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A MACHINE LEARNING FRAMEWORK FOR PREDICTING EFFICIENT SHIP DESIGN PARAMETERS

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ABSTRACT

The determination of principal particulars represents the initial step in any vessel design process, serving as the essential input for subsequent design phases. The precise calculation of principal particulars of vessels holds paramount importance across their lifecycle, spanning design, construction, and operational phases. These determinations have relied on complex and time-consuming calculations, as well as iterative methodologies requiring an in-depth comprehension of naval architecture principles. Nonetheless, recent progressions in machine learning (ML) and data-driven technologies have introduced novel opportunities to increase the accuracy and effectiveness of this process. In this study, a dataset comprising 405 entries of inland cargo vessels in Bangladesh is analyzed to identify the most effective model for predicting key ship design parameters. Machine learning techniques, including feedforward neural networks, random forests, and K-nearest neighbors, are employed, and performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) values are utilized for evaluation. Results indicate that K-nearest neighbors (KNN) demonstrated superior performance across multiple metrics, suggesting its efficacy in enhancing the accuracy of determining key ship design parameters. The findings highlight the potential of KNN for improving the accuracy and efficiency of determining principal ship particulars, paving the way for further exploration in the field.

Keywords: *Machine Learning, Artificial Neural Network, Ship Design Parameters, Random Forest, K-nearest Neighbors*

1. INTRODUCTION

The development of accurate and efficient ship design methodologies remains a critical challenge in the maritime industry. The initial stages of vessel conceptualization involve the determination of principal particulars, including length, breadth, draft, depth, block coefficient, displacement, engine power, and ship speed. Traditionally, these parameters have been established through iterative and complex calculations, requiring extensive expertise in naval architecture. This time-consuming process often necessitates multiple design iterations, prolonging the overall design cycle. To address these challenges and accelerate the ship design process, the application of machine learning has emerged as a promising avenue. Using historical data and advanced algorithms, machine learning models can be trained to predict principal particulars based on relevant input parameters. This approach holds the potential to streamline the design process, reduce development time, and improve the accuracy of parameter estimation.

This study investigates employing machine learning techniques to predict key ship design parameters for inland cargo vessels operating in Bangladesh. By analyzing a dataset comprising 405 vessels, the research aims to develop predictive models capable of accurately estimating principal particulars such as length (L_{WL}), breadth (B), draft (T), depth (D), block coefficient (C_B), engine power (P_{ME}). The input parameters for these models are Deadweight (DWT) and speed (V_s). By utilizing algorithms such as artificial neural networks, random forests, and K-nearest neighbors, and evaluating their performance through metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2), this study aims to demonstrate the effectiveness of machine learning in transforming the naval architecture landscape.

2. LITERATURE REVIEW

Machine learning (ML) has emerged as a transformative technology with significant potential for the maritime industry. Recent advancements in ML algorithms and the increasing availability of data have led to its application in various naval architecture domains.

Recent studies highlight the transformative potential of machine learning (ML) in ship design and operation. Panda [1] analyzed ML's application in naval architecture, emphasizing its role in enhancing wave-prediction models, real-time decision-making, and optimizing marine systems. Similarly, Rawson and Brito [2] focused on ML in maritime safety evaluations, advocating for methodological improvements to boost model accuracy and reliability. The prediction of fuel consumption and hydrodynamic performance through ML has been a key focus. Kim et al. [3] proposed an ML approach for accurate fuel consumption prediction, vital for efficient ship operation. Gupta et al. [4] applied ML models, including probabilistic artificial neural networks (ANN) and regression models like NL-PCR and NL-PLSR, to estimate hydrodynamic performance, highlighting their effectiveness in managing fluctuations due to marine fouling and antifouling systems.

In specialized applications such as ice navigation, Sun et al. [5] developed an ANN model that significantly outperformed traditional formulas in predicting ship resistance in ice-covered waters, essential for polar operations. Tadros et al. [6] targeted improvements in marine diesel engine efficiency to reduce fuel consumption and SO_x emissions, demonstrating ML's role in enhancing engine performance and sustainability.

ML has also optimized ship design and traffic management. El Mekkaoui et al. [7] used deep learning to predict ship speeds for better traffic management. Huang et al. [8] discussed ML's potential in sustainable ship design, noting the need for more research on data quality and model interpretability. Gypa et al. [9] introduced an interactive optimization methodology for marine propeller design, integrating human-computer interaction with support-vector machine models to enhance optimization processes.

Despite significant advancements in applying machine learning to various areas of naval engineering, there remains a noticeable gap in research focused on inland vessel design, particularly in regions like Bangladesh, where these vessels are essential for transportation. Inland vessels face unique design challenges, such as shallow waters and varying environmental conditions, which differ from those of ocean-going ships. Addressing this gap is crucial for developing more efficient, reliable, and environmentally sustainable vessels. This study aims to compare ML models in predicting inland vessel parameters, thereby enhancing the precision and efficiency of the design process and contributing to a more sustainable and effective inland shipping industry.

3. METHODOLOGY

This study utilizes a structured framework to examine the prediction of vessel particulars, incorporating a comprehensive methodology that comprises three principal phases: data collection and preprocessing, model training, and model evaluation.

3.1 Data Collection and Preprocessing

After reviewing the inland ship data from Bangladesh sourced from Hasan's PhD thesis [10], a dataset of 405 inland cargo ships was selected for analysis. Table 1 outlines the key attributes of the dataset used to predict vessel design parameters in Bangladesh's inland ships. This includes Length (L_{WL}), Breadth (B), Draft (T), Depth (D), Block Coefficient (C_B), Deadweight Tonnage (DWT), Speed (V_s), and Engine Power (P_{ME}). The table provides units, and statistical measures (minimum, maximum, average) for each attribute, offering a clear overview of the dataset characteristics in the study.

Table 1. Attributes of Dataset

Attribute	Units	Min	Max	Average
Length (L_{WL})	meters	17.30	83.53	52.87
Breadth (B)	meters	4.32	16.00	9.54
Draft (T)	meters	1.2	4.76	3.29
Depth (D)	meters	1.5	5.7	3.79
C_B	-	0.61	0.83	0.74
Dead-weight (DWT)	tonnes	125.00	3560.00	1042
Speed (V_s)	Knots	5	13.00	9.13
Engine Power (ME)	kW	85	2364.00	540.89

3.2 Outliers Detection and Removal

Outliers can significantly impact model performance. To maintain analysis integrity, it is crucial to identify and manage outliers. Figure 1 combines histograms and box plots to illustrate the statistical distribution of each parameter, highlighting the median, quartiles, and potential outliers, marked in red. Figure 1 displays a set of combined boxplots and histograms for eight different attributes: Length, Breadth, Draft, Depth, Block Coefficient, Deadweight Tonnage, Engine Power, and Speed. Box plots visualize data distribution, central tendency, and outliers. Outliers, marked by red circles, are points beyond 1.5 times the interquartile range (IQR) or 3 standard deviations. These plots help identify trends and anomalies for data cleaning.

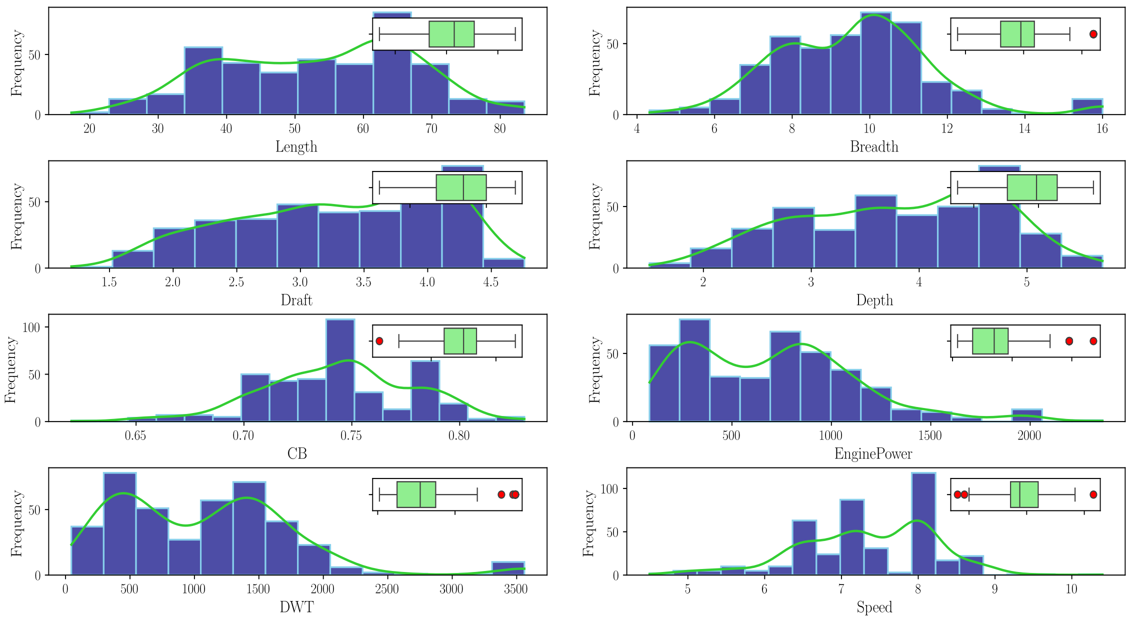

Figure 1. Outliers Detection

Table 2. Summary of Outlier Detection

Attribute	Outliers Detected	Detection Method
Length	0	Z-score
Breadth	11	IQR
Draft	0	Z-score
Depth	0	Z-score
CB	1	Both Z-score & IQR
DWT	11	IQR
Speed	3	IQR
Engine Power	10	IQR

Table 2 presents outlier detection results for various attributes using Z-score and Interquartile Range (IQR) methods. Attributes like Length, Draft, and Depth showed no outliers with the Z-score method. Significant outliers were found in Breadth, Deadweight Tonnage (DWT), Speed, and Engine Power using IQR, and in Block Coefficient (CB) using both methods. Each attribute is listed with the number of outliers detected and the corresponding detection method.

4. MACHINE LEARNING ALGORITHMS

4.1 Artificial Neural Network

Neural networks are categorized into two types: biological neural networks, consisting of biological neurons, and artificial neural networks (ANNs), composed of interconnected artificial nodes. ANNs mimic human learning by acquiring knowledge through examples and have excelled in areas like signal processing and pattern recognition, notably in natural language processing (NLP) and computer vision. A typical ANN consists of three layers: input, hidden, and output units. Training these networks involves optimization algorithms such as RMSprop, an adaptive learning rate method that adjusts according to data variability. The RMSprop formula updates the weights using the moving average of the squared gradients, with parameters for the gradient, learning rate, and a small stabilizing constant.

Activation functions, crucial for introducing non-linearity, enable ANNs to model complex relationships. The Rectified Linear Unit (ReLU) function, defined as ReLU (x) = max(0,x), is particularly effective in mitigating the vanishing gradient problem, enhancing the network's ability to learn complex patterns. This function is employed in the input and hidden layers of the network.

4.2 Random Forest

Random forests are an ensemble learning method used for classification and regression tasks. This technique builds numerous decision trees during training. For classification, the class is determined by the majority vote of the trees, while for regression, the final prediction is the average output of all trees. The training employs the bootstrap aggregating (bagging) technique, which involves generating multiple samples (X_b) and (Y_b) from the training data (X) and (Y) by sampling with replacement. Each sample is used to train a tree (f_b). For a new sample (x'), predictions are made by averaging the outputs of all trees:

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x')$$

4.3 K-Nearest Neighbors

The k-nearest neighbors (KNN) algorithm is a non-parametric method used for both classification and regression. It identifies the (k) nearest training examples to a new query point (x') based on a distance metric like Euclidean distance. For regression, the predicted value is the mean of the values associated with these (k) neighbors:

$$\hat{y}(x') = \frac{1}{k}\sum_{i=1}^{k} y_i$$

where (y_i) are the responses of the (k) nearest neighbors to (x'). KNN's simplicity makes it particularly useful for modeling complex but noisy data scenarios.

4.4 Hyperparameter Tuning

This section describes key hyperparameters used to configure the machine learning models. These parameters are systematically tuned to optimize model performance for the research goals. The feedforward neural network specifically employs a random search with repeated cross-validation for hyperparameter tuning. This approach is known for efficiently selecting hyperparameters from a defined set, aiming to find the best configuration that balances model complexity and accuracy.

Table 3. Hyperparameter Tuning (ANN)

Hyperparameters	Optimal Value
Optimization Algorithm	rmsprop
Activation Function (Input Layer)	relu
Number of Hidden Layers	1
Activation Function (Layer 0)	relu
Neurons in Hidden Layer 0	256
Loss Function	MSE
Batch Size	23
Number of Epochs	1000

Table 3 summarizes the neural network's setup, employing 'rmsprop' for optimization and 'relu' activation in input and single hidden layers. The hidden layer has 256 neurons, balancing complexity, and efficiency. It uses 'Mean Squared Error' as the loss function, with a batch size of 23 and trained for 1000 epochs for effective learning and performance, balancing efficiency, and capability for modeling.

Hyperparameter tuning for the Random Forest model followed a systematic approach, using random search. Table 4 shows the model's key settings, including ‘max_depth’ of 10, ‘max_features’ as ‘sqrt’, and ‘min_impurity_decrease’ set to 0.2. It uses 400 ‘n_estimators’ for ensemble learning, with ‘min_samples_leaf’ set to 2 and ‘min_samples_split’ set to 5. The maintains a random_state of 42.

Similarly, Table 5 summarizes the key hyperparameters for the K-nearest neighbors algorithm used in the study. It provides the optimal values for parameters such as the number of neighbors, weight function, and distance metric, crucial for predictive modeling. Through detailed hyperparameter tuning of the Feedforward Neural Network, Random Forest, and K-nearest neighbors models, this study demonstrates a commitment to optimizing model architectures and configurations. This meticulous approach aims to ensure the production of high-quality and reliable results.

Table 4. Hyperparameter Tuning (RF)

Hyperparameters	Optimal Value
max_depth	10
max_features	sqrt
max_leaf_nodes	None
min_impurity_decrease	0.2
min_samples_leaf	2
min_samples_split	5
n_estimators	400
oob_score	TRUE
random_state	42

Table 5. Hyperparameter Tuning (KNN)

Hyperparameters	Optimal Value
n_neighbours	6
weight	distance
metric	minkowski

5. RESULTS AND DISCUSSION

5.1 Model Evaluation

Evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2) assess machine learning model performance. MSE calculates the average squared differences between predicted and actual values:

$$MSE = \frac{\sum (y_i - \hat{y}_i)^2}{n}$$

where (y_i) is the actual output, ($\hat{y}_i$)is the predicted output, and (n) is the number of samples.

RMSE is the square root of MSE, measuring error magnitude:

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$$

R^2 indicates the proportion of variance in the dependent variable predictable from the independent variables:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - y_{mean})^2}$$

where (y_{mean}) is the mean of actual outputs. R^2 values range from -∞ (worse than mean prediction) to 1 (perfect prediction).

5.2 K-Fold Cross Validation

K-fold cross-validation combats bias and variance in model evaluation by splitting the data into folds for repeated training and testing, especially valuable for limited data. Table 6 compares the performance of three predictive models—Neural Network (NN), Random Forest (RF), and K-Nearest Neighbors (KNN)—across 10 folds using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2. Overall, the KNN model consistently outperforms the others, exhibiting higher R^2 values and lower MSE and RMSE, indicating superior predictive accuracy and reliability. The RF model generally shows the poorest performance with lower R^2 values, suggesting higher predictive errors. NN performs moderately, with its effectiveness falling between KNN and RF.

Table 6. Evaluation Metrics for 10-Fold Cross-Validation

K-Fold	Model	MSE	RMSE	R^2
1	NN	0.207	0.455	0.771
1	RF	0.352	0.593	0.615
1	KNN	0.212	0.460	0.781
2	NN	0.241	0.491	0.758
2	RF	0.407	0.638	0.576
2	KNN	0.213	0.462	0.762
3	NN	0.294	0.542	0.648
3	RF	0.469	0.685	0.429
3	KNN	0.285	0.534	0.651
4	NN	0.269	0.519	0.706
4	RF	0.397	0.630	0.569
4	KNN	0.261	0.511	0.721
5	NN	0.231	0.481	0.777
5	RF	0.393	0.627	0.617
5	KNN	0.229	0.479	0.794
6	NN	0.294	0.543	0.646
6	RF	0.381	0.617	0.547
6	KNN	0.293	0.541	0.661
7	NN	0.230	0.480	0.810
7	RF	0.442	0.665	0.637
7	KNN	0.231	0.481	0.831
8	NN	0.300	0.547	0.695
8	RF	0.454	0.674	0.537
8	KNN	0.287	0.536	0.709
9	NN	0.227	0.477	0.790
9	RF	0.389	0.624	0.638
9	KNN	0.224	0.473	0.790
10	NN	0.249	0.499	0.779
10	RF	0.425	0.652	0.627
10	KNN	0.218	0.467	0.811

5.3 Model Comparison

405 Bangladeshi inland cargo ship data entries are processed, resulting in 392 entries after outlier and duplicate removal. 80% (313 entries) are used for training, while the remaining 20% (79 entries) constitute the testing dataset. The models are trained with optimized hyperparameters and evaluated on the testing dataset using evaluation metrics, as outlined in Section 5.1. Multiple evaluation metrics are utilized to assess the predictive performance of the neural network (NN), random forest (RF) and k-nearest neighbors (KNN) models. The outcomes, shown in Figure 2-5, provide insights into the models' efficacy across diverse ship features. Figure 6 in illustrates the comparison between actual and predicted values.

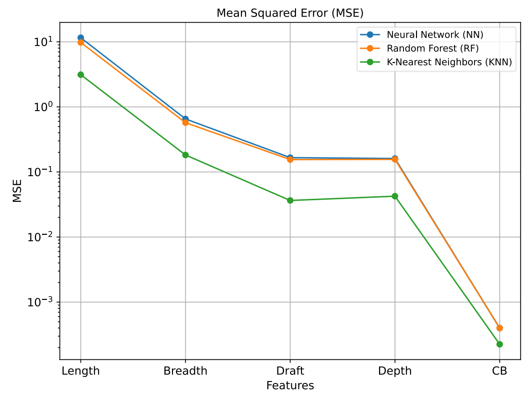

Figure 2. MSE Comparison

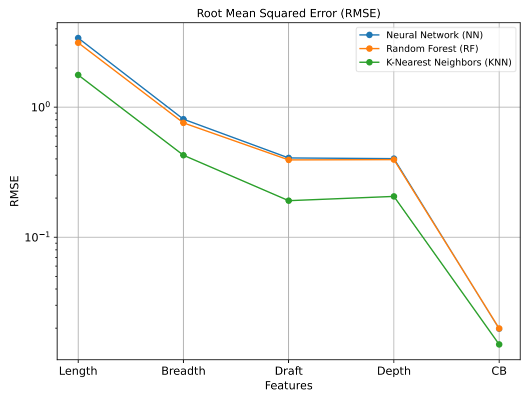

Figure 3. RMSE Comparison

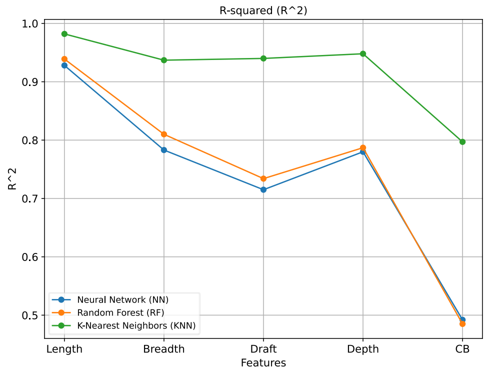

Figure 4. R^2 Comparison

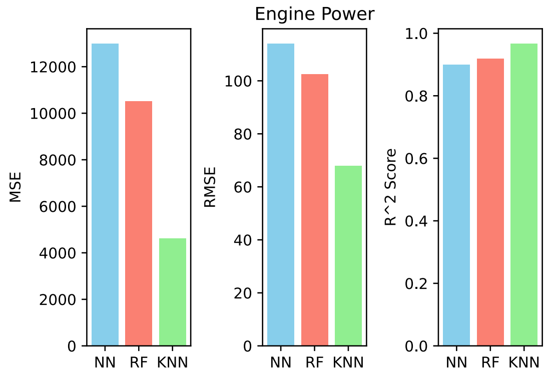

Figure 5. MSE, RMSE, R^2 comparison for Engine Power

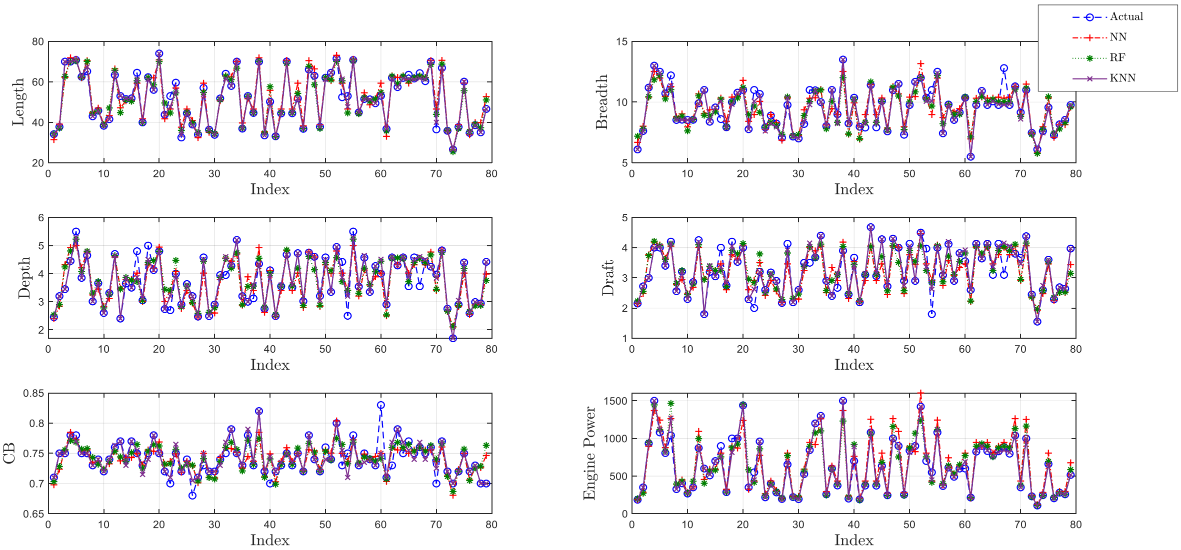

Figure 6: Actual vs Predicted Result

In Figure 2-5, for 'Length', the KNN model has significantly lower MSE (3.125824) and RMSE (1.768) compared to NN (MSE: 11.556, RMSE: 3.399) and RF (MSE: 9.769, RMSE: 3.126), and it achieves the highest R^2 value of 0.982, indicating excellent model fit. 'Breadth' also sees the best performance from KNN with an MSE of 0.182329, RMSE of 0.427, and R^2 of 0.937, considerably outperforming NN and RF. The feature 'Draft' follows a similar pattern, with KNN showing an MSE of 0.036481, RMSE of 0.191, and the highest R^2 of 0.94.

For 'Depth', KNN has an MSE of 0.042436 and RMSE of 0.206, with an R^2 of 0.948, once again outshining the other models. The CB feature shows the lowest error values across models, but KNN still leads with an MSE of 0.000225, RMSE of 0.015, and an R^2 of 0.797. Lastly, Engine Power has the largest error magnitudes with NN showing an MSE of 12980.76 and RMSE of 113.933; RF with MSE of 10504.34 and RMSE of 102.491; and KNN presenting the best results with an MSE of 4610.138404, RMSE of 67.898, and the highest R^2 of 0.966.

These figures demonstrates that the K-Nearest Neighbors (KNN) model significantly outperforms the Neural Network (NN) and Random Forest (RF) models in predictive accuracy across all features, achieving the lowest error rates and highest R^2 values. Particularly, KNN shows remarkable precision in 'Length' and 'Engine Power' with error rates multiple times lower and R^2 values notably higher than those of NN and RF.

Overall, the KNN model exhibits superior prediction accuracy and consistency across all features when considering these specific error metrics and determination coefficients.

6. CONCLUSIONS

This research conducts a comparative analysis of various machine learning algorithms to determine vessel particulars using data from inland cargo vessels in Bangladesh. It explores the efficacy of different ML techniques in predicting crucial design parameters. This research marks a pioneering initiative in Bangladesh, employing machine learning techniques, notably Neural Networks, Random Forest and K-nearest neighbors, to predict inland vessel particulars. Despite challenges posed by limited ship data availability, the study successfully developed and evaluated predictive models for essential design parameters of inland cargo ships.

In future studies, it is suggested to analyze more types of vessels besides cargo ships, like passenger ferries or oil tankers commonly found in the region. Using more advanced machine learning techniques, like ensemble methods or deep learning, could improve the accuracy of predicting vessel details. Adding more features to the dataset and including data from various sources may also boost the models' performance. Comparing different ways of preparing data and evaluating models could help identify the best methods for vessel parameters prediction tasks.

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