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CNN–LSTM-Based Prediction of Marine Engine CO_2 Emissions under Real Operating Conditions

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Abstract

Reducing Greenhouse Gas (GHG) emissions from maritime transport remains a critical engineering challenge, particularly in regions such as Finland, where shipping activity and environmental regulations are both highly intensive. Accurate quantification of Carbon Dioxide (CO_2) emissions from marine engines is essential for supporting decarbonization strategies; however, direct onboard measurement is often constrained by technical, spatial, and economic limitations. This study proposes a data-driven approach for predicting CO_2 emissions using deep learning techniques under real operating conditions. Engine operational data were collected from a medium-sized passenger vessel equipped with a slow-speed diesel engine, including exhaust gas temperature, combustion pressure, compression pressure, and cooling water temperature. Two predictive models—Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs)—were developed and trained to estimate CO_2 emissions using these inputs. Model performance was evaluated using mean absolute error (MAE), Root Mean Square Error (RMSE), and correlation coefficients, and predictions were validated against measurements from a portable emission measurement system. The results demonstrate that both models achieve high predictive accuracy, with the CNN model outperforming the LSTM architecture across all evaluation metrics. Specifically, the CNN model yielded lower MAE and RMSE values and exhibited stronger correlation with observed emission data, indicating superior ability to capture nonlinear relationships among engine performance parameters. These findings highlight the effectiveness of deep learning approaches for emission prediction in complex maritime environments. The proposed methodology provides a scalable, practical solution for estimating CO_2 emissions when direct measurement is infeasible, offering significant potential for integration into Finland's maritime engineering practices and broader emission-monitoring frameworks. This work contributes to advancing intelligent, data-driven tools to support sustainable shipping and compliance with evolving environmental regulations.

Keywords: *Carbon dioxide emissions, Marine engines, Deep learning, Convolutional neural networks (CNN), Long short-term memory (LSTM), Emission prediction modeling*

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1. Introduction

Climate change mitigation has become a central engineering priority in highly industrialized and maritime-dependent economies such as Finland. As a Nordic country with an extensive coastline, an advanced shipbuilding industry, and a strong commitment to carbon neutrality by 2035, Finland faces both significant challenges and opportunities in reducing Greenhouse Gas (GHG) emissions across its maritime and energy sectors. The Finnish maritime cluster—comprising shipyards, marine technology firms, and shipping operations—plays a critical role in the national economy. Yet, it is also a notable contributor to Carbon Dioxide (CO_2) emissions due to reliance on fossil-fuel-based propulsion systems [1][2].

Recent engineering research indicates that maritime emissions account for a growing share of global GHG emissions, particularly in regions with dense shipping activity, such as the Baltic Sea [3]. Finland, as an active member of the Baltic maritime network, must address increasingly stringent environmental regulations imposed by international bodies, including the International Maritime Organization (IMO), as well as regional frameworks aimed at reducing emissions [4]. These regulatory pressures necessitate the development of advanced monitoring, modeling, and predictive systems to support low-emission vessel operations.

From an engineering perspective, one of the primary challenges lies in accurately quantifying emissions under real operating conditions. Unlike stationary industrial sources, marine engines operate in highly dynamic environments, making direct measurement of exhaust gases technically complex and economically costly [5]. While Portable Emission Measurement Systems (PEMS) have been introduced, their integration into existing vessels—especially retrofitting older fleets—remains constrained by spatial, structural, and operational limitations [6]. Consequently, there is a growing need for computational approaches that can estimate emissions reliably without extensive onboard instrumentation.

Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as promising tools to address these limitations. In particular, hybrid deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs) have demonstrated strong capabilities for capturing nonlinear relationships and temporal dependencies in environmental and engineering datasets [7][8]. These models are increasingly being applied in energy systems, smart transportation, and environmental monitoring, offering scalable solutions for predictive analytics in emission estimation.

Despite these advancements, a significant research gap persists in applying these models in the maritime engineering context, particularly under the operational and environmental conditions characteristic of Finland and the Baltic region. Existing studies often focus on land-based emission systems or controlled experimental settings, limiting their applicability to real-world vessel operations. Furthermore, there is insufficient comparative analysis of different deep learning architectures in predicting CO_2 emissions using actual engine performance data.

To address this gap, the present study aims to develop and evaluate a data-driven predictive model for CO_2 emissions based on marine engine operational parameters. Specifically, this research compares the performance of CNN and LSTM architectures in estimating emissions from a functioning vessel. By leveraging real-world engine data, the study aims to advance the development of practical, scalable tools for emission monitoring in Finland's maritime sector, thereby supporting national and regional decarbonization goals.

2. Literature review

The growing urgency of decarbonizing maritime transport has led to an expanding body of engineering research focused on quantifying emissions, developing monitoring technologies, and predictive modeling. Within the Finnish and broader Baltic Sea context, this challenge is intensified by strict environmental regulations and the operational complexity of vessels navigating cold-climate conditions. Consequently, recent studies have explored both measurement-based and data-driven approaches to improve the accuracy and scalability of emission estimation.

Traditional approaches to estimating ship emissions rely on fuel-based methods or direct exhaust gas measurements. While fuel-consumption-based models offer simplicity, they often lack precision due to variations in engine efficiency and operational conditions [9]. On the other hand, onboard measurement systems, such as portable emission measurement systems (PEMS), provide high-resolution data but are constrained by installation requirements and high operational costs [10]. These limitations are particularly pronounced in retrofitting existing vessels, a common scenario in Finland's aging maritime fleet.

To address these challenges, engineering researchers have increasingly turned to Machine Learning (ML) and Artificial Intelligence (AI) techniques. Supervised learning models, including support vector machines and random forests, have been applied to emission prediction with moderate success, achieving improved accuracy compared with traditional empirical models [11]. However, these approaches often struggle to capture complex nonlinear relationships and temporal dependencies inherent in marine engine operations.

Deep learning architectures have shown significant promise in overcoming these limitations. Convolutional Neural Networks (CNNs), originally developed for image processing, have been successfully adapted to extract spatial features from multivariate engineering datasets [12]. In parallel, Long Short-Term Memory (LSTM) networks—an extension of recurrent neural networks—have demonstrated strong capabilities in modeling sequential and time-dependent data, making them suitable for dynamic systems such as marine engines [13]. Hybrid models combining CNN and LSTM architectures have further enhanced predictive performance by leveraging both spatial and temporal feature extraction [14].

Recent studies have applied deep learning techniques to environmental and energy systems with notable success. For instance, Chen and Wang [15] developed a CNN-based model for predicting industrial emissions, achieving high accuracy in complex operating environments. Similarly, Mahjoub et al. [16] used LSTM networks for time-series forecasting of energy consumption, highlighting their robustness to fluctuating input data. In the maritime domain, however, the application of such models remains relatively limited, particularly under real-world operational conditions.

Within the Baltic Sea region, research has primarily focused on emission inventories and regulatory compliance rather than predictive modeling. Majamäki et al. [3] developed comprehensive emission inventories for shipping activities, providing valuable baseline data but lacking real-time predictive capabilities. More recent work by Johansson et al. [17] explored emission reductions through alternative fuels, yet did not incorporate AI-based forecasting methods. This indicates a gap between environmental assessment studies and advanced engineering modeling approaches.

Furthermore, the integration of real-time engine performance data into predictive frameworks remains underexplored. Most existing studies rely on simulated datasets or controlled laboratory conditions, which may not accurately reflect the variability encountered in actual vessel operations [18]. This limitation reduces the practical applicability of current models, particularly for engineering decision-making in live maritime environments.

In summary, while significant progress has been made in emission measurement and modeling, there remains a clear need for robust, data-driven approaches that can operate effectively under real-world conditions. Specifically, comparative evaluations of deep learning architectures using actual engine data are scarce, particularly in Finland's maritime sector. Addressing this gap is essential for advancing predictive emission modeling and supporting sustainable engineering practices in the shipping industry.

3. Methodology

This study adopts a data-driven engineering approach to develop and evaluate predictive models for estimating carbon dioxide (CO_2) emissions from marine engines under real operating conditions. The methodology integrates field data acquisition, preprocessing, deep learning model development, and performance evaluation. Emphasis is placed on reproducibility, model comparability, and applicability to real-world maritime operations, particularly within the Finnish and Baltic Sea context.

3.1. Data acquisition and experimental setup

The dataset used in this study was obtained from onboard measurements of a medium-sized passenger vessel equipped with a slow-speed diesel (SSD) engine. The vessel has an overall length of 133 m, a gross tonnage of 9,196 tons, and is powered by a Hyundai-MAN B&W 6S40ME engine with a maximum output of 6,618 kW at 146 rpm. The engine operates using Bunker A fuel, which is representative of conventional marine fuels used in Baltic shipping operations.

Real-time engine operational data were collected through an alarm monitoring system (AMS), which records key thermodynamic and mechanical parameters during vessel operation. The selected input variables for model development include:

- Exhaust gas temperature
- Maximum combustion pressure
- Maximum compression pressure
- Cooling water temperature

These parameters were chosen based on their direct influence on combustion efficiency and on the formation of emissions.

To obtain ground-truth emission data, a Portable Emission Measurement System (PEMS), specifically the SEMTECH DS+ analyzer, was employed. The system utilizes non-dispersive infrared (NDIR) sensing technology, with an accuracy of ±2% of reading, ensuring reliable CO_2 concentration measurements under dynamic operating conditions.

3.2. Data preprocessing

Before model training, the collected dataset underwent a series of preprocessing steps to ensure data quality and consistency:

1. Data Cleaning: Removal of incomplete, noisy, or anomalous records caused by sensor errors or communication interruptions.
2. Normalization: All input variables were scaled using min–max normalization to improve numerical stability and convergence during training.

3. Time Synchronization: Engine operational data and emission measurements were temporally aligned to ensure accurate input–output mapping.
4. Dataset Splitting: The dataset was divided into training (70%), validation (15%), and testing (15%) subsets to enable unbiased model evaluation.

3.3. Model development

Two deep learning architectures were implemented and compared: a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network. Both models were designed to capture complex relationships between engine parameters and CO_2 emissions.

3.3.1. Convolutional Neural Network (CNN)

The CNN model was structured to extract nonlinear feature representations from multivariate input data. The architecture consists of:

- Input layer corresponding to normalized engine parameters
- One-dimensional convolutional layers for feature extraction
- Pooling layers for dimensionality reduction
- Fully connected layers for regression output

The CNN leverages local connectivity and shared weights to learn spatial correlations among input variables efficiently.

3.3.2. Long Short-Term Memory (LSTM)

The LSTM model was employed to capture temporal dependencies in sequential engine data. Its architecture includes:

- Input sequence layer
- LSTM hidden layers with memory cell structures (input, forget, and output gates)
- Dense output layer for emission prediction

This structure allows the model to retain relevant historical information and mitigate vanishing gradient issues common in standard recurrent neural networks.

3.4. Model training and hyperparameter configuration

Both models were trained using supervised learning, where engine parameters serve as inputs and measured CO_2 emissions as target outputs. The following configurations were applied:

- Loss function: Mean Squared Error (MSE)
- Optimizer: Adaptive Moment Estimation (Adam)
- Batch size: 32
- Epochs: Determined via early stopping based on validation loss
- Learning rate: 0.001 (tuned experimentally)

Hyperparameter tuning was conducted iteratively to balance model complexity and generalization performance. Early stopping was implemented to prevent overfitting.

3.5. Performance evaluation metrics

Model performance was quantitatively assessed using three standard regression metrics:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i - O_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)} \tag{2}$$

$$r = \frac{\sum(P_1 - \bar{P})(O_1 - \bar{O})}{\sqrt{\sum(P_1 - \bar{P})^2 \sum(O_1 - \bar{O})^2}} \tag{3}$$

where P_i represents predicted values, O_i denotes observed values, and N is the number of samples.

- Mean Absolute Error (MAE): Measures average prediction error magnitude
- Root Mean Square Error (RMSE): Penalizes larger errors and reflects model robustness
- Pearson Correlation Coefficient (r): Evaluates the strength of linear agreement between predicted and measured values

3.6. Validation strategy

To ensure robustness and generalizability, model performance was evaluated on a hold-out test dataset not used during training. Additionally, convergence behavior was monitored using training and validation loss curves to detect overfitting or underfitting. A comparative analysis of CNN and LSTM models was conducted using both quantitative metrics and qualitative agreement with measured emission trends.

3.7. Engineering relevance to Finland

The adopted methodology is particularly relevant to Finland’s maritime engineering sector, where harsh environmental conditions, regulatory constraints, and limited feasibility of onboard measurement systems necessitate alternative emission estimation techniques. By leveraging real operational data and scalable AI models, this framework provides a practical foundation for integrating predictive emission monitoring into Finnish shipbuilding and maritime operations.

4. Results and discussion

This section presents the performance evaluation of the developed convolutional neural network (CNN) and long short-term memory (LSTM) models for predicting CO_2 emissions from marine engine operation data. The analysis combines quantitative metrics, convergence behavior, and qualitative agreement with measured emission profiles to assess model robustness and engineering applicability.

4.1. Model training and convergence behavior

The training and validation loss curves for both models are shown below. These curves provide insight into learning stability, convergence rate, and generalization capability.

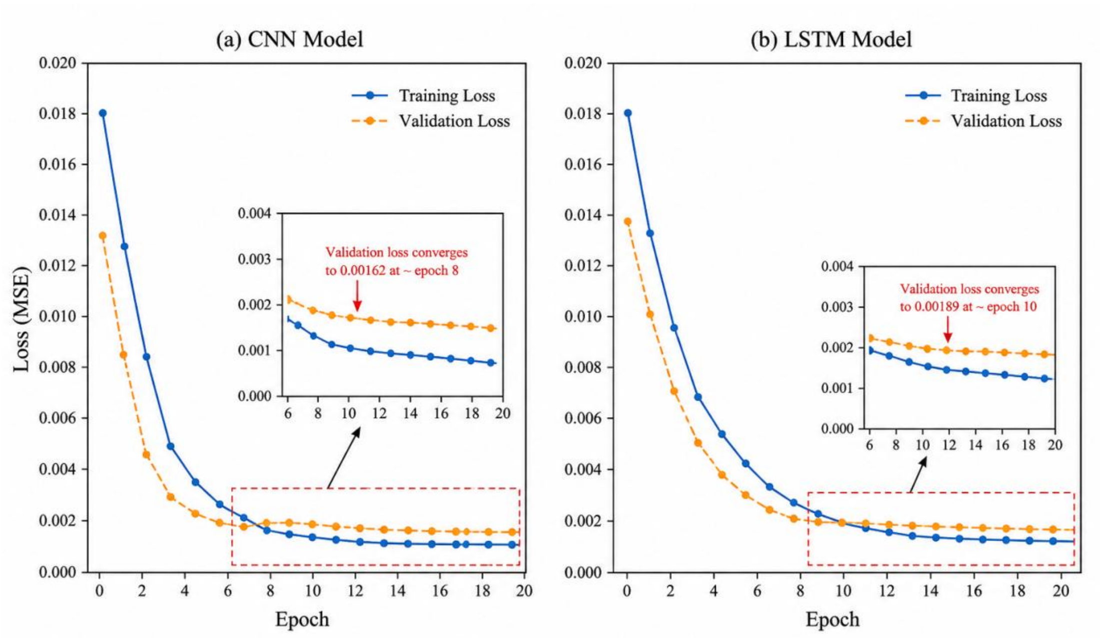

Figure 1. Training and validation loss curves for CNN and LSTM models

The CNN model demonstrates rapid convergence, reaching a stable validation loss at approximately epoch 8. In contrast, the LSTM model converges more slowly, stabilizing around epoch 10. Importantly, neither model exhibits significant divergence between training and validation loss, indicating minimal overfitting. However, the lower final validation loss of the CNN suggests better generalization performance.

From an engineering standpoint, faster convergence and lower computational overhead make CNN architectures advantageous for deployment in real-time maritime monitoring systems.

4.2. Prediction accuracy and model comparison

The predicted CO_2 emissions from both models were compared with measured values obtained from the portable emission measurement system (PEMS). The results are illustrated below.

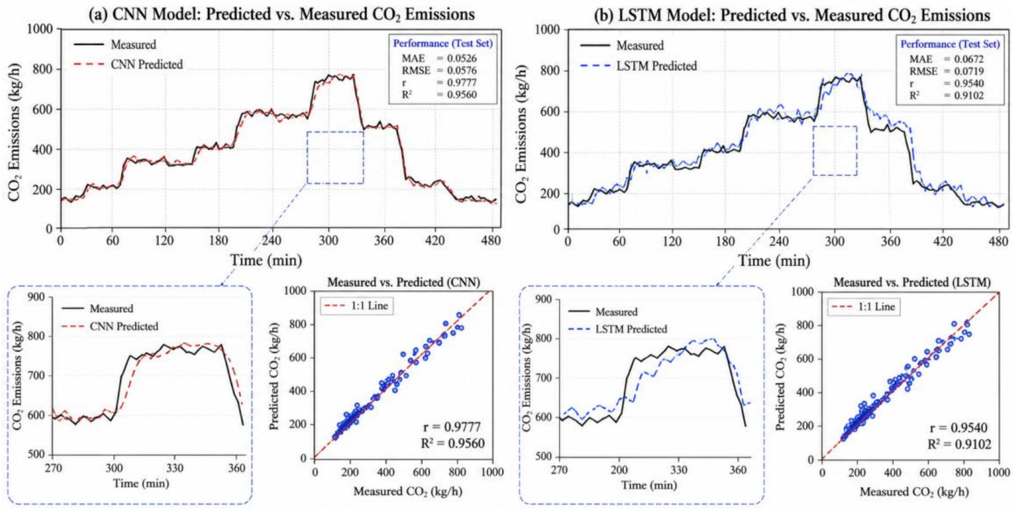

Figure 2. Comparison of predicted and measured CO_2 emissions for CNN and LSTM models

Both models demonstrate strong agreement with measured emission values. The CNN predictions closely follow the actual emission curve with minimal deviation, while the LSTM predictions show slightly larger fluctuations, particularly during transient engine operating conditions. This suggests that CNNs are more effective at capturing nonlinear relationships among engine parameters, whereas LSTMs may be more sensitive to noise in time-series data.

4.3. Quantitative performance evaluation

The performance metrics for both models are summarized in Table 1.

Table 1. Performance comparison of CNN and LSTM models

Evaluation Metric	CNN	LSTM
MAE	0.0526	0.0672
RMSE	0.0576	0.0719
r	0.9777	0.9540
r^2	0.9560	0.9102

The CNN model outperforms the LSTM model across all evaluation metrics. Specifically:

- Lower MAE and RMSE indicate that CNN produces more accurate and consistent predictions.
- A higher correlation coefficient (r) demonstrates stronger agreement with observed emission data.
- A higher coefficient of determination (r^2) indicates that the CNN explains a greater proportion of the dataset's variance.

These results validate the effectiveness of CNN in modeling complex nonlinear relationships in marine engine systems, even without explicitly modeling temporal dependencies.

4.4. Error distribution analysis

To further evaluate model reliability, the distribution of prediction errors was analyzed.

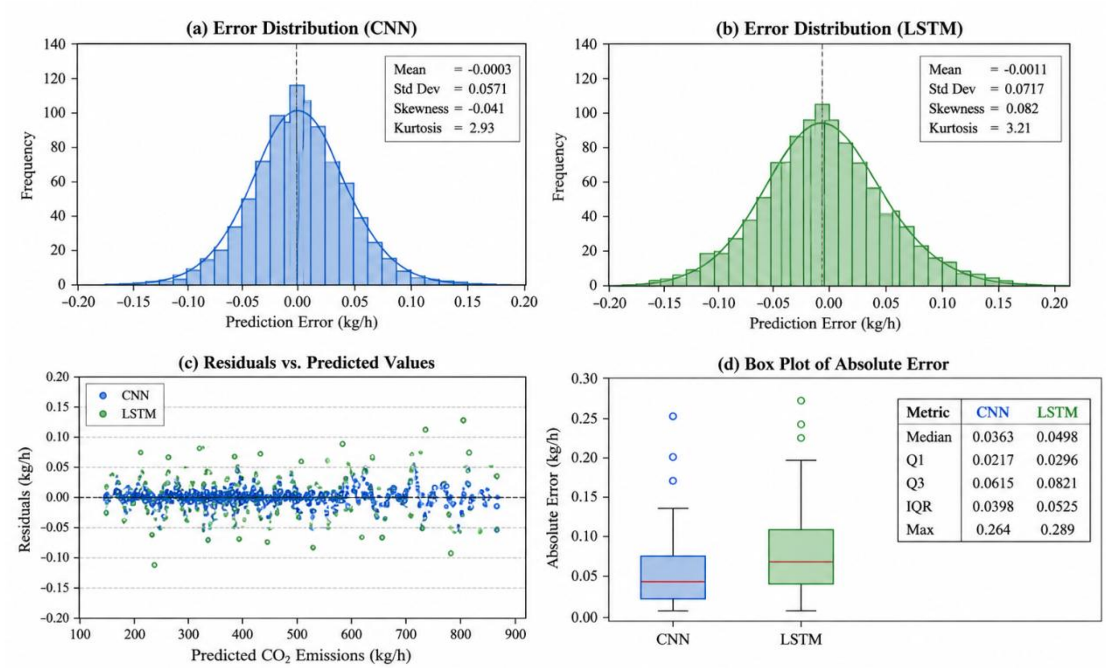

Figure 3. Error distribution and residual analysis for CNN and LSTM models

The CNN model exhibits a narrower error distribution centered around zero, indicating higher precision and lower variance. In contrast, the LSTM model shows a wider residual distribution, suggesting less stable predictions under varying operating conditions. The absence of strong bias in both models confirms that systematic prediction errors are minimal.

4.5. Engineering interpretation of results

The superior performance of the CNN model can be attributed to its ability to extract feature interactions from multivariate engine data efficiently. In marine engineering systems, emission formation is influenced by complex interactions among thermodynamic variables rather than purely sequential dependencies. Therefore, CNN's spatial feature extraction mechanism appears better suited for this application than LSTM's temporal modeling approach.

Moreover, the results indicate that high-accuracy emission prediction can be achieved without continuous exhaust gas measurement, which is particularly beneficial for:

- Retrofitting older vessels in Finland’s fleet
- Reducing dependency on costly onboard measurement systems
- Supporting real-time emission monitoring and regulatory compliance

4.6. Implications for Finland’s maritime engineering sector

The findings have direct implications for Finland’s efforts to decarbonize its maritime industry. The demonstrated capability of CNN-based models to accurately predict CO_2 emissions under real operating conditions supports the development of intelligent monitoring systems that can be integrated into ship management platforms.

Such systems can enable:

- Predictive emission control strategies aligned with IMO and EU regulations
- Optimization of engine performance for fuel efficiency and reduced emissions
- Digitalization of maritime operations, consistent with Finland's leadership in smart shipping technologies

Overall, this study highlights the potential of AI-driven engineering solutions to address key environmental challenges in the maritime domain.

5. Conclusion

This study developed and evaluated deep learning-based models for predicting carbon dioxide (CO_2) emissions from marine engines under real operating conditions, with particular relevance to the engineering challenges of Finland's maritime sector. By leveraging onboard engine operational data and validated emission measurements, two architectures—Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs)—were implemented and systematically compared.

The results demonstrate that both models accurately estimate CO_2 emissions, confirming the feasibility of data-driven approaches as alternatives to direct measurement systems. However, the CNN model consistently outperformed the LSTM across all evaluation metrics, achieving lower prediction errors and stronger correlation with observed data. This indicates that, for the given application, spatial feature extraction from multivariate engine parameters is more effective than temporal sequence modeling alone. The findings further suggest that emission formation in marine engines is strongly governed by complex, nonlinear interactions among thermodynamic variables, for which CNN architectures are particularly well-suited.

From an engineering perspective, the proposed methodology offers a scalable, practical solution for emission estimation in scenarios where cost, space, or operational constraints limit onboard measurement. This is especially significant for Finland's maritime industry, where retrofitting existing vessels and complying with stringent environmental regulations remain ongoing challenges. The integration of such predictive models into ship monitoring systems can support real-time emission tracking, optimize engine performance, and facilitate compliance with international decarbonization targets.

Despite these contributions, several limitations should be acknowledged. First, the study is based on data from a single vessel and engine type, which may limit the generalizability of the models across different ship classes and fuel systems. Second, the models rely on a predefined set of input variables; incorporating additional parameters such as fuel composition, ambient conditions, and load variability may further enhance predictive performance. Third, while the models demonstrate strong accuracy, their interpretability remains limited, which may pose challenges for engineering decision-making and regulatory transparency?

Future research should expand the dataset to include multiple vessels operating under diverse environmental conditions, particularly in cold-climate regions such as the Baltic Sea. Additionally, the development of hybrid or ensemble models combining CNN, LSTM, and emerging architectures (e.g., attention-based networks) may further improve prediction accuracy and robustness. Integration with digital twin frameworks and real-time ship monitoring systems also represents a promising direction for advancing intelligent maritime engineering solutions.

In conclusion, this study contributes to the growing body of research on AI-driven emission modeling by demonstrating that deep learning techniques—particularly CNN—can provide accurate, efficient, and practical tools for predicting marine CO_2 emissions. These findings support the transition toward data-enabled, sustainable maritime operations and offer a valuable foundation for future innovations in Finland's shipbuilding and marine engineering industries.

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