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Machine Learning-Based Prediction Techniques for the Evaluation of Diesel Engine Performance

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Abstract

The current study investigates the performance parameters of the DI diesel engine when it is powered with a diesel and mixed with various blends (CB10 to CB50) of Calophyllum Inophyllum biodiesel. The characteristics of diesel fuel and C. Inophyllum biodiesel are very similar and its properties also meet the ASTM requirements. C. Inophyllum is a feedstock that is economically attractive due to its high yield, when it is transesterified. A 4- stroke, single-cylinder diesel engine was adopted to test the performance using diesel and biodiesel blended fuel samples. From the results, The BTE for the biodiesel blended fuel samples were reduced maximum up to 12.68 % compared to diesel fuel. Lowest BSFC for the CB10 fuel (i.e. 0.24 kg/kW hr) were observed compared to remaining blended fuel samples and CB50 fuel exhibits highest EGT compared all the fuel samples. The performance of diesel engine running on mixtures of diesel and biodiesel blends can be predicted by using this study and also examines the potential Machine Learning (ML) techniques, such as Linear Regression (LR), Random Forest (RF) and Support Vector Regression (SVR). In the prediction of performance parameters, the random forest model shows better than other methods for attaining the highest accuracy.

Major Findings: *The CB10 blend showed the highest BTE among all biodiesel blends, though diesel outperformed all in both BTE and BSFC. Machine learning techniques proved effective for forecasting diesel engine performance, aiding biodiesel blend optimization.*

Keywords: *Biodiesel Blends, Machine Learning, Optimization, Performance*

1.0 Introduction

In the automotive sector, diesel engines play a significant role. They are extensively utilized in the transportation and agricultural areas because of their greater fuel efficiency and reduced fuel consumption compared to alternative engine types[1]. Researchers are currently focusing on substitute fuels due to the depletion of fossil fuels and uncertainties about how the use of fossil fuels affects environmental issues like air pollution and global warming. Among the numerous potential alternative fuels, biodiesel has advanced quickly lately due to its characteristics being very similar to those of diesel fuel[2]. However, the investigational on engine performance and emission parameters is very time-consuming and costly, and it is not very effective. Because of this, there has been a lot of interest lately in optimizing engine performance, combustion, and emissions using input factors like engine load, injection advance value, engine speed, fuel blend, etc[3]. Aswathanrayan *et al.*, uses the potent desirability-based optimization technique to overcome these obstacles by maximizing the performance and emission characteristics of a mono-cylinder diesel engine running on neem oil biodiesel blends augmented with alumina nanoparticles. A number of classy machine learning methods, like random forest, decision tree, and linear regression. When

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equated to linear regression and decision tree models, the random forest model showed the utmost prediction accuracy for performance (test R^2 = 0.9620, test MAPE = 3.6795%), making it the most dependable statistical method for predicting BSFC. The random forest model also outperformed other approaches in forecasting emissions, achieving the utmost accuracy with a test R2 of 0.9826 and the least test MAPE of 9.3067%[4]. Uludamar *et al.,* emphasizes how the sophisticated machine learning techniques, particularly the Ensemble of Trees and Radial Basis Neural Network (RBNN), can be used to anticipate vibration and noise in biodiesel and hydrogen-enriched engines. Their results shows that the suggested RBNN and Ensemble of Trees models are effective in forecasting vibration and noise, with satisfactory outcomes. During the test procedure[5], the models obtained an MAE of 0.074 dB[A], RMSE of 0.162 dB[A], and R^2 of 0.9973 for noise, and an MAE of 0.126 m/s^2, RMSE of 0.431 m/s^2, and R^2 of 0.9991 for vibration[5]. Bukkarapu *et al*., carried out an investigation, if support vector machine regression may be used to link engine characteristics with biodiesel content. The resulting models are validated with a satisfactory mean absolute percentage error of less than 7% using two supplementary biodiesels that were not employed for calibration. To find the ideal composition for reducing emissions of unburned Hydrocarbons (HC), Carbon Monoxide (CO), and Nitrogen Oxides (NOx), as well as Brake Specific Fuel Consumption (BSFC), the models are also fed into a genetic algorithm. 92% longer chain esters and 8% shorter chain esters are present in the optimized biodiesel[6]. Mustafa *et al.,* using biodiesel blends made from waste frying palm oil, this study predicts the engine performance and exhaust emissions for five distinct neural networks to determine how inputs impact outputs. The performance and engine pollutants of a have been forecasted for biodiesel blends using the Artificial Neural Network (ANN) model. The findings indicate that the fifth network is adequate for every output. With the exception of a few emissions, the fifth network's mean percentage errors are less than five, and its R^2 values are 0.99. The mean errors for emissions like CO, NOx, and UHC were higher[7]. Shivakumar *et al.,* carried out engine tests by means of Waste Cooking Oil (WCO) as the biodiesel blended with diesel to examine the impact of injection timing on the emissions and performance of a mono cylinder, 4-stroke stationary, changeable compression ratio CI engine. The engine's pollutants characteristics and performance were predicted using Artificial Neural Networks (ANN). Both performance factors and emission characteristics were represented by different models. According to ANN results, the experimental values and the ANN predicted values for a number of engine performance metrics and exhaust emission characteristics showed a satisfactory association. The Mean Relative Error values (MRE) were within an acceptable range of 8%[8]. Pawar *et al.,* concluded that by using machine-learning algorithms, it is feasible to better comprehend the complex relationships that exist between engine behavior and nanoparticle characteristics. The development of more efficient and environmentally friendly engine designs was made possible by this methodology, which offers a thorough understanding of how nanoparticles will affect the emissions and performance of biodiesel engines[9]. Aneesh *et al.,* focused and prepared SVM models which were trained using 147 data points obtained from operating the HCCI engine with seven biofuels mixed into gasoline. They estimated that the significance of each fuel parameter in predicting the engine parameters during investigation. Comparing the HCCI mode to the traditional diesel combustion mode, the optimized fuel composition was decreased the NO by 76% and the ISEC by 18%[10]. From the above literature survey it is concluded that many researchers explored the feasibility of various biodiesel blends to run the diesel engine but forecasting the performance of a diesel engine also have an important aspect in this area of research. The comparative evaluation of different ML models in terms of prediction accuracy, generalizability across multiple fuel blends (*Calophyllum* biodiesel blends CB10-CB50), and load variations is insufficiently addressed and it is a considerable research gap that observed from the literature. In this manuscript authors determined the influence of *Calophyllum inophyllum* biodiesel blends (CB10 to CB50) and predicting their performance of diesel engine using machine learning techniques.

2.0 Materials and Methods

Transesterification has been shown one of the most effective processes for producing biodiesel. After collecting the *Calophyllum inophyllum* seeds from local market are allowed for drying process. The oil was

removed from the dry seeds by mechanical pressing then any residual impurities or sediments in the crude oil were removed by the filtering process. Through a process called transesterification, which lowers the viscosity of the crude oil, the *Calophyllum inophyllum* methyl ester was produced. The transesterification process includes addition of Sodium Hydroxide (NaOH) after methanol and raw oil mixing in a 6:1 volumetric ratio. A catalyst was used to accelerate the chemical process, such as NaOH. *C. Inophyllum* oil, methanol, and NaOH are heated to 60 °C while being constantly stirred for six hours. The mixture was permissible to settle down; forming an upper layer of *C. Inophyllum* methyl ester and a bottom layer of glycerol was separated. The *C. Inophyllum* biodiesel was blended with diesel in five different proportions such as CB10, CB20, CB30, CB40 and CB50 in volumetric approach. The properties of various biodiesel blends were shown in Table 1. Increasing the concentration of *Calophyllum inophyllum* biodiesel led to a consistent increase in fuel density, viscosity, and ignition-related temperatures (flash and fire point), while decreasing the calorific value. Higher density and viscosity (e.g., CB50 at 859 kg/m^3 and 3.68 cSt) can lead to longer spray penetration and altered atomization, resulting in delayed combustion and more distributed pressure rise. Elevated ignition points at higher blends indicate safer fuels but contribute to slower ignition characteristics. As the calorific value declines (from 43,410 to 40,345 kJ/kg), combustion energy reduces. As shown in Table 1, the density and viscosity of the fuel increased with higher CB blend ratios, ranging from 835 kg/m^3 to 859 kg/m^3 and 3.18 cSt to 3.68 cSt, respectively. These changes are attributed to the polar ester components in biodiesel. Simultaneously, the calorific value declined from 43,410 to 40,345 kJ/kg, potentially reducing power output. However, the elevated flash and fire points (from 52 °C to 89 °C and 58 °C to 96 °C, respectively) enhanced fuel safety and contributed to smoother combustion profiles at higher loads.

3.0 Experimental Set Up and Procedure

3.1 Engine Setup Details

The engine tests were conducted on Kirloskar made TV1 model water cooled, direct injection, mono cylinder diesel engine paired with eddy current dynamometer by using *Calophyllum inophyllum* biodiesel in various blends. The engine test set up was represented in Figure 1. The volumetric air flow rate was monitored with a U tube manometer and an orifice meter, while the fuel consumption rate has been evaluated with Infrared (IR) sensors placed at the crown and base of the glass bulb. K-type thermocouples were placed at several locations along the heat exchanger to detect the temperature and assess the heat lost in cooling and exhaust gases. The engine specifications were tabulated in the Table 2.

3.2 Uncertainty Analysis

There are several factors that contribute the uncertainty analysis during the experimentation like type of

Table 1. Properties of *C. inophyllum* biodiesel blends and diesel

Properties	ASTM Standards	Diesel	CB10	CB20	CB30	CB40	CB50
Density (kg/m^3) @ 15 ^{0} C	ASTM D1298	835	840	844	849	855	859
Flash point (^{0}C)	ASTM D93	52	58	64	69	78	89
Fire point (^{0}C)	ASTM D93	58	67	71	78	87	96
Kinematic Viscosity cst @ 40^0 C	ASTM D445	3.18	3.28	3.36	3.48	3.56	3.68
Calorific Value (kJ/kg)	ASTM D240	43,410	42,620	42,425	41,985	41,262	40,345



Figure 1. Single cylinder DI diesel engine.

instrument selected, experimental conditions and accuracy of the instrument while taking the readings. The accuracy of the experimentation was mainly depends on the uncertainty analysis. The uncertainty analysis was determined by using the measured parameters of brake power, speed, BSFC, BTHE, EGT, by using the various instruments used in the experiment.

Percentage of Uncertainty

= Square root of {(uncertainty of BSFC)^2 + (uncertainty of BTHE)^2 + (uncertainty of EGT)^2 + (uncertainty of BP)^2 + (uncertainty of speed)^2}.

= Square root of {$(0.6)^2 + (0.8)^2 + (0.2)^2 + (1.2)^2 + (1.8)^2$}

= ± 2.39%.

Table 2. The engine specifications

Model and Make	TV1 and Kirloskar
Type of Engine and Dynamometer	mono cylinder, 4-stroke, Water cooled system CI engine with Eddy current dynamometer
Stroke and Bore	110 mm and 87.5 mm
Compression Ratio (CR) and Co-efficient of discharge (C_d)	17.5:1 and 0.62
Rated power and Rated speed	5.2 kW and 1500 rpm
FIT and FIP	23^0 bTDC and 220 bar

3.3 Machine Learning Model

Diesel engine behavior can be predicted, modelled, and optimized with the help of Machine Learning (ML) techniques. Without the need for explicit physical modelling, machine learning techniques can analyse enormous volumes of sensor and experimental data to find patterns, create predictive models, and aid in decision-making. Because ML algorithms improve fuel performance and predictive accuracy, they are essential to biodiesel research. Because biodiesel combustion is complicated and affected by a number of interrelated factors, including blend structure, engine arrangements, and operating circumstances, sophisticated data-driven methods are required. In order to develop data-driven models for forecasting engine parameters like BTE, BSFC, EGT under varied load and fuel blend conditions, algorithms such as Linear Regression (LR), Support Vector Machines (SVM), and Random Forests (RF) are frequently utilized. The flow diagram for the machine learning model was shown in Figure 2. Statistical performance metrics such as R^2, RMSE, and MAPE were employed to evaluate the predictive accuracy of machine learning models for brake thermal efficiency, brake specific fuel consumption and exhaust gas temperature.

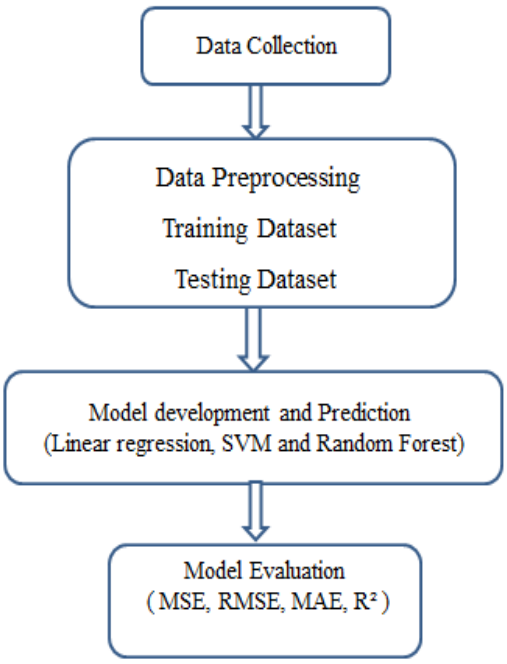


Figure 2. Machine learning model development.

A high R^2 (>0.95) and low RMSE (<0.2) indicated a strong correlation between experimental and predicted values, validating the model's suitability for diesel engine optimization studies.

3.3.1 Linear Regression

For predictive modeling, among the most well-known and straightforward supervised Machine Learning (ML) algorithms is linear regression. A linear correlation between a continuous dependent variable (the target) and one or more independent variables (the characteristics) is demonstrated. When analysing the diesel engine, a linear regression is a valuable method for modeling the effects of engine parameters like load, fuel blend, and other inputs on a target variable like Brake thermal efficiency, BSFC and EGT. The Least Squares Method is usually used to fit a straight line (or hyper plane in multidimensional space) that diminishes the disparity between expected and reality values. Even though it is straightforward, linear regression is effective for prompt baseline predictions, Analysable correlations between variables Recognizing linear dependencies and patterns.

3.3.2 Support Vector Machine (SVM)

A potent supervised learning algorithm that can handle both regression and classification is the Support Vector Machine (SVM). SVM seeks to identify a function that stays as flat as possible while deviating from actual data points by a value no larger than a given margin when in regression mode (SVR). SVM is especially helpful in diesel engine modelling (such as forecasting exhaust gas temperature) when there is a nonlinear relationship between inputs (such as load and fuel blend) and outputs. Despite being small to medium in size, the dataset was intricate. High accuracy and resilience to outliers are required. SVM is very good at capturing nonlinear behaviour in engine performance because it uses kernel functions (like the radial basis function, or RBF) to change input data into superior-dimensional space where a linear relationship can be found.

3.3.3 Random Forest

Random Forest is a decision tree-based ensemble learning technique that builds several trees on arbitrary subsets of data and averages their outputs (for regression) to generate predictions that are more reliable and accurate. Applications of Random Forest in diesel engines are particularly advantageous for: Managing features and nonlinear relationships, simulating intricate phenomena such as BSFC and EGT, Handling noisy and missing-value datasets. Its main advantages are its strong generalization, resistance to overfitting, and ability to reveal the significance of features. These qualities make it a great option for engine system performance prediction and optimization.

4.0 Results and Discussion

4.1 Performance Variables

4.1.1 Brake Thermal Efficiency (BTE)

The distinction of BTE relative to the brake power for all fuels was depicted in Figure 3. For the tested fuels, the BTE values increases with rise in brake power. When compared to biodiesel blends, CB50 has the lowest BTE and CB10 exhibits the highest BTE at all load conditions. The BTE for diesel was higher by 2.8 %, 7.31 %, 10.08 %, 11.42 % and 12.68 % for the CB10, CB20, CB30, CB40 and CB50 fuels respectively. When *Calophyllum inophyllum* biodiesel was added to the diesel, its inherent oxygen content, density, and viscosity increases, but its total calorific value was decreases[11]. As a result, biodiesel blends results lower brake thermal efficiency than that of regular diesel fuel.

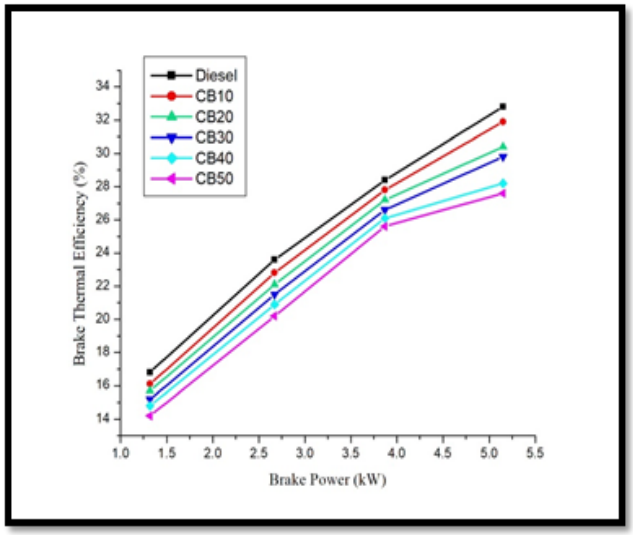


Figure 3. Variation of BTE with brake power.

4.1.2 Brake Specific Fuel Consumption (BSFC)

The distinction of BSFC relative to the brake power for all fuels was depicted in Figure 4. According to the obtained graph, for all samples, BSFC falls as brake power increases. Compared to all test fuels, the diesel fuel has a higher BSFC; this could be because of its higher CV[12]. Because of its higher energy content, the CB10 blend had a lower BSEC than other *Calophyllum inophyllum* blends when compared to other blend ratios[13]. At the peak brake power condition the BSFC values are noted as 0.24, 0.26, 0.275,0.296, 0.318 and 0.336 for the diesel, CB10, CB20, CB30, CB40 and CB50 fuel samples respectively.

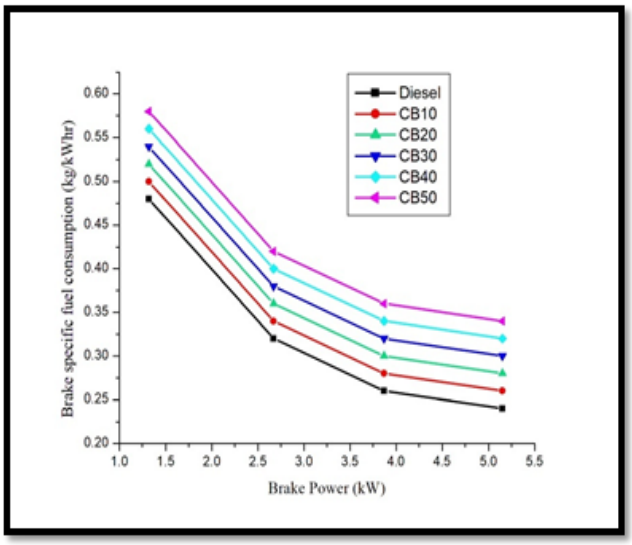


Figure 4. Variation of BSFC with brake power.

4.1.3 Exhaust Gas Temperature (EGT)

The distinction of EGT relative to the brake power for all fuels was illustrated in Figure 5. When compared

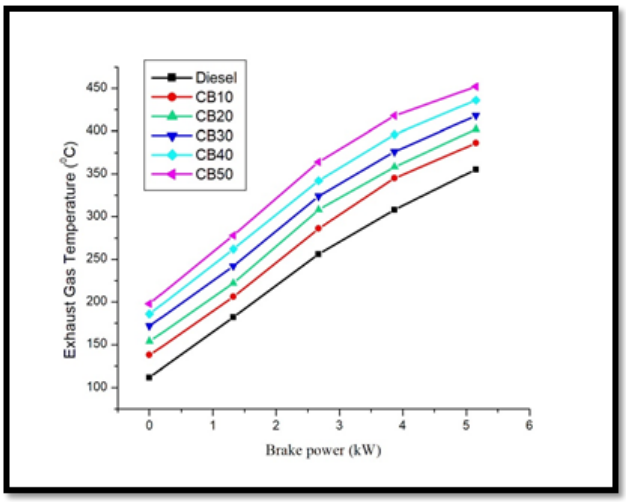


Figure 5. Variation of EGT with brake power.

to diesel fuel, it is clear that every blended fuel sample of *Calophyllum inophyllum* has higher exhaust gas temperatures, as demonstrated by the Figure 5. This is due to the higher diffusion combustion phase or late burning rate, which results in a longer ignition delay and more oxygen present of the biodiesel[14]. The diesel fuel exhibits 8.76 %, 11.4 %, 13.2 %, 15.6 % and 18.2 % lowest EGT compared to the CB10, CB20, CB30, CB40 and CB50 fuel samples respectively at peak load condition. The CB10 fuel sample shows lower EGT than all remaining blended fuels at all loads.

4.2 Machine Learning Modeling and Evaluation

4.2.1 Brake Thermal Efficiency Model

Figure 6 shows the assessment of actual and predicted BTE values for all the fuel samples at all load conditions. All the values obtained from the Machine Learning (ML)

Table 3. Statistical metrics for BTE

	Linear regression	Random Forest	Support Vector Regressor
Mean Squared Error (MSE)	0.7635	0.3363	0.2939
Root Mean Squared Error (RMSE)	0.8738	0.4294	0.5422
Mean Absolute Error (MAE)	0.7726	0.1844	0.5169
R^2 Score	0.977	0.9944	0.9911

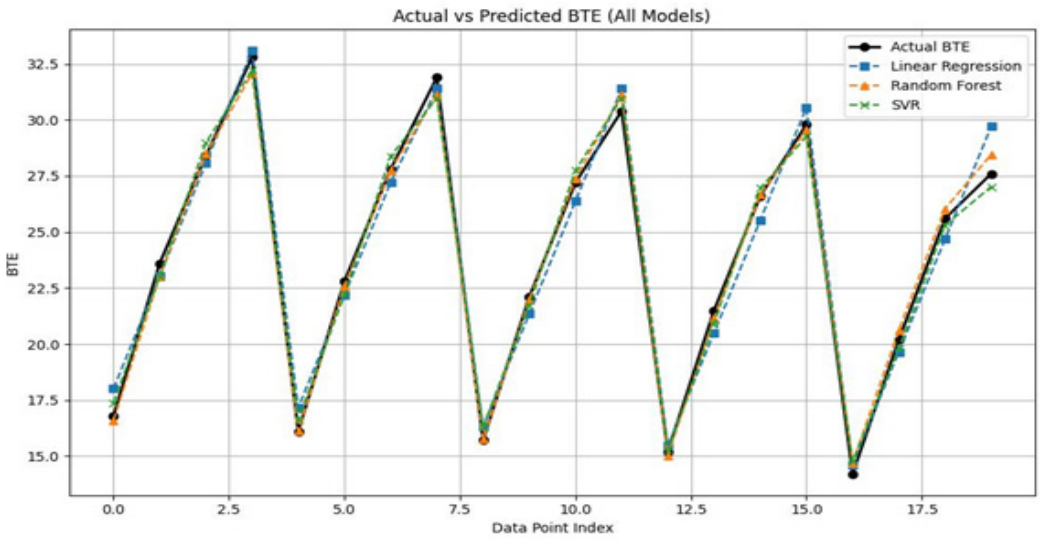


Figure 6. Comparison of actual and predicted BTE values.

methods such as Linear Regression (LR), Random Forest (RF) and SVM exhibits the same trend. The statistical metrics for BTE was shown in Table 3. The MSE for linear regression, random forest and support vector regressor were predicted as 0.7635, 0.3363 and 0.2939 respectively. The R^2 values were measured as 0.977, 0.9944 and 0.9911 for the linear regression, random forest and support vector regressor respectively. By comparing these three methods random forest shows more accurate method.

4.2.2 BSFC model

Figure 7 shows the assessment of actual and forecasted BSFC values for all the fuel samples at all load conditions. All the values obtained from the Machine Learning (ML) methods such as Linear Regression (LR), Random Forest

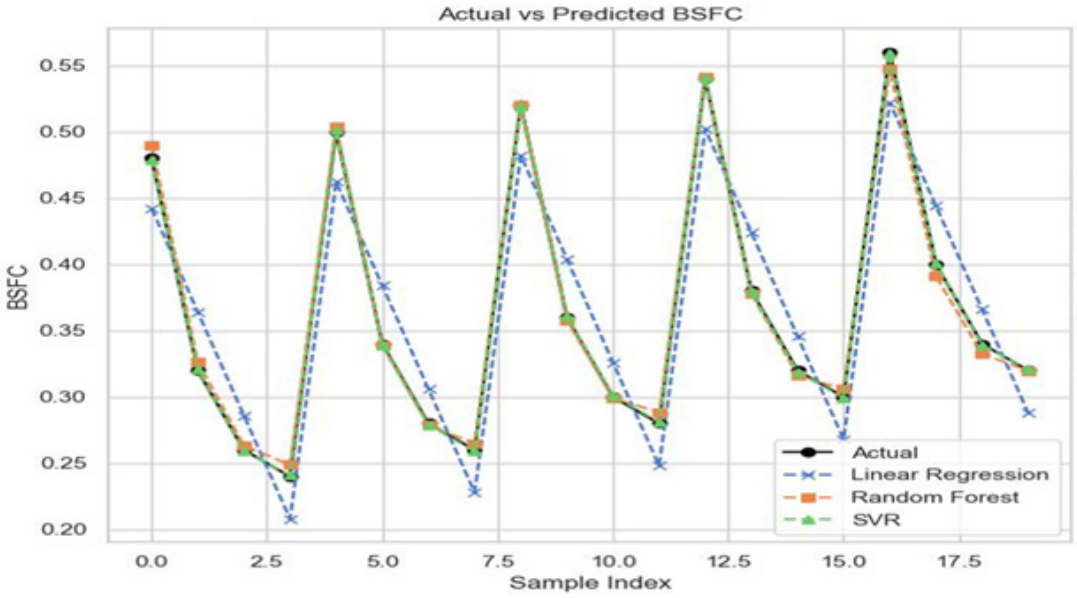


Figure 7. Comparison of actual and predicted BSFC values.

Table 4. Statistical metrics for BSFC

	Linear regression	Random Forest	Support Vector regressor
Mean Squared Error (MSE)	0.00122	0.0001	0.0008
Root Mean Squared Error (RMSE)	0.0046	0.0083	0.028
Mean Absolute Error (MAE)	0.03396	0.00598	0.00182
R^2 Score	0.874	0.8971	0.892

(RF) and SVM exhibits the same trend. The statistical metrics for BSFC was shown in Table 4. The MSE for linear regression, random forest and support vector regressor were predicted as 0.00122, 0.0001 and 0.0008 respectively. The R^2 value was measured as 0.874, 0.8971 and 0.892 for the linear regression, random forest and support vector regressor respectively. By comparing these three methods random forest shows more accurate method.

4.3. EGT Model

Figure 8 shows the assessment of actual and forecasted BSFC values for all the fuel samples at all load conditions. All the values obtained from the Machine Learning (ML) techniques such as Linear Regression (LR), Random Forest (RF) and SVM exhibits the same trend. The statistical metrics for EGT was tabulated in Table 5. The MSE for linear regression, random forest and support vector regressor were predicted as 205.42, 62.95 and 71.89

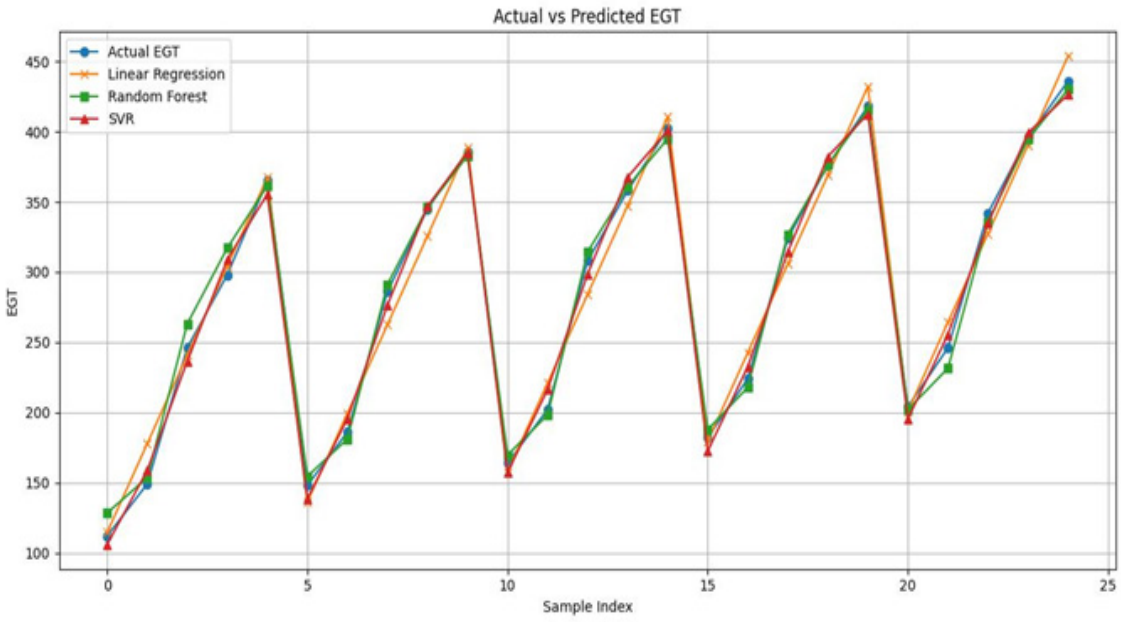


Figure 8. Comparison of actual and predicted EGT values.

Table 5. Statistical metrics for EGT

	Linear regression	Random Forest	Support Vector regressor
Mean Squared Error (MSE)	205.42	62.95	71.89
Root Mean Squared Error (RMSE)	14.33	7.93	8.48
Mean Absolute Error (MAE)	12.14	6.17	8.11
R^2 Score	0.9775	0.9831	0.9815

respectively. The R^2 values were measured as 0.9775, 0.9831 and 0.9815 for the linear regression, random forest and support vector regressor respectively. By comparing these three methods random forest shows more accurate method.

5.0 Conclusion

The following findings were obtained from an experimental investigation of *Calophyllum inophyllum* biodiesel blended fuel samples with diesel in this study. When equated to diesel fuel and various biodiesel blends, the BTE of for all blended fuels shows lowered values but CB10 exhibits higher than other blended fuels. In addition BSFC for diesel fuel exhibits minimal value than the other fuel samples in all load conditions. This study also investigates the forecasting models based on linear regression, random forest and SVR techniques to predict performance variables of a diesel engine fuelled by blends of biodiesel. When compared to Linear Regression and SVM models, the Random Forest (RF) model showed the maximum predictive accuracy for performance (R^2 = 0.9944, 0.8971 and 0.9831), making it the most dependable statistical method for forecasting performance parameters such as BTE, BSFC and EGT. In order to optimize the use of biodiesel blends in diesel engines, machine learning is a useful tool that offers strong insights to the evaluation of its performance parameters.

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Nomenclature

BTE	Brake Thermal Efficiency
BSFC	Brake Specific Fuel Consumption
EGT	Exhaust Gas Temperature
SVM	Support Vector Machine
RF	Random Forest
CB10	90 % of Diesel + 10 % *Calophyllum inophyllum*
CB20	80 % of Diesel + 20 % *Calophyllum inophyllum*
CB30	70 % of Diesel + 30 % *Calophyllum inophyllum*
CB40	60 % of Diesel + 40 % *Calophyllum inophyllum*
CB50	50 % of Diesel + 50 % *Calophyllum inophyllum*
DI	Direct Injection
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error