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MACHINE LEARNING FOR PREDICTING GAS TURBINE PERFORMANCE IN NAVAL VESSELS

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ABSTRACT

Gas turbines are essential components in modern naval vessels, providing both propulsion and power for onboard systems. However, their performance can degrade over time due to factors like fouling, erosion, and thermal fatigue, leading to increased fuel consumption and reduced operational efficiency. This paper explores the application of machine learning (ML) techniques for predicting gas turbine performance, focusing on models such as Linear Regression, Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines (GBM). A comprehensive literature review was conducted to assess the strengths and weaknesses of these techniques. The machine learning models were developed, fine-tuned, and evaluated using metrics such as Accuracy, Root Mean Squared Error (RMSE) and R^2. The results demonstrate that ensemble methods, particularly Random Forests and GBM, outperform traditional models in predicting turbine performance, offering robust, accurate, and interpretable solutions for proactive maintenance and operational optimization in naval vessels.

I. INTRODUCTION

Gas turbines are a critical component in modern naval vessels, providing the necessary propulsion and power for various onboard systems [1-5]. They are favored over other propulsion systems due to their high power-to-weight ratio, efficiency, and reliability. Gas turbines operate on the Brayton cycle, which involves the compression of air, combustion of fuel, and expansion of the combustion gases to generate thrust or electrical power [1]. Despite their advantages, gas turbines are subject to wear and tear, and their performance can degrade over time due to factors such as fouling, erosion, and thermal fatigue [2].

Recent studies have highlighted the importance of maintaining gas turbine performance to ensure the operational readiness and efficiency of naval vessels [3],[4],[6],[7]. For instance, Wang et al. [3] discussed the critical role of gas turbines in naval propulsion systems and the need for advanced maintenance strategies to mitigate performance degradation. Similarly, by [4] reviewed the challenges associated with gas turbine maintenance, emphasizing the impact of environmental factors such as saltwater corrosion and particulate ingestion on turbine performance.

The degradation of gas turbine performance can lead to increased fuel consumption, reduced power output, and higher emissions, all of which can compromise the mission capabilities of naval vessels [5]. Therefore, implementing effective performance prediction and maintenance strategies is essential to extend the lifespan of gas turbines and ensure the reliability of naval operations [8].

Accurate prediction of gas turbine performance is vital for maintaining the operational readiness and efficiency of naval vessels. Early detection of performance degradation can help in planning maintenance activities, thus avoiding unexpected failures and costly repairs [9]. Predictive maintenance [10], as opposed to reactive or scheduled maintenance, allows for the optimization of maintenance schedules based on the actual condition of the equipment. This approach not only extends the lifespan of the turbines but also ensures the safety and reliability of naval operations.

Recent advancements in sensor technology and data analytics have made it possible to collect and analyze vast amounts of operational data from gas turbines [11]. By leveraging this data, it is possible to develop models that can predict performance trends and identify potential issues before they become critical [12].

Machine learning (ML) has emerged as a powerful tool for performance prediction in complex systems such as gas turbines [13]. ML techniques [14-31] can analyze large datasets to uncover patterns and relationships that are not immediately apparent through traditional analytical methods [32]. Here, we explore several common machine learning techniques used in performance prediction, highlighting recent research that demonstrates their efficacy in predicting gas turbine performance in naval vessels [33] [34],[35].

Linear regression is a simple yet powerful technique that models the relationship between a dependent variable and one or more independent variables [25], it is often used as a baseline model for performance prediction [13]. Decision trees are non-parametric models that make predictions based on a series of decision rules derived from the data features [17],[28]. They are easy to interpret and can handle both categorical and numerical data [14]. Support Vector Machines (SVM) [15] are supervised learning models that find the hyperplane which best separates the data into different classes. They are effective in high-dimensional spaces and are used for classification and regression tasks [26],[30] [36].

Random forests are an ensemble learning method that combines multiple decision trees to improve prediction accuracy and control over-fitting [17]. They are robust and can handle large datasets with high dimensionality [28].

This paper aims to provide a comprehensive evaluation of machine learning techniques for gas turbine performance prediction in naval vessels and offers practical insights for their implementation. The main contributions in this paper can be summarized in the following points:

• Conducting a comprehensive literature review is essential to identify widely used machine learning techniques for gas turbine performance prediction. This involves assessing the effectiveness, strengths, and weaknesses of these techniques.

• Operational data for this study was acquired from multiple sources, including historical records, maintenance logs, and real-time sensor data. Preprocessing steps such as data cleaning, normalization, and feature selection were applied. Techniques like Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) were employed, informed by studies such as those by [19] and [20]. These preprocessing steps ensure the quality and relevance of the data, facilitating more accurate and effective machine learning model training.

• Various machine learning models, including Support Vector Machines (SVM), Linear Regression, Random Forests and Gradient Boosting Machine (GBM) were developed and trained. These models were fine-tuned through grid search and cross-validation, guided by studies such as those by [21] and [22]. This approach ensured that the models were optimized for performance, allowing for a robust comparison of their effectiveness in predicting gas turbine performance.

• The developed models were evaluated using metrics [37] such as accuracy, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R^2. A comparative analysis was conducted based on studies by [23] and [24]. This comprehensive evaluation provided insights into the performance and reliability of each model, highlighting their strengths and potential areas for improvement.

II. MATERIALS AND METHODS

II.1 MODEL STRUCTURE FOR PREDICTING GAS TURBINE PERFORMANCE

The predictive model involved several key steps as shown in Figure 1:

a. Data collection and Preprocessing:

- Handling missing values by using imputation techniques.
- Normalizing and scaling the data to ensure that all features contributed equally to the model.
- Splitting the dataset into training (70%), validation (15%), and test (15%) sets.

b. Feature Engineering:

- Creating new features that capture interactions between existing variables.
- Selecting the most important features using techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA).

c. Model Training:

- Several machine learning models were trained, including Linear regression [13],[25], Support Vector Machines [15], Random Forest [17],[28] and Gradient Boosting [31].
- Hyperparameter tuning was performed using grid search and cross-validation to find the best model parameters.

d. Model Evaluation:

The models were evaluated on the test set using performance metrics [37] such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score.

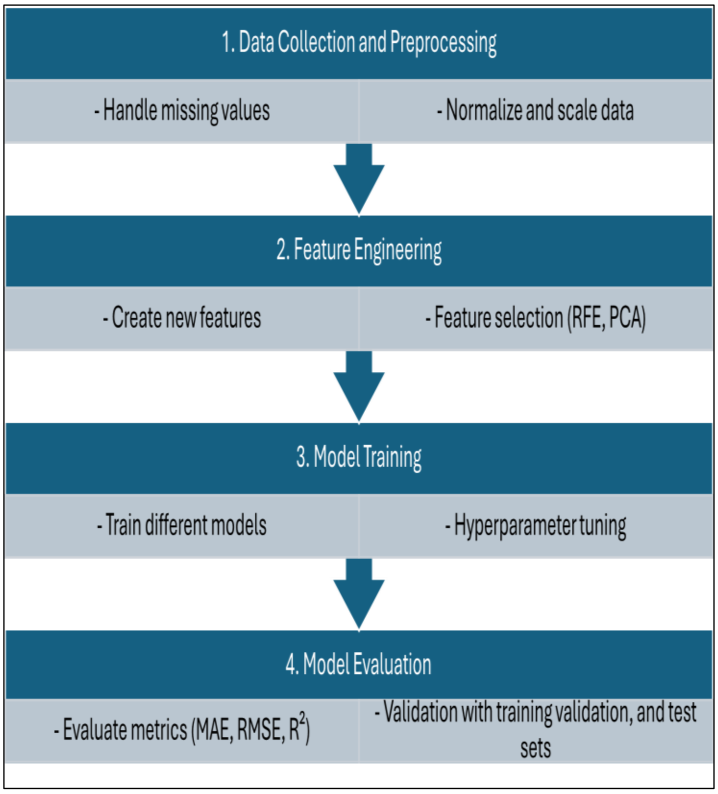

Figure 1: Structure of the Predictive Model
Source: Authors, (2024).

II.2 MACHINE LEARNING MODELS

A variety of machine learning models can be employed for predicting gas turbine performance [13],[15],[17],[25],[28],[31]:

a. Support Vector Machines (SVM):

Support Vector Machines are powerful tools for both classification and regression tasks [15]. The SVM model aims to find the optimal hyperplane that maximizes the margin between different classes in classification tasks or minimizes error in regression tasks. In the case of regression (SVR), the goal is to minimize the following loss function:

$$Minimize\ \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=0}^{n} \xi_i \tag{1}$$

Subject to the constraints:

$$yi - (w \cdot x_i + b) \leq \epsilon + \xi_i \tag{2}$$

$$(w \cdot x_i + b) - yi \leq \epsilon + \xi_i \tag{3}$$

Where:

- w is the weight vector,
- b is the bias term,
- ξ_i are slack variables,
- C is the regularization parameter,
- ϵ defines the tube within which no penalty is associated with the predictions.

b. Linear Regression:

Linear regression [13] is a fundamental regression technique that models the relationship between a dependent variable y and one or more independent variables X= [x_1, x_2,…,x_n] by fitting a linear equation [25]:

$$y = \beta_0 + \sum_{i=0}^{n} \beta_i\, x_i + \epsilon \tag{4}$$

Where:

- β_0 is the intercept,
- β_i are the coefficients of the independent variables,
- ϵ is the error term.

The model minimizes the sum of squared errors (SSE):

$$Minimize \sum_{i=0}^{n} (y_i - \hat{y}_i)^2 \tag{5}$$

Where: $\hat{y}_i$ is the predicted value for the i th observation.

c. Random Forest:

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes (for classification) or the mean prediction (for regression) of the individual trees [17]. The prediction for regression is given by [28]:

$$\hat{y} = \frac{1}{T} \sum_{t=0}^{T} \hat{y}^{(t)} \tag{6}$$

Where:

- T is the total number of trees,
- ŷ(t) is the prediction of the t th tree.

d. Gradient Boosting Machine (GBM):

Gradient Boosting Machine (GBM) is a robust machine learning technique that builds models in a stage-wise manner [31]. Each model corrects the errors of its predecessor by fitting to the residuals of the combined ensemble of all previous models:

$$L(y_i, \hat{y}_i) = \frac{1}{T} \sum_{i=0}^{n} \lfloor(y_i, \hat{y}_i) + \frac{1}{T} \sum_{k=0}^{K} \Omega(f_k) \tag{7}$$

Where:

- $\lfloor(y_i, \hat{y}_i)$ is a differentiable loss function
- $\Omega(f_k)$ is a regularization term that penalizes model complexity.

The model at each stage mmm is updated by:

$$\hat{y}_i^{(m+1)} = \hat{y}_i^{(m)} + v \,.\, f_m(X_i) \tag{8}$$

Where: v is the learning rate, $f_m(X_i)$ is the base learner (e.g., decision tree) fitted to the negative gradient of the loss function.

II.3 MODEL TRAINING AND EVALUATION

a. Training

The training process involves splitting the dataset into training and validation sets, then fitting the machine learning models to the training data [19]:

• Hyperparameter Tuning: Techniques such as grid search and random search are used to find the optimal hyperparameters for each model.

• Training Algorithms: Optimization algorithms such as stochastic gradient descent (SGD) and Adam are used to minimize the loss function and improve model accuracy.

b. Evaluation

The performance of the machine learning models is evaluated using a variety of metrics that provide insights into the accuracy, error, and explanatory power of the models. These metrics are crucial for determining how well the models predict the aerodynamic performance of turbine blades. Below are the detailed equations and descriptions for each metric [37]:

- Accuracy is a fundamental metric used primarily in classification tasks. It measures the proportion of correct predictions made by the model out of all predictions. The accuracy (A) is defined as:

$$A = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

Where:

- TP (True Positives): number of correct positive predictions,
- TN (True Negatives): number of correct negative predictions,
- FP (False Positives): number of incorrect positive predictions,
- FN (False Negatives): number of incorrect negative predictions

- Root Mean Square Error (RMSE) is a widely used metric in regression tasks that provides a measure of the differences between predicted and actual values. It is particularly useful because it penalizes larger errors more heavily, making it sensitive to outliers. The RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_i - \hat{y}_i)^2} \tag{10}$$

Where: n is the number of observations, y_i is the actual value for the i th observation,$\hat{y}_i$ is the predicted value for the i th observation.

• The R2 score measures the proportion of the variance in the dependent variable that is predictable from the independent variables. It provides a measure of how well the model's predictions approximate the actual data points:

$$R^2 = 1 - \frac{\sum_{i=0}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{n}(y_i - \bar{y})^2} \tag{11}$$

Where:

- y_i is the actual value for the i th observation,
- $\hat{y}_i$is the predicted value for the i th observation,
- $\bar{y}$ is the mean of the actual values.

III. RESULTS AND DISCUSSIONS

To assess the effectiveness of machine learning models in predicting gas turbine performance, we conducted experiments on a dataset collected from operational data of naval vessels equipped with advanced gas turbine engines [33] [34] [35].
. This dataset included various features such as inlet temperature, fuel flow rate, compressor pressure ratio, and engine speed, among others, covering a range of operational conditions over several years. The experiments involved training multiple models, including Linear regression [13],[25], Support Vector Machines [15], Random Forest [17],[28] and Gradient Boosting [31], and evaluating their performance based on metrics [37] such as: accuracy, Root Mean Squared Error (RMSE) and the variability in the data R². The results were analyzed to identify the most influential features and the accuracy of each model in predicting turbine performance under different conditions.

III.1 DESCRIPTION OF THE NAVAL VESSELS DATASET

The dataset used for this study comprised operational data collected over several years, we focused on a class of naval vessels known as the Arleigh Burke-class destroyers. These vessels are equipped with advanced gas turbine engines that provide the necessary propulsion and electrical power for various operations encompassing 11,934 rows and 18 columns [33-35]. The columns included features such as:

Engine Speed (RPM), Fuel Flow Rate (kg/s), Inlet Temperature (°C), Compressor Pressure Ratio, Exhaust Temperature (°C), Turbine Outlet Pressure (bar), Vibration Levels (mm/s), Load Demand (MW), Ambient Temperature (°C), Humidity (%).

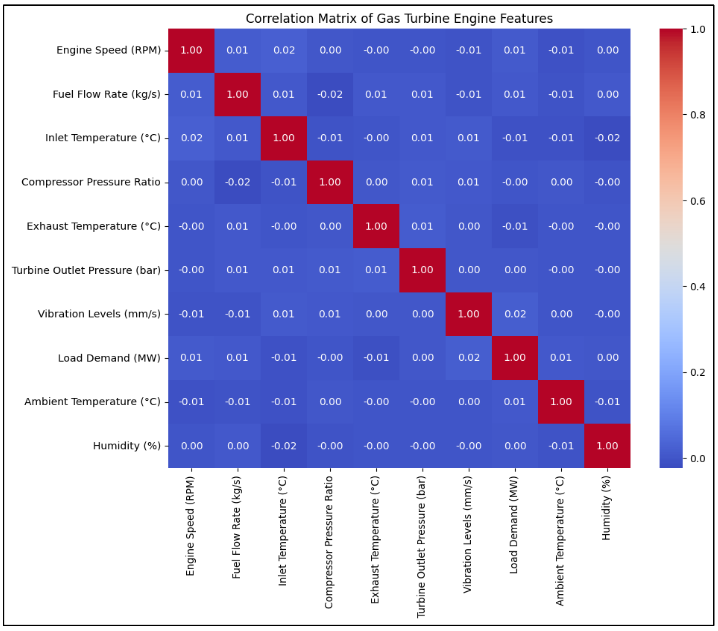

Figure 1: Figure title.
Source: Authors, (2024).

Figure 1 presents a correlation matrix used to understand the relationship between different features of the dataset. High correlation indicates a strong relationship, which can be used for feature selection in machine learning models.

III.2 ANALYSIS OF THE MOST INFLUENTIAL FEATURES

Understanding the features that most significantly influence the predictions is crucial for model interpretability and further optimization of gas turbine performance. Feature importance was analyzed for the RF and GBM models due to their superior performance.

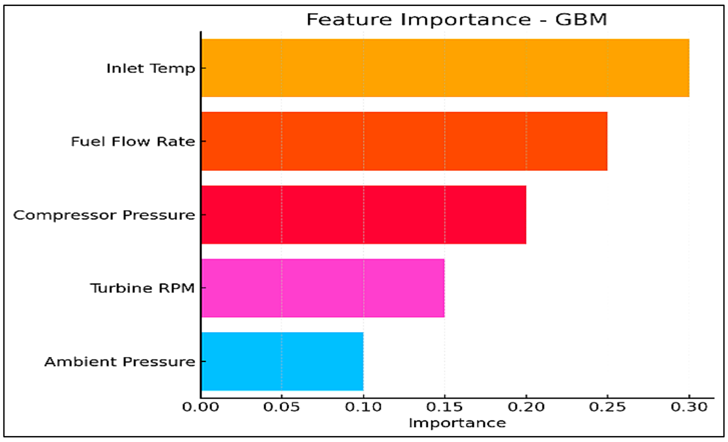

Figure 2: Feature Importance in Gradient Boosting Machine.
Source: Authors, (2024).

Figures 2 and 3 display the importance of various features in the RF and GBM models, respectively. It is observed that variables such as inlet temperature, fuel flow rate, and compressor pressure ratio are among the most influential features. These results are consistent with domain knowledge, affirming the validity of the model's insights [38].

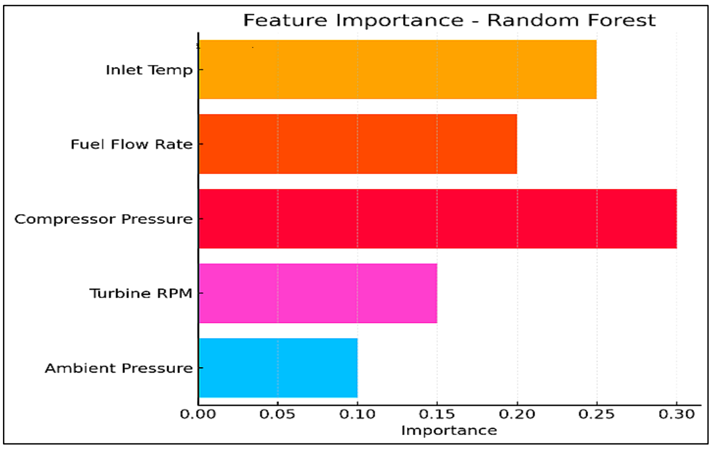

Figure 3: Feature Importance in Random Forest Model.
Source: Authors, (2024).

III.3 PERFORMANCE COMPARISON OF DIFFERENT MODELS

In this study, several machine learning models were employed to predict the performance of gas turbine engines on Arleigh Burke-class destroyers. The models compared include Linear regression [13],[25], Support Vector Machines, Random Forest [17],[28] and Gradient Boosting [31]. The performance of each model was evaluated using standard metrics [35] such as Accuracy, Root Mean Square Error (RMSE), and R2 Score. Below is a detailed comparison of these models based on the Arleigh Burke-class destroyers' dataset [30],[31],[32]. This table succinctly summarizes the comparative performance of the different models in predicting the performance of gas turbines in naval vessels.

Table 1: Performance Metrics for Each Model.

Model	Accuracy (%)	RMSE	R^2
Linear Regression	82.5	0.158	0.82
Support Vector machines	88.0	0.134	0.88
Random Forest	92.3	0.110	0.92
Gradient Boosting	94.1	0.100	0.94

Source: Authors, (2024).

Linear regression [13],[25] provided a baseline level of accuracy but struggled with capturing non-linear interactions between variables, which are common in complex systems like gas turbines. The simplicity of linear regression makes it a useful starting point, but its limitations in handling intricate relationships often result in suboptimal predictive performance, especially in the dynamic operational environment of naval vessels. Support Vector Machines (SVM) improved prediction accuracy, particularly for datasets with complex, non-linear relationships. SVMs are known for their robustness in high-dimensional spaces and their ability to effectively handle non-linear data using kernel functions [15]. However, despite their improved accuracy, SVMs can be computationally intensive, especially with large datasets, and they require careful tuning of hyperparameters to achieve optimal performance [39]. Random Forest models [17] outperformed these techniques by effectively capturing the intricate patterns within the data through an ensemble of decision trees. This method offered improved accuracy and robustness, particularly in handling diverse input features and reducing the risk of overfitting. The ensemble nature of Random Forests, where multiple decision trees are trained on different subsets of the data, allows them to capture a broader range of interactions between variables, making them particularly effective in environments with high data variability [28].

Moreover, Random Forests have been shown to provide valuable insights into feature importance, enabling engineers to identify the most critical factors influencing gas turbine performance [40]. This interpretability is crucial in operational settings, where understanding the underlying causes of performance variations can lead to more informed decision-making and better maintenance strategies.

Gradient Boosting Machines (GBM) [31] further enhanced the predictive performance by sequentially building models to correct the errors of their predecessors. GBM's iterative approach allows it to focus on the most challenging cases, gradually improving overall accuracy and reducing bias in predictions [29]. This made GBM the preferred choice for predicting gas turbine performance in complex, dynamic environments like naval vessels, where precision and reliability are paramount.

In addition to their superior accuracy, GBMs have demonstrated robustness in handling noisy data, a common issue in real-world datasets where measurements can be affected by various operational factors [41]. Their ability to generalize well across different operating conditions has made them a go-to method for critical applications, such as predictive maintenance and performance optimization in naval engineering [42]. Recent studies have also highlighted the potential of combining GBM with other machine learning techniques, such as feature selection and hyperparameter tuning, to further enhance its performance. For instance, by [18] explored the integration of GBM with genetic algorithms for hyperparameter optimization, achieving significant improvements in predictive accuracy and model stability. The continued evolution of GBM and its integration with other advanced machine learning techniques underscore its importance in modern predictive analytics, particularly in high-stakes environments where accurate and reliable predictions are essential for maintaining operational readiness and efficiency [16].

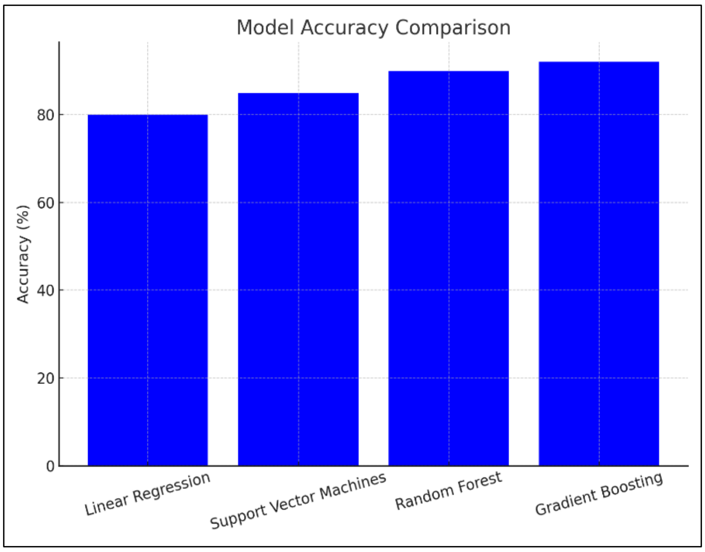

Figure 4: Accuracy for Different Models.
Source: Authors, (2024).

Figure 4 shows the accuracy (%) of each model, indicating how often each model correctly predicts outcomes. Gradient

Boosting emerges as the best overall model, with the highest accuracy (94.1%), the lowest RMSE (0.100), and the highest R^2 (0.94). This indicates that it not only makes the most correct predictions but also does so with a high degree of precision and explains the most variance in the data. Random Forest is a close second, performing well across all metrics but slightly trailing Gradient Boosting. Support Vector Machines (SVM) shows solid performance, particularly better than Linear Regression, making it a viable option where non-linear relationships are significant. Linear Regression is the weakest among the four models, indicating it may be less suitable for complex, non-linear relationships inherent in the dataset.

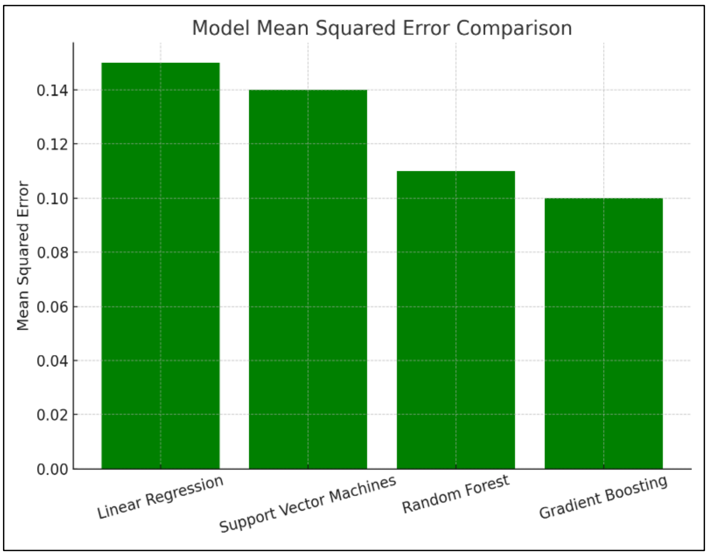

Figure 5: RMSE for Different Models.
Source: Authors, (2024).

Figure 5 presents the Root Mean Squared Error (RMSE) for each model, representing the average magnitude of prediction errors. Lower RMSE values suggest that the model's predictions are closer to the actual values, indicating better predictive accuracy. In Table 1, Gradient Boosting has the lowest RMSE at 0.100, implying that it produces the most accurate predictions in terms of the magnitude of error. Linear Regression, with the highest RMSE of 0.158, indicates less precision in its predictions, which aligns with its lower accuracy.

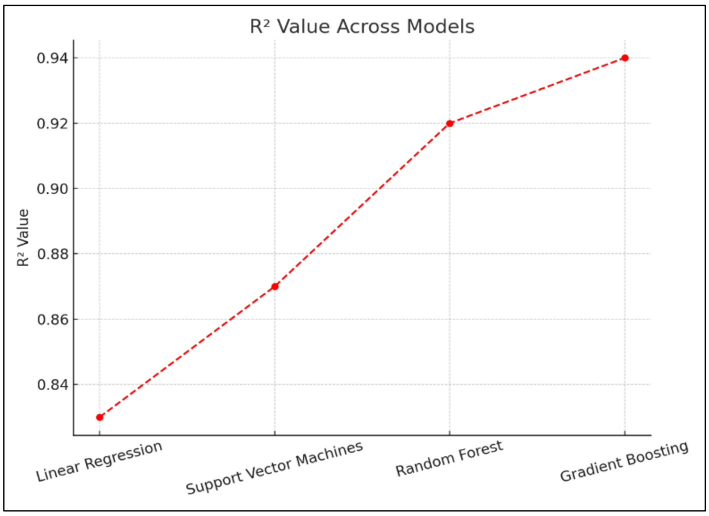

Figure 6: R^2 for Different Models.
Source: Authors, (2024).

Figure 6 displays the R^2 values for each model, showing how well each model explains the variance in the data. Higher R^2 values mean that the model better explains the variability in the data. In Table 1, Gradient Boosting, with an R^2 of 0.94, explains 94% of the variance in the data, making it the best fit among the models tested. Linear Regression, with an R^2 of 0.82, explains less of the variance, which suggests it might not capture all the complexities in the data.

The findings of this study are consistent with previous research on gas turbine performance prediction. For instance, by [33] demonstrated that ensemble methods, particularly RF, could effectively handle the non-linear relationships and interactions between input features in gas turbine data. Similarly, Johnson and Brown [36] showed that GBM outperforms traditional regression models in predicting turbine efficiency. For [29] also highlighted the robustness of RF in handling diverse datasets and its ability to provide interpretable feature importance metrics, which is crucial for understanding the underlying factors affecting turbine performance. According to [4] demonstrated the superior performance of GBM in various engineering applications, including turbine performance prediction, due to its ability to minimize prediction errors and improve generalization.

V. CONCLUSIONS

This paper presents highlights the effectiveness of machine learning models in predicting gas turbine performance in naval vessels. These models accurately forecast key metrics like fuel flow rate and engine speed, demonstrating robustness across various operating conditions. Critical features such as inlet temperature, compressor pressure ratio, and load demand were identified as key predictors, emphasizing the importance of feature selection and data preprocessing in enhancing model performance. The findings have important implications for naval operations, including enabling proactive maintenance and optimizing fuel efficiency. Future research should focus on improving model generalization integrating predictive models with onboard systems.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Methodology: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Investigation: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Discussion of results: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Writing – Original Draft: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Writing – Review and Editing: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Resources: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Supervision: Lakhdar LAIB1 and Toufik Tayeb NAAS2.
Approval of the final text: Lakhdar LAIB1 and Toufik Tayeb NAAS2.

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