



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 9, September 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.524

9940 572 462

6381 907 438

ijrset@gmail.com

www.ijrset.com

Predicting Diesel Engine Performance using Machine Learning Algorithms

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ABSTRACT: The study suggests the application of machine learning techniques for predicting engine performance and emission characteristics, potentially reducing time and costs associated with traditional engine trials. Various machine learning models including XG Boost, random forest regressor, decision tree regressor, and linear regression were employed for prediction, with the XGBoost model demonstrating the highest accuracy, as indicated by an R2-Score of 0.999, allowing for thorough analysis of its performance compared to actual values.

KEYWORDS: Machine learning; Prediction; Optimization.

I. INTRODUCTION

The application of machine learning algorithms has greatly enhanced performance across various fields, such as information technology (Mahdavinejad-2018), medical applications (Kononenko-2001), engineering (Reich-1997), and construction (Ahmad-2017), as well as many other sectors (Tarca-2007; Lary-2018; Sharma-2020). In the realm of predicting engine emissions, machine learning models have been shown to be highly effective, with researchers examining various techniques like Artificial Neural Networks (ANN), Support Vector Regression (SVR), Decision Trees (DT), and Random Forest (RF) (Agbulut-2021). A comparison between ensemble learning methods and Support Vector Machines (SVM) using the Root Mean Square Error (RMSE) as a performance metric has demonstrated that ensemble techniques generally produce lower error rates.

In certain cases, the boosted decision tree algorithm has been effectively applied to predict mean effective pressure in natural gas engines, yielding results closely aligned with experimental data and exhibiting minimal error (Liu-2020). Moreover, for a dual-fueled biogas–biodiesel engine, an ensemble-boosted regression tree outperformed an ANN in predicting emissions when evaluated based on various statistical parameters (Sharma-2022; Singh-2018). These findings provide both experimental support and a theoretical basis for adopting HCNG fuel in internal combustion engines and for utilizing intelligent algorithms in engine standardisation technology (Hao-2020).

Investigations into the use of random forest machine learning models have focused on predicting engine ignition variables as a way to reduce costly engine dynamometer trials (Liu-2020). Stringent emission standards and the demand for cleaner operation of fluidized bed units have prompted the development of dynamic pollutant emission models aimed at establishing cost-effective and environmentally friendly pollutant removal operation modes (Yu-2021).

The main objective is to assess the applicability of several machine learning (ML) methods—such as artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), general regression neural networks (GRNN), radial basis functions (RBFN), and support vector regression (SVR)—for predicting the performance and exhaust emissions of diesel engines (Do-2021). The goal is to approximate various air–fuel ratios, motor shaft speeds, and fuel flow rates within performance limits based on ignition efficiency and exhaust emission indices using a turboprop multilayer feedforward artificial neural network model (Kayaalp-2021).

This study uses machine learning tools for constrained multi-objective optimization of a Homogeneous Charge Compression Ignition (HCCI) engine. Machine learning tools have also been employed to analyze the behavior of a single-cylinder engine utilizing three different fuels with the HCCI strategy (Ghareghani-2021). Additionally, a machine-learning algorithm—derived from linear regression—has been created to predict the 3D spray topology for different fuels and ambient conditions (Hwang-2021). To address the significant time delay and robust nonlinear characteristics of the ignition process, a dynamic correction prediction model accounting for the time delay has been proposed (Tang-2021).

This literature review concentrates on efficient fuels and emerging machine learning (ML) techniques, which show great potential for predictive and optimization tasks in this domain. Although data-driven approaches that leverage real-time sensor data are becoming more prevalent, challenges such as standardized datasets and real-world implementation remain. Our research aims to utilize ML to predict and optimize the performance and emissions of a diesel engine, ultimately enhancing efficiency and environmental sustainability.

The experimentation includes various machine learning methods like random forest regressor, decision tree regressor, linear regression, and XGBoost being employed for prediction. It is important to note that the random forest regressor follows a bagging approach, while the other three are boosting methods. In this study, hyperparameter optimization is key to identifying the most accurate predictive model. Cross-validation techniques are applied to prevent overfitting and ensure accurate predictions on unseen data. A comparative analysis of the algorithms is conducted using performance metrics such as the R^2 value, which is critical for evaluating their predictive accuracy.

II. IMPORTING AND ANALYSING

Finding and loading datasets into the Python interpreter is the crucial step in the data import process, which creates the foundation for further research. Usually obtained from CSV formats, these datasets are meant to supply information for preprocessing and analysis. It is necessary to import necessary Python libraries, including Pandas, NumPy, Seaborn, Matplotlib, and Warnings, in order to analyze the dataset. In order to ensure smooth analysis, the Warnings library is essential in handling any warnings that may arise during execution. Making use of the Pandas library's features, we import the experiment data and begin additional analysis and research.

Preprocessing the full dataset is necessary to ensure accurate data for modeling purposes, mainly to correct for potential inaccuracies in manually recorded experimental data. The goal of this preprocessing effort is to standardize the values so that machine learning algorithms can process them appropriately. We provide a solid basis for our research and modeling efforts by importing the necessary Python modules and carefully preparing the dataset, which includes cleaning and transformation steps. (Vadlamudi Chandramouli, 2023)

III. MISSING VALUE CHECK

After the dataset was examined carefully to look for any missing values, it was discovered that all features, especially the zeroth index, consistently lacked data. It was decided to remove the entire row that contained the null value in order to solve this problem. The code excerpt that exemplifies this resolution is shown in Figure 1.

```
import pandas as pd
import numpy as np
# import dataframe

import pandas as pd
df = pd.read_csv('/content/DIESEL - Sheet1 (1).csv')
df
# find the missing values

print(df.isnull().sum())
```

Figure 1: Missing value check Coding

Following that, the dataset was split into training and testing sets in an 80:20 ratio. For sensitivity analysis, it is advised to look into different ratios such as 70:30, 75:25, 85:15, or 90:10. As Table 1 illustrates, randomization was used in this division process to reduce bias and ensure a representative sample selection.

Table 1. Data Set For Diesel

Load (%)	Brake Specific Energy Consumption (kJ/kWh)	Brake Thermal Efficiency (%)	Nitrous Oxides (ppm)	Carbon Monoxide (% Vol)	Carbon DiOxide (% Vol)	Hydro carbons (ppm)	Smoke (%)
0	0	0	37	0.05	1.6	25	20.2
20	21582.73381	16.68	140	0.05	2.3	25	29
40	15915.11936	22.62	279	0.06	3.8	23	34.5
60	12653.77856	28.45	480	0.07	5.2	29	44
80	11169.71765	32.23	575	0.2	6.4	36	57.5
100	11360.05049	31.69	629	0.66	7.5	38	68.5

IV. CORRELATION ANALYSIS

A strong basis for ensuing modeling and assessment tasks was created by performing a correlation analysis and splitting the dataset into training and testing sets. The code provided creates a correlation heatmap that displays the DataFrame 'df's correlation matrix and includes correlation coefficient annotations. Finding the direction and strength of relationships between variables is made easier with the help of this visualisation, which is important for research analysis and interpretation. The code excerpt that exemplifies this resolution is shown in Figure 2. Based on Table 1, it can be observed that the correlation analysis reveals the following Figure 3.

```
# correlation analysis heat map representing
import matplotlib.pyplot as plt
import seaborn as sns
# Calculate the correlation matrix
corr_matrix = df.corr()
# Create a heatmap of the correlation matrix
sns.heatmap(corr_matrix, annot=True)
# Set the title of the heatmap
plt.title('Correlation Heatmap')
# Display the heatmap
plt.show()
```

Figure 2 Correlation analysis coding

V. PREDICTION MODELLING

Following data preparation, the prediction modeling phase involves choosing the right algorithms, such as decision trees, random forest regressors, linear regression, and XGBoost regressors, based on the particulars of the task at hand. The model development process is streamlined, enabling effective training and validation, by splitting the dataset into training and testing sets. In order to find the best method for solving the regression problem and determine which model is most suited for precise prediction and analysis, a thorough investigation of all possible regression models is carried out. This methodical investigation of regression algorithms advances the trustworthiness of predictive modeling results and aids in generating well-informed decisions, both of which are essential for accomplishing research goals.

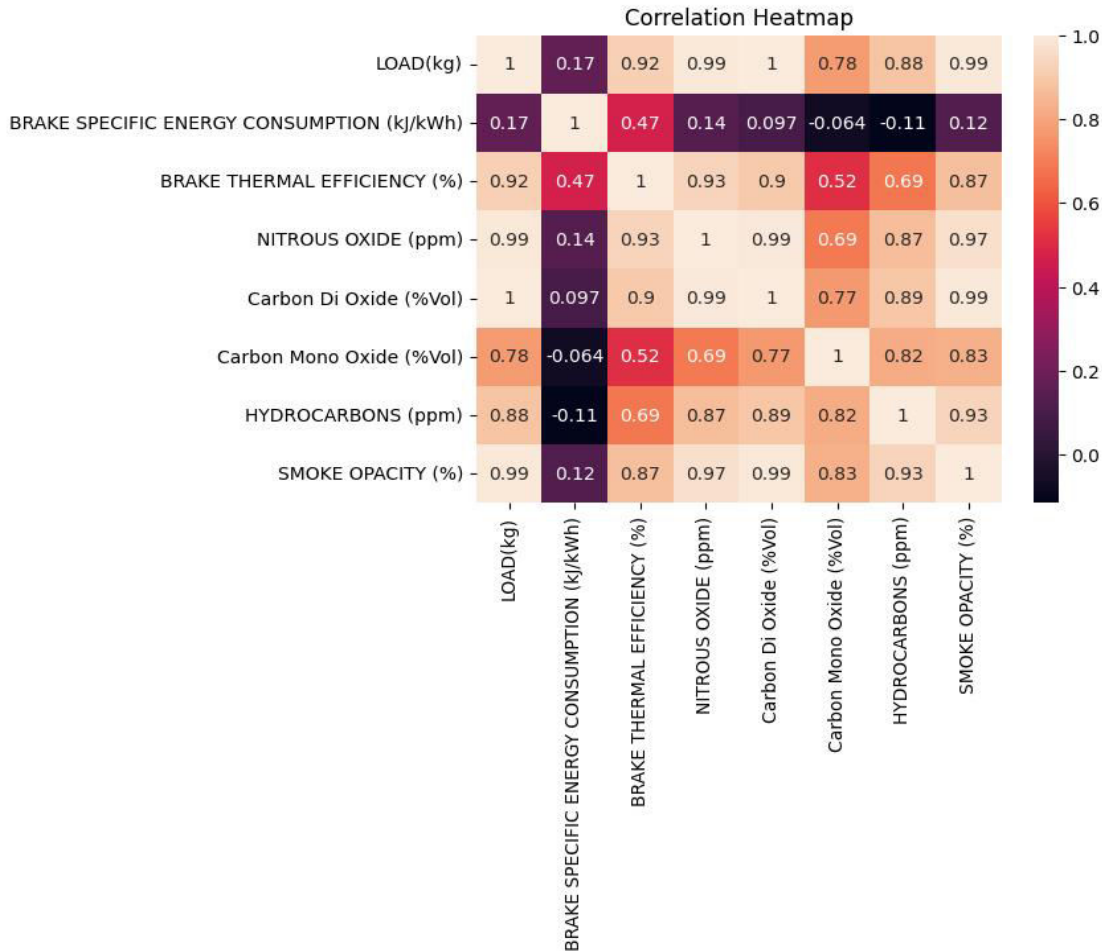


Figure 3. Heatmap representing correlation

VI. MACHINE LEARNING METHODOLOGY

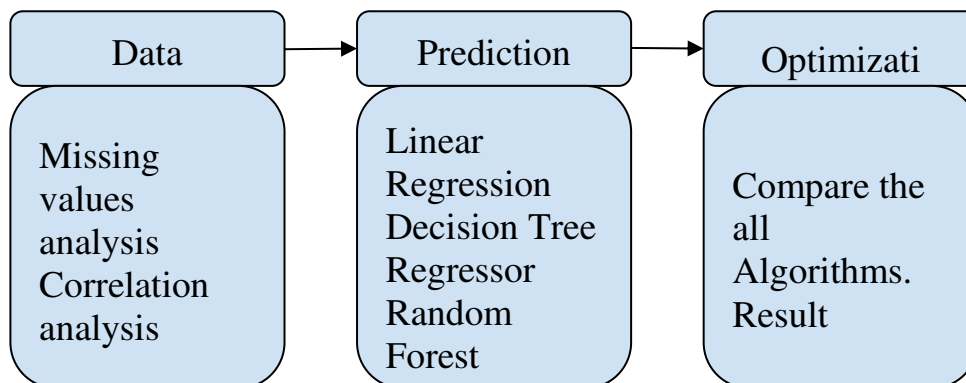


Figure 4. Methodology

VII. RESULT AND DISCUSSION

Linear regression:

A simple statistical technique used in predictive analysis to clarify the link between continuous variables is called linear regression. Referred to as linear regression, it depicts the linear relationship between the independent (X-axis) and dependent (Y-axis) variables. Simple linear regression refers to situations where there is only one input variable (x), whereas multiple linear regression includes situations where more than one input variable is taken into account. The relationship between the variables is represented by a straight line with a slope in the final model.

Figure 5 portrays the linear correlation between the dependent and independent variables, indicating that as the independent variable (x) increases, the dependent variable (y) also increases. The blue line depicted on the graph represents the best-fit straight line, derived from the available data points, with the objective of identifying a line that optimally represents the data.

Linear regression utilises the traditional slope-intercept form to determine the best-fit line, which can be expressed as follows:

$$y = mx + c \rightarrow y = a_0 + a_1x$$

Where,

y = Dependent Variable,

x = Independent Variable,

a₀ = intercept of the line,

a₁ = Linear regression coefficient or slope.

In this equation, y represents the dependent variable, x represents the independent variable, m represents the slope of the line, and c represents the y-intercept.

Table 2. Actual Values and Predicted Values for Brake Thermal Efficiency

Actual Values	Predicted Values
0	1.82254212e-12
16.68	1.66800000e+01
22.62	2.26200000e+01
28.45	2.84500000e+01
32.23	3.22300000e+01
31.69	3.16900000e+01

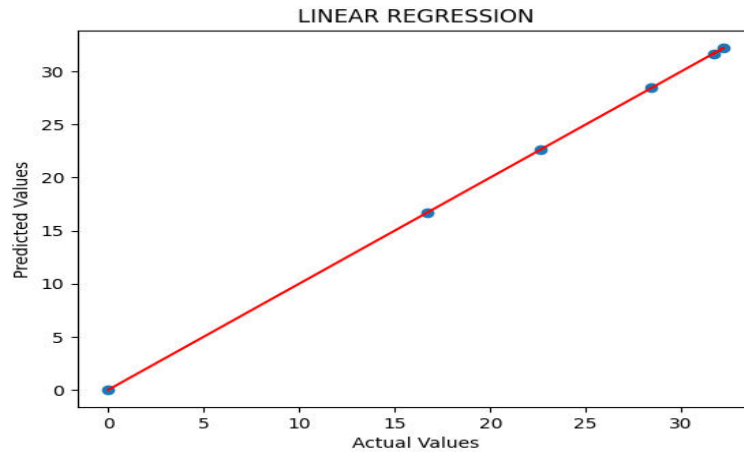


Figure 5. The best-fit line for linear regression.

Decision Tree Regressor:

The Decision Tree algorithm is a popular and useful technique for supervised learning. It may be used for both Regression and Classification tasks, but in real-world applications, Classification is the main focus. This tree-structured classifier consists of Root Nodes that represent the whole sample and branch out to other nodes. Interior Nodes capture information from the dataset, while branches represent decision rules. Leaf Nodes reflect the final outcomes. The algorithm makes its way through the tree to relevant leaf nodes by asking a series of True/False questions. It then averages the values of the dependent variable to arrive at final predictions. Iterative procedures show that the Decision Tree algorithm is effective at precisely predicting values for data points. The decision tree regressor's analysis shows lower residuals than with linear regression, which lowers the error function and raises the model's score overall, making the model more broadly applicable. Based on the squared function, Figure 6 shows how the tree grows and divides, with leaf nodes predicting target values as shown in Table 3.

Table 3. Actual Values and Predicted Values for Brake Thermal Efficiency

Actual Values	Predicted Values
0	0
16.68	16.68
22.62	22.62
28.45	28.45
32.23	32.23
31.69	31.69

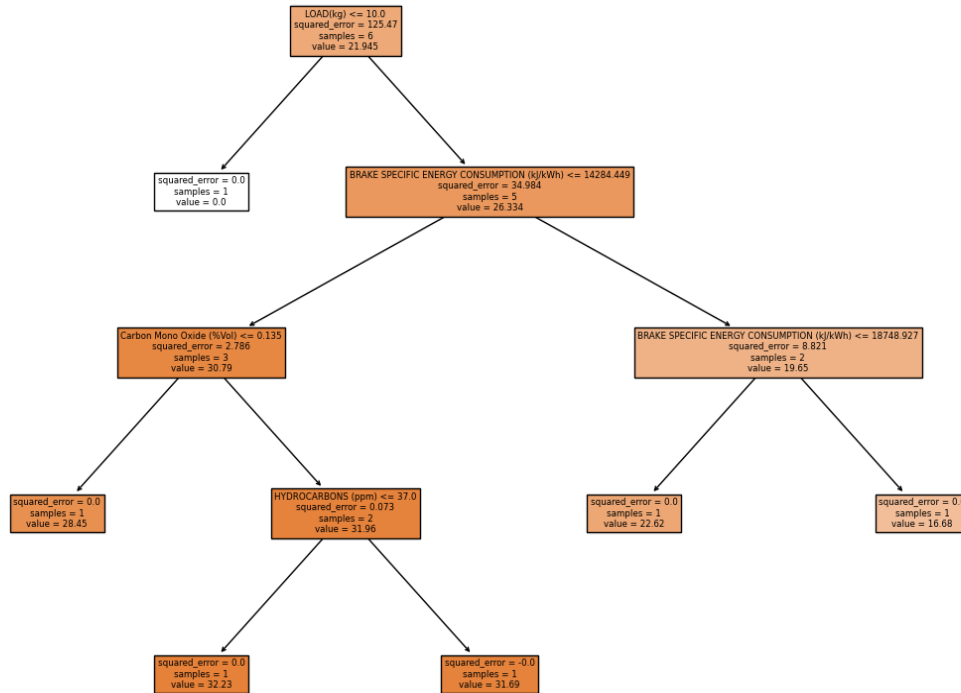


Figure 6. Decision Tree Regressor.

Random Forest Regressor (RF) :

The Random Forest Regressor (RF) is a bagging-based ensemble learning method that is widely used for regression and classification applications. It uses a set of decision trees to make predictions. To do this, it provides bootstrap samples, which are subsets chosen at random and replaced, to a number of decision trees, each of which produces a different output. The ultimate forecast is then ascertained by summing the results obtained from every decision tree. Figure 7 shows a graphical representation, and Table 4 contains the actual and expected values.

Table 4. Actual Values and Predicted Values for Brake Thermal Efficiency

Actual Values	Predicted Values
0	4.5102
16.68	14.1745
22.62	21.6410
28.45	28.3407
32.23	31.2360
31.69	31.1485

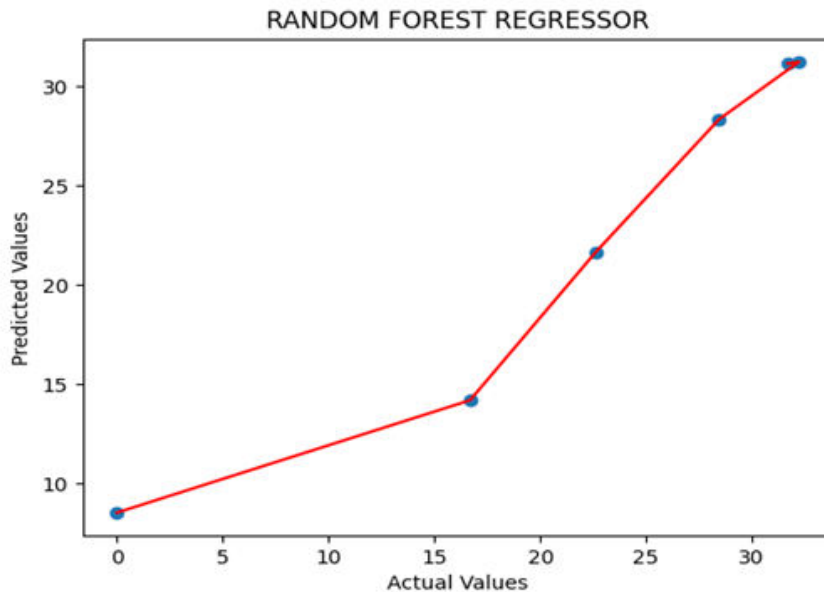


Figure 7. Actual values vs Predicted values for random forest regressor

XGBoost:

Extreme Gradient Boosting, or XGBoost, is a powerful toolkit that outperforms competing algorithms in prediction and classification problems due to its significant benefits in speed, scalability, and parallel computation. It produces a very efficient model by boosting weak learners into robust ones and adding a second-order Taylor expansion to reduce overfitting. The formulas that are supplied outline the goal function and the iterative procedures that are used to optimize outcomes in the XG Boost algorithm, which adds to a thorough comprehension of how it operates. By iteratively propagating errors from previous models, the XG Boost technique gradually reduces errors by putting the dataset through a series of models with different weights. With accuracies of 99.99% and 100% on the training and testing datasets, respectively, the high scores obtained indicate the model's low variance, low bias, and universality, demonstrating its capacity to make accurate predictions on unobserved data. Figure 8 shows a graphic representation, and Table 5 shows the actual and expected values.

Table 5. Actual Values and Predicted Values for Brake Thermal Efficiency

Actual Values	Predicted Values
0	1.0487355e-03
16.68	1.6680065e+01
22.62	2.2620056e+01
28.45	2.8449972e+01
32.23	3.2228901e+01
31.69	3.1689964e+01

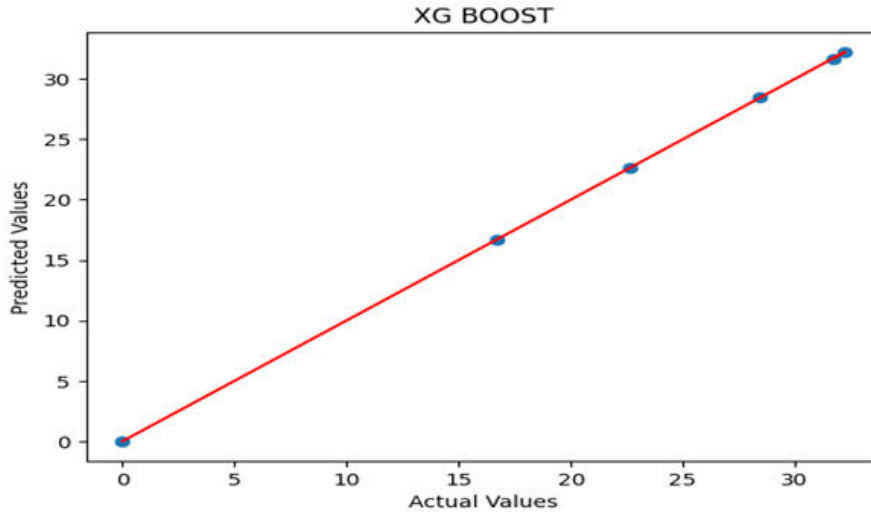


Figure 8. Actual values vs Predicted values for XG Boost.

Model Evaluation

The goal of regression analysis is to create a connection between the dependent variable's observed values and the values that the models predict. A range of performance metrics, such as R²-Score, RMSE (Root Mean Squared Error), MSE (Mean Squared Error), and MAE (Mean Absolute Error), are employed to assess the efficacy of individual regression models.

One often used metric to assess the goodness-of-fit of regression models is R Squared (R²). It has a range of 0 to 1, where 1 denotes an ideal fit free of errors and 0 indicates that the model is unable to explain any variability in the response data around the mean.

The R Squared equation is as follows,

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

y_i represents the real yield.

\hat{y}_i represents the yield of prediction.

\bar{y}_i is the mean value

Comparison of Algorithms:

Evaluation metrics, such the R-Score, are essential for determining how effective machine learning models are. An engine's performance and emission characteristics are critical factors in engineering applications, therefore choosing and optimizing a model requires assessing them using pertinent metrics. It is possible to obtain insights into the efficacy of several learning algorithms, such as XG Boost, Random Forest Algorithm, Decision Tree Regressor, and Linear Regression, by comparing their performances.

A robust model fit with the provided dataset is indicated by a higher R²-Score, which is closer to 1. Table 6's analysis shows that, aside from XG Boost, the R²-Score values for the majority of algorithms roughly resemble 1, indicating a favorable alignment with the data. Based on the evaluation metrics, it may be concluded that ensemble learning algorithms show promise.

It is suggested that ensemble learning algorithms be further investigated and applied in pertinent engineering contexts as a result of the evaluation metrics' findings, which indicate that these algorithms have the capacity to anticipate the performance of the single-cylinder, four-stroke diesel engine.

Four distinct algorithms were used to forecast the braking thermal efficiency of diesel engines: XGBoost, Decision Tree Regressor, Random Forest Regressor, and Linear Regression. The braking thermal efficiency of diesel engines was tested and training data was produced using these techniques. Of these algorithms, XGBoost performed better in terms of accuracy than the others.

This finding implies that XGBoost performs better at accurately predicting brake thermal efficiency and capturing the intricate relationships included in the data. As such, XGBoost might be regarded as the recommended approach for additional study and real-world implementation in diesel engine brake thermal efficiency prediction.

Table 6. Comparison of Algorithms on Evaluation Matrices.

Learning Algorithms	Trained Value	Test Value
Linear Regression	1	1
Decision tree regressor	1	1
Random forest regressor	0.9143151271123654	1
XG Boost	0.9999999969218480	1

VIII. CONCLUSION

By combining ensemble learning methods with machine learning algorithms, it was possible to forecast Brake Thermal Efficiency from experimental data. The models, which included XG Boost, Decision Tree Regressor, Random Forest Regressor, and Linear Regression, were assessed by allocating 80% of the data for training and 20% for testing. When XG Boost was compared to experimental data, it outperformed Linear Regression, Decision Tree Regressor, and Random Forest Regressor in terms of predictions that were closest to the real results. As a result, the best model for this task was determined to be XG Boost.

This study underscores the effectiveness of the XG Boost machine learning algorithm in offering a precise and efficient method for estimating engine performance and emissions characteristics. Its capabilities hold promise for applications seeking expedient and economical means of predictive modelling in similar contexts.

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