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Ship Fuel Consumption Prediction Model Based On Ship Logbook Data: A Case Study

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ABSTRACT

In this paper, an artificial intelligence (AI)–based model is proposed to accurately predict fuel consumption using operational data from ship logbooks. A ship logbook contains historical operational parameters such as ship speed, trim, draft, cargo load, ballast conditions, engine load, and weather conditions, which significantly impact energy usage. For training, two years of voyage data (2023–2024) from the bunker ship ASHICO VICTORIA were used. Fuel consumption is estimated as a function of these features. A total of 22 machine learning and deep learning algorithms were trained, tested, and compared, including Linear Regression, Ridge, SVR, HuberRegressor, Random Forest, Gradient Boosting, XGBoost, Artificial Neural Networks, and Deep Neural Networks. Performance was evaluated using MAE, RMSE, and R^2. Testing with raw data achieved MAE≈0.12, RMSE≈0.17, and R^2≈0.93. This study supports energy management, operational optimization, and emission reduction in line with international regulations.

1. INTRODUCTION

According to UNCTAD 2024 [1], Global maritime trade grew by 2.4% in 2023 after a 2022 contraction, with over 80% of global trade. The Review of Maritime Transport 2024 urges resilient infrastructure, low-carbon transition, and action against fraudulent ship registrations to safeguard and decarbonize global shipping. And the 2023 IMO STRATEGY report, 3% of global anthropogenic greenhouse gas (GHG) emissions is contributed by the shipping sector. In Paris Agreement, the IMO set the 2050 target [2] seeking to cut GHG emissions by at least 50% comparing to 2008 level. Achieving this goal requires both the retrofitting of existing fleets and optimizing the design and operational performance of newbuilds. According to Fan et al. [3], ship fuel-consumption modelling generally falls into two categories: (1) Physics-based models, which rely on hydrodynamic and propulsion theory, (2) Data-driven or machine learning and deep learning models (ML/DL), which learn complex, nonlinear relationships directly from operational data.

Fuel consumption prediction plays a crucial role in energy-efficiency optimization, as it supports hull-form refinement, propulsion system design, and operational decision-making such as speed scheduling and trim optimization. Accurate estimation of fuel consumption also facilitates compliance with Energy Efficiency Existing Ship Index/ carbon intensity indicator (EEXI/CII) regulations and contributes to long-term decarbonization strategies. Physics-based models estimate Ship Fuel Consumption by quantifying ship resistance and propulsion performance. In these models calm-water resistance and added resistance are considered due to environmental influences such as waves and wind. Computational Fluid Dynamics (CFD) methods have been widely used for this purpose [4]. These models provide reliable baseline predictions. However, they struggled when applying to real operational conditions, ship speed, weather conditions, load, and human factors etc. not captured by theoretical formulations. As maritime working environments mostly have been shifted to Internet of Things (IoT) sensors, Automatic Identification System (AIS) data, and digital logbooks, there has been a clear movement toward AI-driven predictive frameworks to enhance accuracy and adaptability and Machine learning (ML) and data-mining techniques can model nonlinear dependencies across operational, mechanical, and environmental variables with higher adaptability than traditional physics-based models [4, 5].

Over the past decade, machine learning (ML) and data mining (DM) have revolutionized Ship Fuel Consumption (SFC) prediction by training those models to learn nonlinear patterns from operational, mechanical, and environmental variables etc. What better than physics-based methods is that ML/DL models can dynamically adapt to multi-variable interactions, offering improved precision and robustness in real-world applications.

Very early studies utilized statistical and regression-based models for SFC, while recent works apply advanced ML algorithms such as Neural Networks (NN), Random Forest (RF), Gradient Boosting (GB), and Support Vector Regression (SVR) [6]. These methods achieved good ability to capture nonlinear relationships between inputs (speed, trim, load) and fuel consumption. For instance, Wickramanayake and Bandara [7] found that RF achieved the highest predictive accuracy using metrics such as MAE, RMSE, and Bias. Feature-selection methods such as the Boruta Algorithm (BA) combined with NNs achieved $R^2 \approx 0.88$ in vehicle-fuel studies.

Recent studies proved that AI-based models perform better than traditional physics-based methods in operational settings. In maritime contexts, Uyanık et al. [8] evaluated various ML models such as Multiple Linear Regression, Ridge and LASSO Regression, Support Vector Regression, Tree-Based Algorithms, Boosting Algorithms to container and dry-bulk ships. Papandreou and Ziakopoulos [9] applied XGBoost for Very Large Crude Carrier (VLCC) for fuel modelling, while Wang et al. [10] applied a statistical method called Least Absolute Shrinkage and Selection Operator LASSO and Multiple Linear Regression (MLR) for resistance-related prediction. Deep learning methods such as Artificial Neural Networks (ANN) [11] and Bi-LSTM [12], are applied to predict ship fuel consumption. However, many previous studies rely on large sensor-rich datasets, which are not available on smaller or older vessels. Furthermore, few works systematically compare a wide range of both ML and DL models using the same real-world dataset under a unified evaluation protocol. A comprehensive multi-model benchmark is necessary to identify robust algorithms under realistic, data-limited maritime conditions.

To address these gaps, this study presents a comprehensive benchmark of 22 ML and DL algorithms for predicting ship fuel consumption using real-world logbook data from the bunker vessel ASHICO VICTORIA. The evaluated models include linear regressors (Lasso, ElasticNet, Huber), ensemble methods (Random Forest, ExtraTrees, Gradient Boosting), boosting variants (XGBoost, NGBoost, LightGBM-tuned), and deep-learning models (ANN, DNN, TabNet). This multi-model framework integrates data preprocessing, feature-importance analysis, and standardized evaluation metrics to provide the most extensive ML–DL comparison for ship-fuel modelling based on real operational data. The results support practical, scalable solutions for data-driven fuel-efficiency optimization, contributing to IMO 2050 decarbonization objectives.

2. RESEARCH METHODOLOGY

2.1 Problem Definition

Consider an operational data source S for a bunker vessel, consisting of records collected from ship logs, noon reports, and available sensors. Each record is represented as $r_i = (r_{i1}, r_{i2}, \dots, r_{in}) \in S$, where r_{ij} is the value of attribute A_j at index i. Typical attributes include:

- Time stamp (date and time of observation),
- Ship speed over ground
- Drafts (forward, aft; sometimes midship values),
- Displacement or loading condition (if available),
- Main engine power or RPM (if available),
- Wind speed and direction (when recorded),
- Sea state or Beaufort scale (if recorded).

Our objective is to predict the instantaneous or segment-level fuel consumption rate of the main engine FC_{ME} under a given operational state. Depending on data granularity, this may be expressed as: FC_{ME} in tons per day, or specific fuel consumption for a specific distance.

Let $x_i \in \mathbb{R}^d$ denote the feature vector derived from attributes of record i, after cleaning and feature engineering, and let y_i denote the corresponding fuel consumption quantity. The prediction task is: Given a training subset $\{(x_i, y_i)\}_{i=1}^{N_{train}}$ of limited size, learn a regression model.

$$\widehat{M} : x \longmapsto y \tag{1}$$

that can accurately predict fuel consumption for new operational states.

In contrast to time-series deep learning studies that exploit long temporal sequences. Here the challenge is that N_{train} is small, records may be irregular in time, and some variables are missing or uncertain. As a result, the model must be data-efficient, robust to noise, and well-regularized.

2.2 Evaluation Metrics

Because the target variable y is continuous, fuel consumption prediction is a regression task. We evaluate model performance using standard regression metrics

- Mean Absolute Error (MAE),
- Root Mean Square Error ($RMSE$),
- Mean Absolute Percentage Error ($MAPE$),
- Coefficient of Determination (R^2).

Given n test samples with true values y_i and predictions $\hat{y}_i$, and with $\bar{y}$ the mean of true values:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3}$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{5}$$

where:

- n is the total number of samples in the test dataset,
- i is the index of an individual sample, with $i = 1, 2, \dots, n$,
- y_i denotes the observed (true) value of fuel consumption for the i-th sample,
- $\hat{y}_i$ denotes the predicted value of fuel consumption produced by the model for the i-th sample,
- $\bar{y}_i$ denotes the mean of the observed fuel consumption values in the test dataset.

MAE and RMSE quantify the absolute and squared deviations between prediction and reality, with RMSE penalizing large errors more strongly. MAPE expresses the error in relative percentage terms, which is useful to assess operational impact. R^2 indicates how much of the variance in the fuel consumption is captured by the model; values closer to 1 indicate better explanatory power.

In the limited-data regime, we pay particular attention to:

- Stability of metrics across different train–test splits,
- Consistency between validation and independent test performance,
- Practical magnitude of MAE and MAPE in relation to daily fuel consumption.

Maritime datasets are inherently multivariate, nonlinear, and small-scale, which makes it critical to test multiple algorithmic families rather than relying on a single model. To evaluate model accuracy and robustness, three widely used regression metrics were adopted: Mean Absolute

Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). MAE measures the average magnitude of prediction error and is particularly suitable for maritime datasets with moderate variability. RMSE penalizes larger deviations more heavily, making it useful for detecting unstable predictions under varying operating conditions. R^2 quantifies how much of the variance in fuel consumption can be explained by the model. By benchmarking 22 diverse algorithms under a unified evaluation protocol, this study ensures that the chosen models such as Gradient Boosting Regressor are not only statistically superior but also physically consistent with marine engineering principles governing fuel dynamics.

To be able to build the models for predicting ship fuel consumption with real-world operating and environmental conditions such as Ship speed, distance run, trim, draft, wind speed, wave height, and cargo load. However, Engine RPM data were not included here because the ship's logbooks did not contain complete or continuous RPM records throughout the 2023-2024 voyage. A comprehensive multi-model benchmarking strategy was adopted to be able to cover across most prediction models. A total of 22 machine learning and deep learning algorithms trained, compared and tested with the historical real-world data that are collected from a bunker ship named ship (ASHICO VICTORIA) with a voyage of (2023-2024) 2 years. This benchmark ensures that both linear dependencies and nonlinear interactions among operational variables are thoroughly explored and the whole outline of work is shown as a flow model as below in Fig. 1.

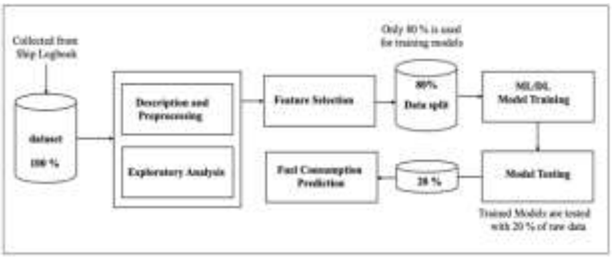

Fig. 1. A Proposed model for Fuel Consumption Prediction Based on Ship Logbook data (own).

The model flow can be interpreted as follow as shown in Fig. 1. The workflow starts with data acquisition, preprocessing, feature selection, model training, and testing etc. into a structured pipeline to ensure consistency, accuracy, and reproducibility throughout the study. The process begins with the collection of operational data from the ship's logbook, which includes voyage such as distance run, vessel speed, cargo load, wave height, wind speed, trim, and fuel consumption. To guarantee data quality and uniform structure, allowing machine learning algorithms to learn effectively without noise or missing values, the data is clean by removing duplicates, treating outliners etc. Exploratory analysis is treated to the dataset with statistical profiling, correlation heatmaps, and feature importance ranking to understand underlying relationships between variables. After data processing, the most impactful input variables are selected for model training. Some inputs such as Date and voyage IDs are not considered as input variables. Then, the cleaned dataset is divided into 80% for model training and 20% for model testing, as indicated in the flowchart. Only dataset of 80% is used to train machine learning and deep learning models, while the remaining 20% is kept for independent testing. A total of 22 Machine Learning and Deep Learning (ML/DL) models are trained using that separated 80% of training dataset. This allows us to consider algorithm choice for prediction model and for further studies. Finally, the trained models are tested with separated 20% of raw data. Performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) are computed for comparison with each model.

2.3 Data Processing and Analysis

The original dataset given a name as (dataset_ASHICO_VICTORIA_V3.xlsx) consisted of 81 voyage records and seven variables: Distance Run (NM), Vessel Speed (knots), Cargo Load (tonnes), Wave Height (m), Wind Speed (knots), Trim (m), and Fuel Consumption (tons/day). In the following table the first 10 rows are shown in Table 1.

Table 1. Dataset collected from a bunker ship.

No.	Distance Run (NM)	Vessel Speed (knots)	Cargo Load (tonnes)	Wave Height (m)	Wind Speed (knots)	Trim (m)	Fuel Consumption (tons/day)
0	18	9.00	9417.0	3.25	24.3	-0.02	0.880
1	226	9.40	9417.0	3.25	18.4	-0.02	10.500
2	257	10.70	9417.0	3.25	24.3	-0.02	10.480
3	229	9.54	9417.0	3.25	24.3	-0.02	10.490
4	219	9.10	9417.0	3.25	24.3	-0.02	10.500
5	60	9.20	2340.0	1.88	18.4	-2.50	9.200
6	236	9.70	2340.0	1.88	18.4	-2.50	9.790
7	248	10.00	2340.0	1.88	18.4	-2.50	9.800
8	240	10.00	NA	1.88	18.4	-2.35	9.800
9	200	8.90	7000.0	0.88	18.4	-0.94	9.375

After cleaning, the dataset contained 76 valid rows, all numeric, and free of duplicates. Outliers were adjusted using the IQR method, and missing cargo values were filled with the median (5300 tonnes).

To identify the strength and direction of relationships among all numeric variables, a correlation heatmap was checked (Fig. 2). This analysis was conducted to determine which operational and environmental parameters most directly influence fuel consumption, as well as to detect possible stronger or weaker ones for predictors before model training.

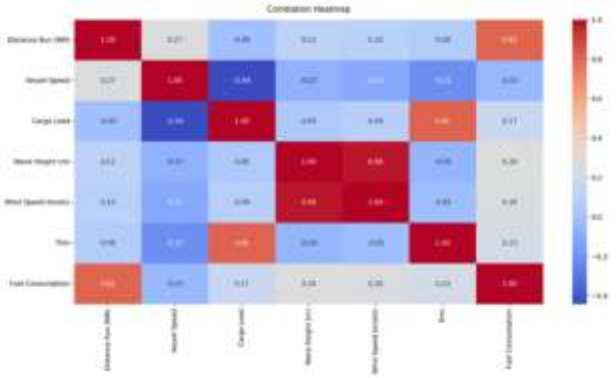

Fig. 2. Correlation heatmap among numeric variables.

Fig. 2 shows that Distance Run and Vessel Speed have the strongest positive correlation with Fuel Consumption, consistent with propulsion theory where higher speed and longer travel increase total resistance. Trim also contributes notably due to its effect on wave-making resistance. Wind and wave height have moderate influence, while cargo load shows weaker correlation because its variation in the dataset was limited. These insights guided feature selection and operational optimization considerations.

To improve model interpretability, guide operational focus toward controllable variables such as speed, trim, etc and to support energy-efficiency optimization, a feature importance analysis was performed using a Random Forest Regressor in Fig. 3. This method complements correlation analysis by capturing nonlinear and interaction effects that linear correlation alone cannot represent. With Distance dominates (~78%), distance is the strongest impact to fuel consumption. The second strongest is Vessel Speed with (~10%), and the third place is Trim with (~7%). This aligns with hydrodynamics too; fuel mainly relates with speed, trim, and frictional resistance. Speed and Trim actually, are actionable levers for voyage optimization (speed policies and trim management) in further studies. Meanwhile, Cargo, Wind, Wave also must have leave constraints as Distance even though their impacts on fuel consumption.

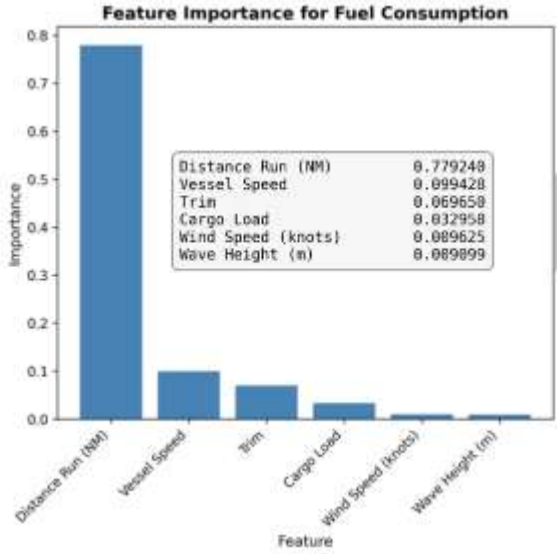

Fig. 3. Feature importance ranking based on Random Forest model.

3. RESULTS AND DISCUSSIONS OF TRAINING

A comprehensive algorithmic benchmarking framework was designed to evaluate fuel-consumption prediction under heterogeneous ship operating conditions. As summarized in Table 2, a total of 22 machine learning and deep learning models were implemented, spanning multiple methodological families. This diversity ensures that the modeling framework can accommodate linear trends, nonlinear interactions, distributional asymmetries, and high-dimensional feature relationships inherent in real-world ship operations.

Classical linear models, including Linear Regression, Ridge, Lasso, ElasticNet, and Huber Regressor, were included as baseline approaches. These models assume additive and approximately linear relationships between fuel consumption and explanatory variables such as speed, draft, trim, and environmental conditions. Regularization techniques (L1, L2, and combined penalties) were used to address multicollinearity and overfitting, while robust regression (Huber) was incorporated to handle potential outliers in operational data.

K-Nearest Neighbors (KNN) and Support Vector Regression (SVR) were employed to capture local nonlinearities without relying on global parametric assumptions. KNN models fuel consumption based on proximity in the feature space, which is useful when similar operating regimes recur across voyages. SVR introduces kernel transformations to project input variables into higher-dimensional spaces, enabling the modeling of nonlinear relationships between ship operation variables and fuel use.

A substantial portion of the benchmark consists of decision-tree-based models, including ExtraTrees, Random Forest, and HistGradientBoosting. These methods partition the feature space hierarchically and are well suited to capturing threshold effects (e.g., draft or wave height regimes) and interaction structures. Ensemble aggregation further improves stability by reducing variance and sensitivity to noise in logbook data.

Several gradient-boosting variants were included, such as Gradient Boosting, NGBoost, XGBoost, XGBoost-DART, CatBoost, LightGBM, LightGBM-Tuned, and HistGradientBoosting-Quantile. These models iteratively refine predictions by correcting residual errors from previous learners, allowing them to model complex nonlinear dependencies and heterogeneous error structures. Probabilistic and quantile-based boosting approaches were incorporated to explore conditional distributions and uncertainty-aware learning, which is particularly relevant for fluctuating environmental conditions.

A Stacking Ensemble model was constructed to integrate multiple base learners within a meta-learning framework. This approach leverages complementary strengths across different algorithm families, allowing higher-level models to learn optimal combinations of diverse predictors.

Neural-network-based approaches, including Artificial Neural Networks (MLPRegressor) and Deep Neural Networks implemented in Keras, were introduced to model high-order nonlinear interactions through layered representations. These architectures are capable of capturing complex feature couplings that may arise from simultaneous variations in speed, loading condition, and sea state, albeit requiring careful data preparation and training stability considerations.

All models were trained and evaluated under a unified experimental pipeline using identical input features and preprocessing steps. Performance metrics such as MAE, RMSE, and R^2 were computed consistently across models to maintain comparability. The inclusion of this broad algorithmic spectrum ensures that the benchmarking exercise systematically explores both model simplicity versus complexity and interpretability versus expressive power, providing a comprehensive methodological foundation for ship fuel-consumption modeling under real-world operational constraints.

The benchmarking of 22 ML/DL models is intentional to ensure that all major algorithmic families linear, tree-based, boosting-based, probabilistic, and neural architectures are systematically evaluated under the same dataset. The results clearly show that tree-based ensemble models (GB, NGBoost, XGBoost, Random Forest) outperform both linear regressors and deep-learning models. The Gradient Boosting Regressor achieved the highest coefficient of determination (R^2=0.6166), the lowest Mean Absolute Error (MAE=0.2818), and the lowest Root Mean Squared Error (RMSE=0.5189). This indicates that the model effectively captures nonlinear relationships between operational parameters (such as vessel speed, trim, and environmental resistance) and fuel consumption shown in Table 2, Figs. 4 and 5.

In the training results, Close competitors, NGBoost and XGBoost, standout as the strongest models with the results of R^2 of 0.61 each, with the errors 2 to 5 %, which is showing that gradient-based ensemble methods are better for small-scale maritime datasets. Tree-based models such as ExtraTrees, Random Forest also performed well with R^2 of 0.59, providing robustness and interpretability with errors of 2-5 %.

Linear models such as Ridge, Lasso also achieved moderate accuracy R^2 of 0.50, with errors of 3-6%, suggesting that for fuel consumption prediction, we cannot only rely on a few algorithms. In our training, the results of neural models such as ANN, DNN, and TabNet showed poorly (negative R^2), primarily due to the limited sample size and small size of dataset, here our dataset size is only (76 valid rows, 7 valid columns). This shows that in further research, we need to collect more data or bigger datasets for training.

Table 2. Summary table of training results.

Rank	Model	MAE	RMSE	R²
1	**Gradient Boosting**	0.2818	0.5189	**0.6166**
2	**NGBoost**	0.2903	0.5231	0.6104
3	**XGBoost-DART**	0.2977	0.5304	0.5995
4	**ExtraTrees**	0.3064	0.5379	0.5881
5	**CatBoost**	0.3370	0.5426	0.5808
6	**XGBoost**	0.2987	0.5450	0.5772
7	**Random Forest**	0.3136	0.5475	0.5732
8	Ridge	0.3690	0.5907	0.5033
9	Lasso	0.3651	0.5938	0.4980
10	ElasticNet	0.3650	0.5942	0.4974
11	Linear Regression	0.3650	0.5946	0.4967
12	HistGradientBoosting	0.3407	0.5995	0.4883
13	Stacking Ensemble	0.3475	0.6025	0.4833
14	LightGBM	0.3164	0.6038	0.4810
15	SVR	0.3697	0.6156	0.4604
16	KNN	0.4284	0.6173	0.4576
17	HistGBM Quantile	0.4604	0.6765	0.3484
18	LightGBM-Tuned	0.4192	0.7220	0.2579
19	Huber Regressor	0.6220	0.7456	0.2085
20	TabNet	0.6342	0.9053	−0.1666
21	ANN (MLPRegressor)	1.7222	2.0764	−5.1378
22	DNN (Keras)	1.7322	2.4387	−7.4668

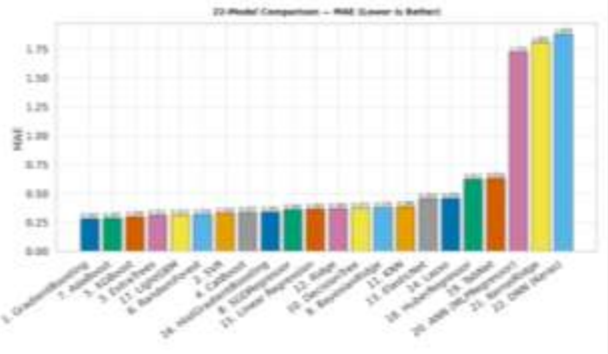

Fig. 4. MAE Comparison for 22 ML/DL models.

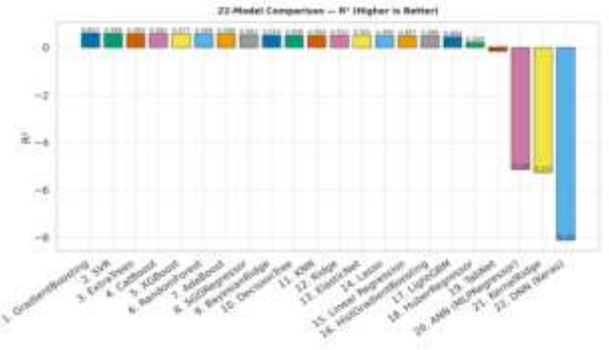

Fig. 5. R^2 Comparison for 22 ML/DL models.

3.1 Model Testing on Unseen Data

In training results, as we see, training results are not very high. However, we will continue testing with unknown data, which means the testing data is not part of the training dataset. Fig. 6 compares actual fuel consumption with predictions from Gradient Boosting (GB) and NGBoost models on unseen data. Both models closely follow the real trend, achieving high accuracy (GB: R^2=0.94; NGBoost: R^2=0.93) with minimal deviation both with 1-2 % error. GB slightly outperforms NGBoost, showing smoother alignment with peak and low consumption phases, confirming its robustness for real-time fuel prediction.

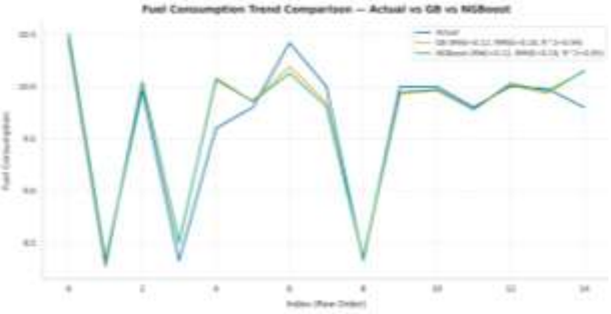

Fig. 6. Test Results of the first 2 models with actual Fuel consumption.

4. CONCLUSION AND FURTHER STUDIES

In this paper, an AI-based ship fuel consumption prediction model is developed, by a comprehensive multiframework of 22 machine learning (ML) and deep learning (DL) algorithms. These models were trained with the real-world ship logbook data collected from a bunker ship named ASHICO VICTORIA with 2 years of voyage record (2023–2024). After cleaning dataset, it only remains (76 rows and 7 columns). With that very small dataset, trained results are not very high with R^2 of around 0.6 however the error rate is very small from 2 to 5 %. When testing with unseen data with the models, achieved the highest predictive accuracy with $R^2 \approx 0.93–0.94$ with the prediction error of 1-2 %. This shows that these models are reliable for practical applications even if a training dataset is very small. These AI based models can capture well of nonlinear dependencies among operational and environmental parameters, providing a reliable solution better than traditional physics-based models. This study also highlight the most influential factors such as speed, trim for further fuel optimization by finding optimized operational parameters to enhance energy efficiency, reduce fuel costs, and support IMO 2050 decarbonization goals. In the future research, some plans will be conducted such as hybrid ensemble integration combing multi-algorithms into one powerful one to improve robustness, and data augmentation and data expansion will be conducted to increase dataset's size with advanced synthetic methods. Real-Time Implementation like linking models to real time updated data will also be applied. And fuel optimization models will be developed to be able to reduce fuel consumption, not just prediction. All these directions will support for intelligent and sustainable maritime operations, bridging AI-driven analytics with practical fuel management and global decarbonization goals.

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