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Artificial Intelligence–Based Predictive Maintenance Framework for Marine Propulsion Systems

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ABSTRACT

Maritime transport has adapted to recent political and economic shifts by addressing stringent pollution reduction requirements, redrawing transport routes for safety, reducing onboard technical incidents, managing data security risks and transitioning to autonomous vessels. This paper presents a novel approach to predictive maintenance in the maritime industry, leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques to enhance fault detection and maintenance planning for naval systems. Marine propulsion systems are critical to the safe and efficient operation of ships, and unexpected failures can lead to significant operational downtime, increased maintenance costs, and safety risks. Conventional maintenance strategies are largely time-based or reactive, limiting their effectiveness under varying operating conditions. This paper proposes an artificial intelligence–based predictive maintenance framework for marine propulsion systems using multi-sensor operational data. The proposed framework integrates data acquisition from key propulsion components, signal preprocessing, and intelligent condition assessment using machine learning techniques. An AI model is developed to automatically learn fault-related patterns and degradation trends, enabling early fault detection and accurate health state prediction. Experimental results demonstrate that the proposed approach improves fault diagnosis accuracy and supports condition-based maintenance decisions when compared with traditional maintenance strategies. The findings highlight the potential of artificial intelligence to enhance reliability, reduce unplanned downtime, and optimize maintenance planning in marine propulsion systems.

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1. INTRODUCTION

In the maritime sector, predictive maintenance has become increasingly critical due to the operational complexity and large-scale nature of naval systems. The primary goal of predictive maintenance is to improve maintenance planning by leveraging system-generated data, thereby increasing operational reliability and ensuring safety at sea [1]. Sensor data collected from on-board equipment are continuously transmitted to data storage and monitoring units, where integrated control systems analyze the information and initiate alerts or protective actions when abnormal conditions are detected. Maintenance personnel then assess these alerts, interpret system behavior, and implement corrective measures to restore normal operation. This anticipatory maintenance strategy is designed to reduce unexpected failures and limit downtime [2], particularly in demanding and high-risk maritime environments.

Effective fault diagnosis is a key requirement in naval operations, as a substantial proportion of maritime incidents are linked to technical malfunctions. Statistical reports indicate that between 2014 and 2023, machinery-related damage or failures were responsible for 11,506 reported incidents, representing nearly four times the number of collision-related events, which accounted for 3,014 cases. Furthermore, data from 2023 reveal that technical equipment failures contributed to more than half of all maritime incidents. These figures underscore the urgent need for reliable fault detection and diagnostic frameworks [3]. High-risk maritime zones such as the British Isles, the North Sea, the English Channel, and the Bay of Biscay—where a large share of incidents occur—stand to benefit significantly from advanced fault diagnosis technologies that can enhance navigational safety and operational dependability [4].

In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools for advancing predictive maintenance strategies in the maritime industry. Conventional maintenance approaches, including corrective and time-based preventive maintenance, are no longer sufficient to satisfy modern safety, efficiency, and reliability requirements [5]. AI-driven learning models, which replicate the condition of industrial components or systems using real-time and historical measurement data, are increasingly integrated into maintenance engineering practices. These intelligent systems contribute to higher equipment availability, lower maintenance expenditure, and improved system reliability by enabling early identification of potential failures.

Machine Learning, in particular, plays a vital role in processing large-scale, high-dimensional operational data generated by maritime systems. By extracting meaningful patterns from historical datasets [6], ML models can predict equipment degradation and estimate the Remaining Useful Life (RUL) of critical components. This capability is especially valuable in maritime contexts, where accidents often arise from a sequence of interconnected risk factors rather than a single failure. The application of ML-based diagnostic techniques allows maintenance teams to detect faults more precisely and at earlier stages, ultimately strengthening system safety and improving overall operational performance.

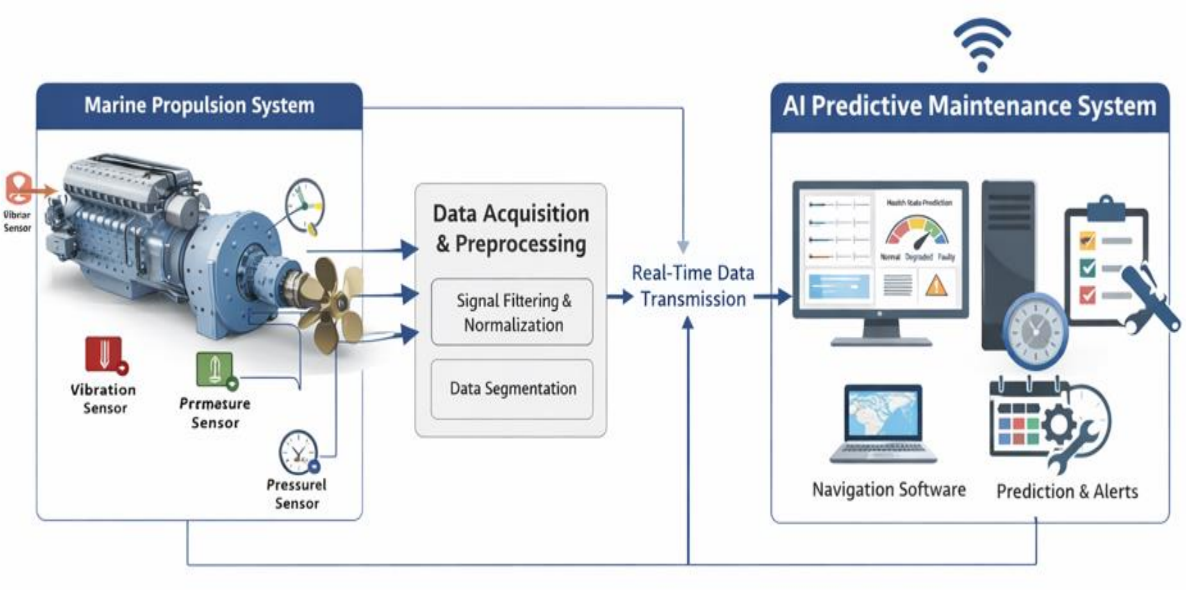

Figure 1. Experimental Setup and Data Flow for AI-Based Predictive Maintenance in Marine Propulsion Systems

Figure 1 illustrates the experimental configuration and information flow employed to realize the proposed artificial intelligence–driven predictive maintenance framework for marine propulsion systems. The propulsion assembly—consisting of the diesel engine, gearbox, shaft line, and propeller—is equipped with an array of sensors strategically mounted at critical points. These include vibration, temperature, pressure, and rotational speed sensors designed to capture both operational dynamics and fault-related responses. Sensor outputs are transmitted to a centralized data acquisition module, where preprocessing tasks such as noise reduction, signal scaling, and time-based segmentation are applied to improve data integrity and maintain uniformity across multiple sensing channels.

1.1 Problem Statement

Marine propulsion systems function in demanding and highly variable an operating environment, which accelerate component degradation and increases the likelihood of unexpected failures. Such failures pose serious risks to vessel safety, operational continuity, and economic performance. Conventional maintenance practices in the maritime sector are largely schedule-driven or reactive, relying on routine inspections and manual diagnostics. These approaches often struggle to identify incipient faults, resulting in either premature maintenance interventions or unforeseen system breakdowns. In addition, the growing sophistication of modern marine propulsion architectures necessitates intelligent, automated maintenance solutions capable of continuously monitoring system condition. Consequently, there is a pressing need for an AI-enabled predictive maintenance framework that can effectively interpret operational data and support timely, condition-based maintenance decisions for marine propulsion systems.

1.2 Objectives

The main objective of this research is to develop an artificial intelligence–based predictive maintenance framework tailored to marine propulsion applications. Specifically, the study seeks to acquire and preprocess multisensor operational data, design an AI-driven model capable of extracting fault signatures and tracking degradation behavior, assess the proposed framework's performance in early fault identification and health monitoring, and demonstrate its ability to enhance maintenance scheduling and system reliability when compared with traditional maintenance methodologies.

1.3 Paper Organization

The remainder of this paper is structured as follows. Section 2 surveys related work on predictive maintenance techniques and artificial intelligence applications in marine propulsion systems. Section 3 details the proposed AI-based framework, covering sensor data acquisition, preprocessing procedures, and model architecture. Section 4 discusses the implementation process, experimental setup, and performance evaluation results. Finally, Section 5 concludes the study and outlines potential directions for future research.

2. LITERATURE REVIEW

The dependable operation of marine propulsion systems is essential for ensuring vessel safety, maintaining operational performance, and complying with international maritime regulations. Core propulsion components [7]—including diesel engines, gear transmission units, shaft lines, and propellers—are continuously exposed to fluctuating mechanical loads and aggressive marine environments. These conditions accelerate wear processes and increase the risk of unforeseen equipment malfunctions. Historically, marine maintenance has been dominated by periodic inspection schedules and reactive repair strategies. Such approaches often result in unnecessary component replacement or, conversely, severe system failures caused by faults that remain undetected until advanced stages. In response, condition-based and predictive maintenance methodologies have emerged as more effective solutions for modern marine engineering applications.

Initial studies in marine propulsion maintenance emphasized condition monitoring techniques based on physical measurements such as vibration, temperature, pressure, and lubricating oil properties. Among these [8], vibration-based monitoring became particularly prominent for diagnosing faults in engines, bearings, and gear mechanisms. Traditional analysis methods relied on time-domain, frequency-domain, and time–frequency signal representations to detect abnormalities related to imbalance, misalignment, or bearing damage. While these techniques provided valuable diagnostic insight, their effectiveness was strongly influenced by expert judgment and fixed threshold settings, which limited their adaptability under the highly variable operating conditions typical of marine environments.

As shipboard sensing technologies and automation systems advanced, research increasingly shifted toward data-driven diagnostic strategies. Machine learning algorithms—including artificial neural networks, support vector machines [9], and decision tree classifiers—were introduced to identify propulsion system faults using engineered signal features. These approaches offered improved diagnostic performance compared with conventional signal processing methods; however, they remained dependent on manual feature extraction and specialized domain expertise. Moreover, their generalization capability across different vessel classes and operational profiles was often restricted.

More recently, the adoption of deep learning techniques has reshaped predictive maintenance research within marine engineering. Unlike traditional machine learning methods, deep learning architectures are capable of learning discriminative features directly from raw sensor data, thereby reducing reliance on handcrafted signal descriptors [10]. Convolutional neural networks have shown strong performance in analyzing vibration and acoustic measurements for fault diagnosis in marine engines and rotating machinery, particularly under noisy and complex conditions. In parallel, recurrent neural networks and long short-term memory models have demonstrated effectiveness in modeling temporal behavior and degradation trends in sequential operational data, making them well suited for continuous health monitoring and remaining useful life prediction in marine propulsion systems.

An increasing number of studies have also investigated multi-sensor data fusion as a means to enhance predictive maintenance accuracy in maritime applications. The integration of heterogeneous signals—such as vibration, thermal, pressure, and acoustic data— [11] has been shown to improve fault detection sensitivity and enable earlier identification of incipient failures. Artificial intelligence–based models are especially well suited for such fusion tasks, as they can learn complementary information from diverse data sources. Nevertheless, much of the existing literature remains focused on individual subsystems or specific fault modes, rather than addressing the holistic maintenance needs of complete marine propulsion systems.

Furthermore, several challenges hinder the practical deployment of AI-based predictive maintenance solutions in real-world marine environments. Variations in sea conditions, load profiles, and environmental disturbances introduce uncertainty into sensor measurements and model outputs. In addition, issues related to model transparency, real-time execution, and scalability across different vessel types are not yet sufficiently resolved. These limitations reveal a clear research gap in the development of an integrated, robust, and scalable artificial intelligence–driven predictive maintenance framework capable of supporting real-time decision-making for marine propulsion systems. Addressing this gap forms the primary motivation for the framework proposed in this study.

3. METHODS AND MATERIALS

3.1 System Overview

The proposed artificial intelligence–driven predictive maintenance framework aims to continuously assess the operational condition of marine propulsion systems and identify potential failures at an early stage. The framework combines multi-sensor data acquisition, signal conditioning, data-driven feature learning, and temporal health evaluation through hybrid CNN–LSTM architecture. By jointly exploiting spatial feature learning and temporal dependency modeling, the approach enables reliable condition monitoring and supports proactive maintenance decisions for marine propulsion systems operating under fluctuating load profiles and complex environmental conditions.

3.2 Sensor Deployment and Data Acquisition

Marine propulsion systems are subjected to persistent mechanical loads, variable operating regimes, and severe marine environments, which necessitate comprehensive and reliable sensing strategies. In this study, a range of sensors is installed at key locations within the propulsion system, including the marine diesel engine, gearbox assembly, shaft bearings, and main propulsion shaft. Vibration measurements are obtained using accelerometers to capture dynamic responses associated with faults such as shaft imbalance, misalignment, and bearing wear. Thermal sensors are employed to track temperature variations in bearings and lubrication circuits, while pressure and rotational speed sensors provide information on load conditions and operational states. All measurements are collected through a centralized data acquisition platform to maintain synchronized sampling across sensor channels. Data are recorded under both healthy operating conditions and representative fault scenarios to reflect realistic marine operational environments. The acquired datasets are organized in a structured format for subsequent preprocessing and model training.

3.3 Signal Conditioning and Data Preprocessing

Sensor signals obtained from marine propulsion systems are frequently affected by noise and external disturbances resulting from vessel motion and varying sea states. To address these challenges, a dedicated preprocessing stage is applied to improve data quality and enhance learning performance. Vibration signals undergo filtering to suppress unwanted frequency components and background noise, whereas temperature and pressure measurements are smoothed to mitigate transient fluctuations. The conditioned signals are then divided into fixed-duration segments, generating samples that capture both steady operational behavior and transient system responses. Normalization is performed to scale all sensor inputs to a common range, promoting numerical stability during neural network training. Care is taken to preserve temporal synchronization among all sensor channels to maintain the physical relationships between measured variables.

3.4 CNN-Based Feature Learning

Automatic feature extraction is achieved using a convolutional neural network, removing the need for manual signal feature design. The CNN processes the preprocessed multisensor data through successive convolutional layers equipped with trainable filters that learn localized fault-sensitive patterns. These learned representations capture key indicators such as impulsive vibration events, abnormal thermal trends, and deviations in operational behavior associated with mechanical deterioration. Pooling operations are incorporated to reduce feature dimensionality while retaining the most informative characteristics. This data-driven feature learning capability allows the model to adapt effectively to diverse operating conditions and fault mechanisms commonly observed in marine propulsion systems.

3.5 Temporal Dependency Modeling with LSTM

Although the CNN extracts spatial features from sensor signals, the progression of system health over time is captured using a long short-term memory network. The LSTM module receives high-level feature sequences produced by the CNN and learns temporal correlations across consecutive data windows. Such temporal modeling is critical for predictive maintenance applications, as faults in marine propulsion components typically evolve gradually rather than appearing abruptly. By capturing long-term degradation patterns and behavioral trends, the LSTM enhances the framework's ability to perform early fault detection and accurate health state assessment.

3.6 Model Training and Predictive Maintenance Implementation

The hybrid CNN–LSTM architecture is trained using labeled datasets representing various health states of the marine propulsion system. A supervised learning paradigm is employed, enabling the model to associate multisensor input sequences with corresponding system conditions. During training, an adaptive optimization strategy is utilized to update model parameters, and regularization techniques are incorporated to prevent overfitting and improve generalization. Once trained, the model is integrated into a predictive maintenance framework that continuously processes incoming sensor data and generates health condition predictions. These outputs facilitate condition-based maintenance planning, help minimize unexpected failures, and contribute to improved reliability and availability of marine propulsion systems.

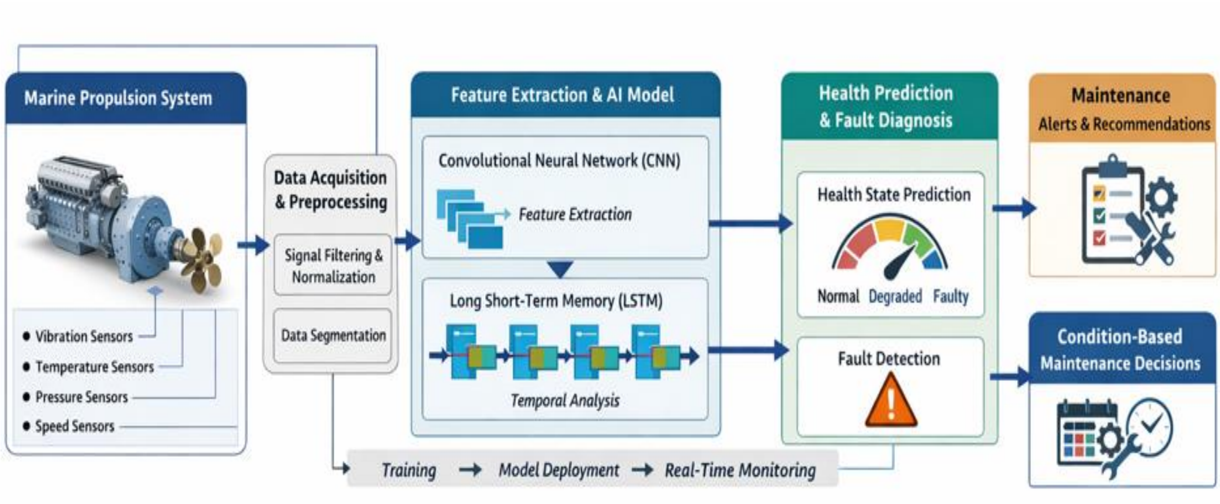

Figure 2. AI-Based Predictive Maintenance Frameworks for Marine Propulsion Systems

Figure 2 depicts the proposed artificial intelligence–driven predictive maintenance architecture developed for marine propulsion systems. The framework originates at the propulsion unit, where essential operational information is continuously gathered from sensors mounted on key subsystems, including the engine, gearbox, propulsion shaft, and bearings. Measurements such as vibration, temperature, pressure, and rotational speed are acquired to capture both normal operating behavior and fault-related responses. These raw sensor outputs are transmitted to a centralized data acquisition unit, where signal conditioning procedures—such as noise suppression, scaling, and time-window segmentation—are applied to enhance data quality and ensure uniformity among sensor channels.

Following preprocessing, the conditioned multisensor data are forwarded to the intelligent feature learning module, which is based on a hybrid convolutional neural network and long short-term memory architecture. The CNN component autonomously learns discriminative representations by identifying localized patterns associated with mechanical deterioration across different sensor modalities. The resulting high-level features are then provided to the LSTM network, which models sequential dependencies and captures long-term degradation behavior across consecutive data segments. This integrated learning strategy allows the framework to represent both instantaneous fault characteristics and gradual system performance decline.

Using the learned feature representations, the framework performs system health assessment and fault diagnosis by categorizing propulsion system conditions into healthy, degraded, or faulty states. These diagnostic outcomes are subsequently used to trigger maintenance alerts and generate actionable recommendations, enabling condition-based maintenance decision-making. The framework supports multiple operational phases, including model training, deployment, and real-time monitoring, thereby facilitating continuous system health evaluation and proactive maintenance planning. As a result, the proposed approach contributes to improved system reliability, reduced unexpected downtime, and enhanced operational efficiency in marine engineering applications.

3.7 Application of Machine Learning in the Shipping Industry

Machine learning techniques have been increasingly adopted to develop effective condition-based maintenance (CBM) and predictive maintenance (PdM) strategies for maritime systems. İnceişçi and Ayça investigated operational data from an LM-2500 marine gas turbine and applied regression-based models alongside artificial neural networks to predict machinery faults.

Their comparative analysis included linear regression, decision tree regression, k-nearest neighbours, random forest, Bayesian ridge, extra trees, and linear support vector regression, with the ANN model demonstrating superior predictive accuracy.

The reviewed literature highlights the growing importance of machine learning for identifying failure patterns in marine vessels and mitigating safety-critical conditions. However, relatively limited attention has been given to failure prediction and CBM planning for complete ship propulsion systems. To address this gap, the present study investigates the application of advanced supervised and unsupervised machine learning techniques for fault clustering and maintenance prioritization in marine propulsion systems. The effectiveness of the proposed approach is benchmarked against methods reported in prior studies, including regression-based degradation prediction techniques applied to marine gas turbine propulsion systems.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

The proposed artificial intelligence–based predictive maintenance framework was implemented and experimentally validated using multi-sensor operational data collected from major propulsion components, including the marine diesel engine, gearbox, shaft, and bearings. The experimental study focused on assessing the capability of the hybrid CNN–LSTM model to perform reliable fault diagnosis and system health evaluation under realistic marine operating conditions. To ensure robust performance assessment and mitigate overfitting [12], the dataset was partitioned into training, validation, and testing subsets.

The CNN–LSTM architecture was developed using a deep learning platform and trained under a supervised learning paradigm. Synchronized vibration, temperature, pressure, and rotational speed measurements served as model inputs. Convolutional layers were employed to automatically extract spatial fault-related features from the multisensor data, while LSTM layers learned temporal dependencies and degradation trends across sequential time windows. Model performance was evaluated using widely accepted metrics, including accuracy, precision, recall, and F1-score, to quantify the effectiveness of fault classification and health state prediction.

Table 1. Dataset Description for Marine Propulsion System Monitoring

Operating Condition	**Vibration Samples**	**Temperature Samples**	**Speed & Pressure Samples**	**Total Samples**
Normal Condition	1500	1500	1500	4500
Bearing Fault	1500	1500	1500	4500
Gear Fault	1500	1500	1500	4500
Shaft Misalignment	1500	1500	1500	4500
Total	6000	6000	6000	18000

Table 1 summarizes the multi-sensor dataset used for experimental validation. Balanced data distribution across operating conditions ensured unbiased training and fair performance evaluation of the predictive maintenance model.

Table 2. CNN–LSTM Model Parameters for Marine Propulsion System

Parameter	Value
Number of CNN Layers	3
CNN Filters	32, 64, 128
Kernel Size	3 × 3
LSTM Units	64
Batch Size	32
Optimizer	Adam
Learning Rate	0.001
Training Epochs	50
Loss Function	Categorical Cross-Entropy

The selected model parameters provided stable convergence and effective learning of fault-related features under varying marine operating conditions in Table 2.

Table 3. Fault Classification Performance Comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	88.6	87.8	86.9	87.3
Random Forest	91.2	90.6	89.8	90.2
CNN	94.8	94.2	93.7	93.9
CNN–LSTM	**97.3**	**97.0**	**97.1**	**97.0**

The proposed CNN–LSTM model achieved the highest classification accuracy and F1-score, confirming the advantage of combining spatial and temporal feature learning for marine propulsion system maintenance in Table 3.

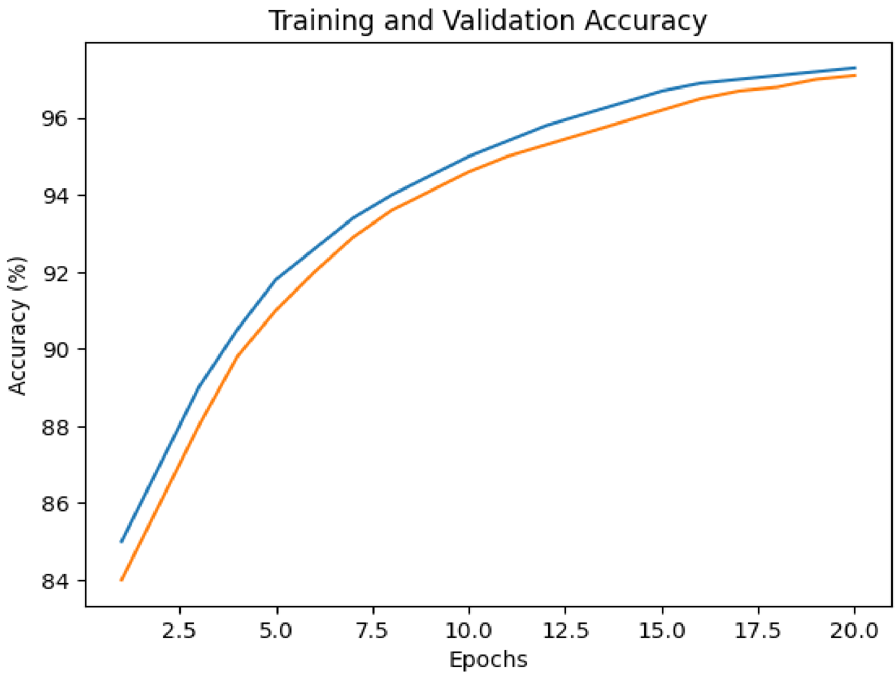

Figure 3. Training and Validation Accuracy

The Figure 3 illustrates the training and validation accuracy of the CNN–LSTM model across epochs. Both curves show a steady and consistent increase, indicating stable learning behavior. The close alignment between training and validation accuracy demonstrates good generalization capability and minimal overfitting, validating the robustness of the proposed AI framework.

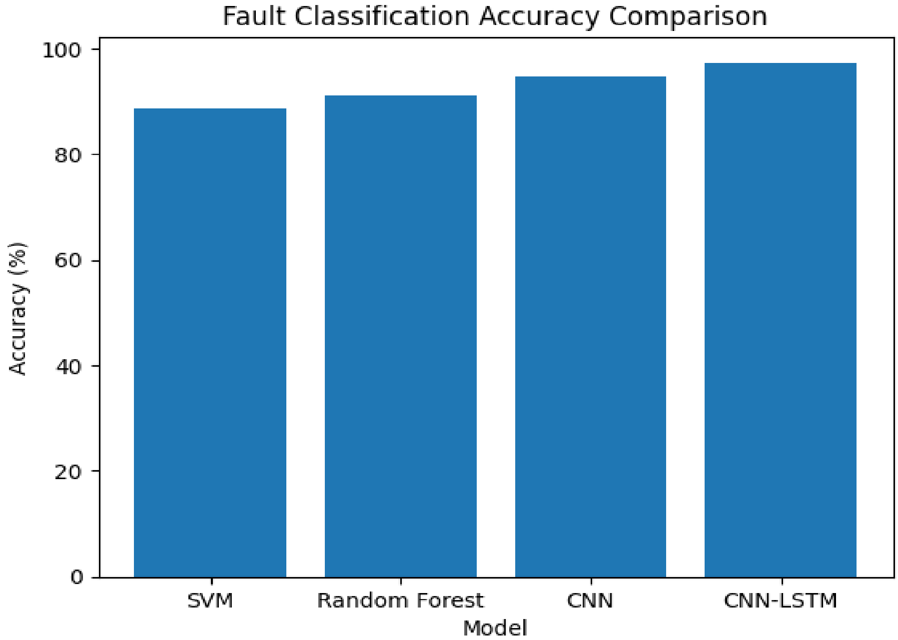

Figure 4. Fault Classification Accuracy Comparison

The Figure 4 compares fault classification accuracy among different machine learning and deep learning models. Traditional methods such as SVM and Random Forest exhibit lower accuracy due to their reliance on handcrafted features. The CNN model improves performance through automated feature extraction, while the CNN–LSTM model achieves the highest accuracy by additionally modeling temporal degradation behavior, highlighting its suitability for predictive maintenance in marine propulsion systems.

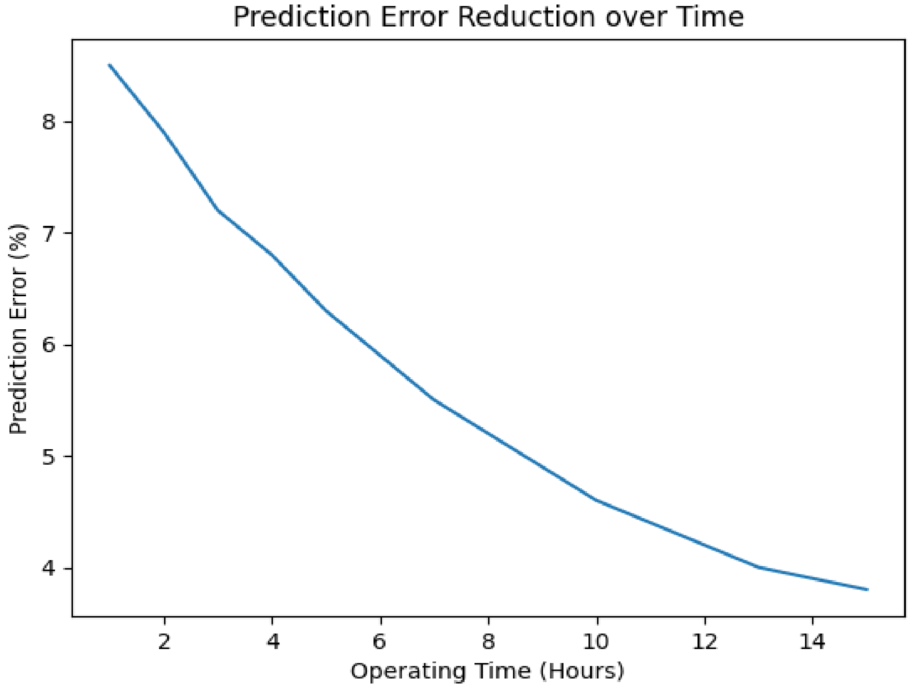

Figure 5. Prediction Error Reduction over Operating Time

Figure 5 illustrates the trend of decreasing prediction error as operating time progresses. As the CNN–LSTM architecture incrementally learns the temporal characteristics associated with system degradation, the prediction error is steadily reduced. This behavior indicates a continuous improvement in health state estimation accuracy and highlights the model's effectiveness in supporting early fault identification and dependable maintenance planning.

5. CONCLUSION AND FUTURE SCOPE

This research proposed an artificial intelligence–driven predictive maintenance framework for marine propulsion systems that combines multisensor data acquisition with a hybrid CNN–LSTM learning architecture. The framework enables robust condition monitoring and timely fault detection by automatically learning both fault-specific features and long-term degradation patterns from operational data. Experimental evaluation demonstrated that the proposed approach achieves higher classification accuracy than traditional machine learning methods and single deep learning models. The observed reduction in prediction error over extended operating periods further validates the framework's suitability for condition-based maintenance and its potential to enhance the reliability of marine propulsion components operating under dynamic marine environments.

While the framework was validated using controlled experimental datasets, future investigations will focus on real-time on-board implementation and comprehensive validation under varying sea states and load conditions. Additional enhancements include the integration of supplementary sensing modalities, such as lubrication oil analysis and exhaust gas monitoring, to further enrich system health assessment. Moreover, incorporating explainable artificial intelligence techniques and edge-computing infrastructures is expected to improve model interpretability, reduce response latency, and facilitate practical deployment in intelligent marine maintenance applications.

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