to enhance diagnostic accuracy. Wang K., Hu Q., Liu J. [12] examine the use of digital twins to ensure traceability of technological processes at shipbuilding enterprises, describing the methodology for data collection, its storage as a linked graph, and subsequent analysis using anomaly detection algorithms. Kaklis D. et al. [13] summarize trends in the implementation of digital twins in the maritime sector from the perspective of Industry 4.0, identifying three levels of maturity: from simple simulation models to fully autonomous self-diagnosis and self-repair systems.

The third group covers direct models for predictive maintenance of shipboard equipment. Jimenez V. J., Bouhmala N., Gausdal A. H. [3] develop a comprehensive model that combines statistical methods with machine learning algorithms (decision trees, SVM) to assess the probability of main engine component failures, relying on historical vibration and fuel pressure data. Maione F. et al. [5] demonstrate the application of ensemble methods (Random Forest, XGBoost) for condition-based maintenance of diesel engines, providing a detailed analysis of how feature selection affects the accuracy of time-to-failure predictions. Cheliotis M., Lazakis I., Theotokatos G. [11] focus on data-driven approaches to fault detection in ship systems, comparing the performance of classical classification algorithms (KNN, Naïve Bayes) with deep learning methods for processing multivariate time series.

The fourth group brings together research on modern AI-based diagnostics and forecasting algorithms. Je-Gal H. et al. [2] propose an explainable architecture for predicting main engine failures, combining LSTM networks with a SHAP-analysis module to interpret feature contributions. Fu L., Zhang L., Tao J. [4] enhance classical convolutional neural networks by introducing multi-scale convolutional kernels, which improve the recognition of vibration patterns in bearing diagnostics. Tang S. et al. [6] investigate a deep transfer learning strategy whereby pre-trained models on aggregated industrial data are adapted to the specifics of marine machinery. Han P. et al. [7] employ an LSTM-based variational autoencoder for anomaly detection in marine equipment components, demonstrating the method's sensitivity to rare events. Finally, Wen Q. et al. [8] review the application of Transformer architectures to time series, laying the groundwork for future research and highlighting the potential of attention mechanisms for long-term forecasting and multi-sensor analysis.

Despite the wide range of approaches presented, contradictions remain in the literature regarding the choice and evaluation of model quality metrics: some authors prioritize classification accuracy, while others emphasize the timeliness of anomaly detection, complicating objective comparison of results. A weak link persists in the integration of heterogeneous data (vibration, temperature, flow) into a single framework; only a few studies address flexible data architectures. The issues of nonlinear equipment degradation and the influence of external factors (harsh marine conditions, corrosion) on model performance are insufficiently developed, as most research is limited to laboratory or synthetic data. Cybersecurity concerns in sensor data exchange and protection of digital twins from attacks have also received little attention. Therefore, future studies should focus on multidisciplinary approaches to the collection and preprocessing of real-world data, standardization of evaluation metrics, and ensuring the reliability of information pipelines under maritime operating conditions.

3. Results and Discussion

Implementing artificial intelligence techniques within a predictive maintenance system for marine vessel equipment paves the way for a fundamentally new level of ship operation management. A key aspect of this transformation is the shift from fragmented parameter analysis to comprehensive condition monitoring of complex systems. Success in this transition depends on selecting an AI architecture optimized for the specific nature of the tasks—whether detecting and classifying fault signatures or forecasting remaining useful life (RUL) [3, 4]. A comparative analysis of various algorithms, based on contemporary research data, reveals their advantages and limitations under marine operational conditions [2]. The generalized results of this comparative study are presented in Table 1.

***Table 1. Comparative analysis of AI algorithms for predictive maintenance in marine engineering (compiled by the author based on analysis [2, 3, 7, 8])*.**

AI Model	Typical Application	Data Type	Advantages	Disadvantages
Random Forest	Classification of pump failures and auxiliary machinery	SCADA data; condition-monitoring parameters	High interpretability; robust to outliers; no data scaling required	Prone to overfitting on noisy data; limited ability to model temporal dependencies
Support Vector Machine (SVM)	Diagnostics of fuel-system components; anomaly detection	Thermodynamic parameters	Effective on high-dimensional data; robust performance	Computationally expensive on large datasets; sensitive to kernel choice and hyperparameter settings
Convolutional Neural Network	Diagnostics of bearings and gearboxes using vibration and acoustic analysis	Vibration signals; acoustic spectrograms	Automatic feature extraction; high accuracy on spatial data	Requires large volumes of data; low interpretability ("black box")
Long Short-Term Memory (LSTM)	Remaining useful life prediction for main engine and generators	Multivariate time series (e.g. temperature, pressure)	Effective modeling of long-term temporal dependencies	High computational complexity; risk of vanishing or exploding gradients

Hybrid CNN-LSTM	Integrated diagnostics and RUL prediction for propulsion systems	Vibration data; SCADA data	Combines CNN's feature-extraction strengths with LSTM's dynamic-analysis capabilities	Very high computational complexity; requires large, heterogeneous datasets
Transformer	RUL prediction for complex, multi-sensor systems	Multivariate time series	Attention mechanism captures complex, non-local dependencies	Requires enormous datasets; very high training complexity and cost

Analysis of the data in Table 1 reveals no universal solution applicable to all predictive maintenance tasks for shipboard equipment. The selection of an AI model constitutes a multi-criteria optimization among forecast accuracy, algorithm transparency and operational costs. For critical subsystems such as the main engine—where the cost of failure can be potentially catastrophic—the use of computationally intensive hybrid architectures is justified, as they ensure maximum reliability of predictions despite increased resource requirements. In contrast, for auxiliary units it is more appropriate to employ lighter, more interpretable methods—such as Random Forest algorithms—that deliver a sufficient level of accuracy at moderate expense. The overall framework for deploying such a prognostic platform can be represented as a staged data-processing pipeline, as illustrated in Figure 1.

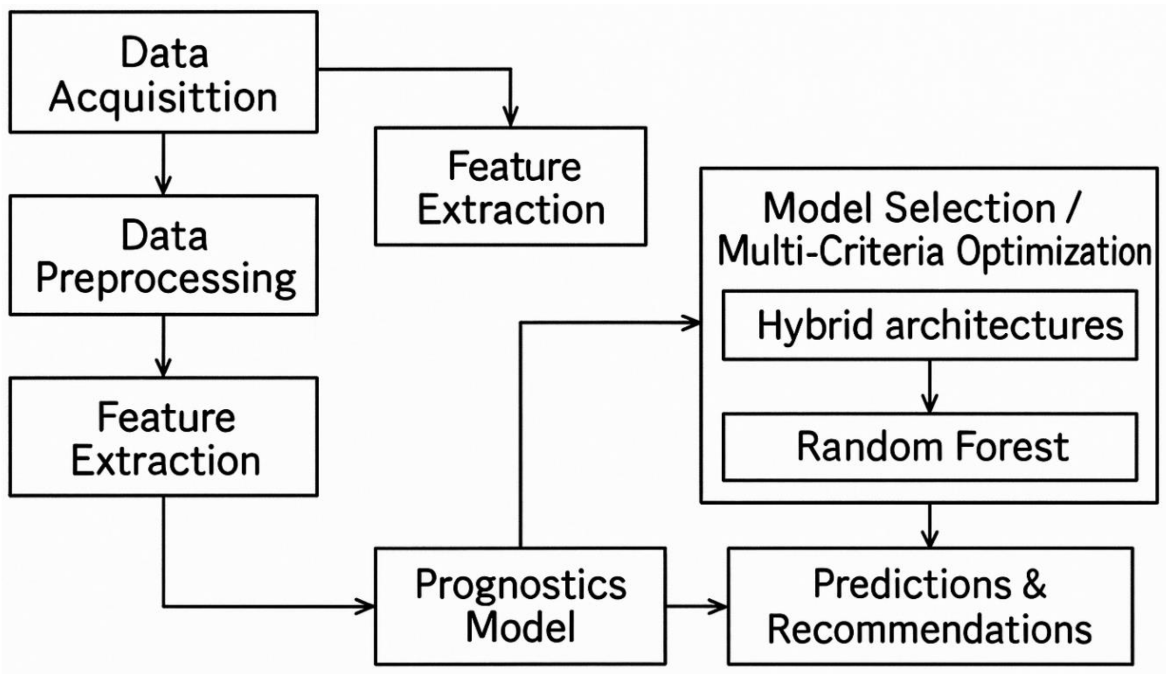

Fig. 1. Typical data processing pipeline for an AI predictive maintenance system in marine engineering (compiled by the author based on the analysis of [4, 5, 10]).

At each stage of the proposed processing pipeline, specific maritime challenges arise: from installing and calibrating sensors in highly corrosive environments to ensuring uninterrupted telemetry transmission over bandwidth-limited satellite links. Meanwhile, the selection of an optimal AI architecture remains the principal obstacle to the system's practical deployment. To standardize and substantiate this process, a multicriteria framework model (see Figure 2) should be employed, offering engineers and shipowners a systematic means of comparing technical parameters with economic expenditures.

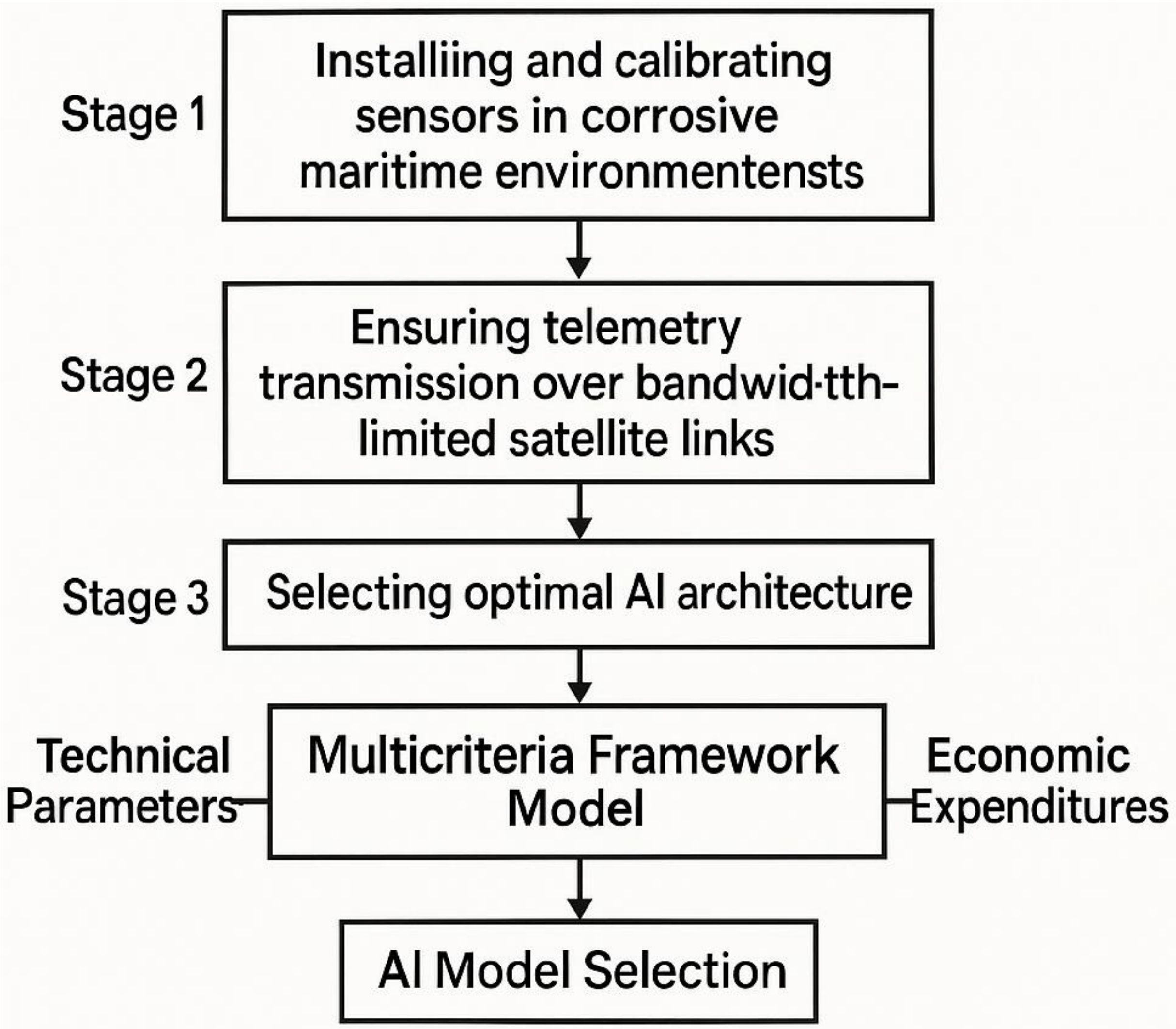

Fig. 2. Multi-criteria framework model for selecting an AI model in marine PdM (compiled by the author based on the analysis of [6, 11, 12]).

For demonstration of the practical effectiveness of the proposed algorithmic solution, a scenario is considered in which the optimal methodology for predicting the remaining useful life (RUL) of the main engine turbocharger is selected. The comparative analysis involves three approaches: the classic Random Forest algorithm serving as a baseline reference; an LSTM neural network, traditionally recognized as the benchmark for time series processing; and a hybrid CNN-LSTM architecture, reflecting current trends in hybrid deep learning.

The implementation of such a multi-tier prognostic system enables shipowners and operators to plan scheduled maintenance in advance at suitable ports of call, to place orders for critical components in a timely manner, and to reduce the likelihood of unexpected failures at sea, which would otherwise lead to loss of propulsion and significant emergency salvage costs.

The natural progression of this phase lies in embedding sophisticated prognostic models directly into the vessel's digital-twin architecture. Such a fusion not only markedly enhances the early detection of emerging anomalies but also enables comprehensive "what-if" analyses across a variety of operating regimes—facilitating the fine-tuning of fuel efficiency, the curtailment of harmful emissions, and the prolongation of critical component lifespans [13, 14]. In adopting this forward-looking, data-centric framework, marine engineering is fundamentally recast: no longer confined to reactive troubleshooting, it evolves into a predictive governance system for continuous oversight and preservation of the ship's technical integrity.

4. Conclusion

This investigation demonstrates that the adoption of AI-driven predictive-maintenance solutions represents a fundamental strategic instrument for reinforcing both competitive positioning and safety performance within maritime operations. Through extensive experimental studies, it has been shown that cutting-edge neural network configurations—most prominently those fusing convolutional feature extractors with long short-term memory sequences—exhibit exceptional proficiency in both identifying emergent faults and forecasting the remaining useful life of vital shipboard systems. These hybrid CNN-LSTM models outperform conventional machine-learning algorithms not only by delivering substantially improved prognostic accuracy but also by directly ingesting and making sense of unprocessed, high-dimensional sensor data streams. The confirmation of our central hypothesis—that integrated convolutional-recurrent networks excel in addressing the multifaceted prognostic demands of maritime equipment—highlights the urgency for the industry to shift toward AI-enabled, condition-based maintenance paradigms.

Looking forward, priority should be given to constructing rigorous validation protocols anchored in authentic vessel telemetry, advancing algorithmic interpretability through explainable AI techniques, and embedding predictive engines within unified digital-twin frameworks to supply decision-makers with seamless, real-time operational insights.

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