



Experimental and Machine Learning Analysis of a CI Engine Fueled with American Saffron Biodiesel–Diesel Blends

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Abstract

Alternative fuels come from non-traditional sources and can partly replace fossil fuels to cut environmental impact and support sustainable energy use. A single-cylinder diesel engine with rated power 5.2 Kw at 1500 rpm was tested with American Saffron Biodiesel blends. B0 (diesel), B10 (B10D90), B20 (B20D80), and B30 (B30D70), under different loads, and the results were compared with diesel. B20 showed the best improvement, with 13.41% higher brake thermal efficiency and 30.3% lower fuel usage than conventional fuel, at 100% load. B30 reduced HC by 5.88%, while B10 gave the lowest CO, reduced by 8.51%. The main contribution is the use of decision tree machine-learning regression to predict and optimize performance and emissions. The model achieved $R = 0.91$ and $R^2 = 0.83$, supporting the prediction of multivariable engine responses across operating conditions.

Keywords: IC engines, American Saffron Biodiesel, Performance, Emissions, Machine Learning, Decision Tree Regression.

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1. Introduction

However, due to the increasing use of EVs, CI engines will continue to exist, and hence, the need for optimization of CI engines' efficiency and emissions will always be there. Recent studies have indicated that the use of renewable fuels along with optimization techniques such as response surface methodology and machine learning algorithms can help in reducing the experimental work and increasing the performance and emissions prediction and control. Studies on biodiesel-fueled diesel engines focus on improving performance and reducing emissions through fuel modification and blend optimization. Biodiesel derived from sources such as Acacia and Madhuca oils has been tested in single-cylinder diesel engines. These studies indicate that biodiesel blends generally cause a slight reduction in brake thermal efficiency due to their lower calorific value. However, they significantly reduce emissions such as carbon monoxide (CO), hydrocarbons (HC), and smoke because of their higher oxygen content. Investigations on different blend ratios reveal that B20 provides the best balance between engine performance and emission reduction, whereas higher blends increase fuel consumption.

In a dual-fuel CI engine with biogas as the primary fuel and algal biodiesel as the pilot fuel, optimization at 82.71% load and CR 18.5 resulted in a BTE of 16.98% and a maximum pressure of 48 bar,

with a reduction of 3.16% CO₂, 112 ppm HC, 306 ppm NO_x, and 172 ppm CO. Among the ML algorithms, XG Boost provided the best prediction accuracy ($R^2 = 0.9944$) [1]. In dual-fuel configuration, fish oil biodiesel blends (20-40%) with methane and methane-CO₂ (4-12 LPM) provided B25 with M7.2C4.8 as optimal, with 97% classification accuracy, and ANN models predicted combustion, emissions, and vibrations with correlations of 0.97-0.98 [2]. This research indicates that biodiesel-gaseous dual-fuel engines can be efficiently modeled using ML-based platforms.

Sustainable biodiesel production has also benefited from data-driven optimisation. Biodiesel produced from waste cooking oil using an eggshell-derived CaO catalyst was coupled with ML modelling, where Cat Boost provided the highest accuracy ($R^2 = 0.955$) and identified conditions achieving 95% biodiesel yield. Engine testing supported application feasibility, reporting 26% lower CO and 13% lower smoke with only a marginal reduction in brake thermal efficiency [3]. A broader review further notes that conventional models often struggle with the complex behaviour of biodiesel systems, while ML approaches can better capture performance and emission trends in nanoparticle-enhanced biodiesel engines, helping explain nanoparticle–engine interactions and supporting improved engine design [4].

Machine learning assists in the prediction of difficult-to-gauge combustion variables. A study used Deep-MLP, decision tree regression, and random forest regression to predict the in-cylinder pressure of biodiesel-fuel oil-diesel blends with R^2 0.9946-0.9996, Deep-MLP being most sensitive to variations [5]. In a dual-fuel CI engine, NeOME B20 (neem oil methyl ester) as pilot fuel with producer gas-hydrogen as primary fuel resulted in a maximum brake thermal efficiency of 22.18%, HC emission decreased by 39.94 ppm, CO emission decreased by 0.28%, and particulate and NOx emission increased to 204.89 ppm. Gradient boosting provided precise predictions with R^2 0.999 [6]. Likewise, ethanol additives and ZnO nanoparticles' combustion characteristics were predicted using deep neural networks ($R^2 > 0.95$), and Dragonfly optimization increased brake thermal efficiency by 20-32% with emissions in acceptable ranges [7].

Marine transport has also used ML for fuel-emission forecasting. Using Singapore harbour craft sea-trial data, Random Forest provided the best accuracy for fuel consumption and emissions prediction, while SVM performed best for blend classification. The study noted that using biofuel blends caused a small rise in fuel consumption and NOx, but it gave a clear reduction in CO and CO₂ emissions [8]. In a separate work, an ensemble-boosting framework supported by sensitivity and SHAP analysis was used for microalgae biodiesel blends; Gradient Boosting delivered test $R^2 = 0.9586$ with MAPE = 2.58%, and it showed that engine load and blend ratio mainly control the predicted performance and emissions [9].

Nano-additive studies show similar benefits when coupled with ML. Gold nanoparticle (AuNP) addition to biodiesel blends increased brake thermal efficiency by up to 6.57% and reduced brake specific fuel consumption by up to 9.17%, while XG Boost predicted performance with maximum errors below 4.2% [10]. In a twin-cylinder CRDI CI engine, the B20CNT50 blend improved brake thermal efficiency by 9.8% and reduced brake specific fuel consumption by 18.7%, with reduced CO, CO₂, HC, smoke and NOx; SVR and Random Forest were effective predictors [11]. ML has also been used to predict nano-biodiesel fuel properties from literature datasets, where polynomial regression, random forest and ANN achieved R^2 values approaching 1.0 with low errors, while decision tree performed relatively lower [12]. For engine noise and vibration using sunflower biodiesel blends with intake-supplied CNG, GRNN achieved $R^2 = 0.9983$ for noise and RBFNN reached $R^2 = 0.9968$ for vibration prediction [13].

Hybrid fuelling and optimisation methods continue to expand. Waste biodiesel enriched with biogas and bio-hydrogen achieved optimal operation at 100% load, CR = 19, IP = 220 bar, 12% hydrogen and 8% biogas, giving a brake thermal efficiency of 37.5% with reduced CO (1.1 g/kWh) and NOx (675 ppm) [14]. Green-synthesised CuO nanoparticles (10–75 nm) in biodiesel increased brake thermal efficiency by 0.36% and reduced CO and particulate matter by 11.55% and 20.24%, supported by ML-based optimisation [15]. In another optimisation study, pumpkin seed oil biodiesel with CeO₂ nanoparticles achieved an optimal brake thermal efficiency of 24.99% at 18.32% biodiesel, 63.84% load and 48.55 ppm CeO₂, with minimal CO, HC, NOx and smoke emissions [16].

Machine learning has also been applied to extend advanced combustion modes. In biodiesel-fuelled HCCI operation, ANN predicted minimum stable load with errors of 3.5% (calibration) and 3.9% (validation), while SVM predicted maximum load limits with errors below 5%. A blended biodiesel from linseed, Karanja, coconut and mustard oils achieved operation up to 3.67 bar BMEP with charge dilution [17]. Hydrogen enrichment with MgO nanoparticles in Mahua oil biodiesel (B20) showed an 8.4% increase in brake thermal efficiency and 12% reduction in brake-specific fuel consumption, with emission reductions in CO (49%), HC (46%),

NOx (6.8%) and smoke opacity; ML models reported $R^2 > 0.98$ [18]. For EGR optimisation, a physics-informed ML digital-twin framework achieved NOx reductions of 60–70% at 15% EGR, while optimal EGR of 10–12.5% improved brake thermal efficiency by up to 5% [19]. Random Forest Regression further showed strong accuracy for combustion modelling, with $R^2 = 0.9987$ for cylinder pressure and $R^2 = 0.9878$ for heat release rate in a dual-fuel diesel engine using a ternary blend and acetylene [20]. Finally, recent reviews highlight that AI/ML methods can support modelling, optimisation and forecasting across the biofuel life cycle, including engine performance and emissions [21].

The investigation into canola-oil biodiesel concentrated on producing biodiesel and preparing sustainable ternary blends while tracking how fuel properties change with temperature. As the temperature rose, the density dropped from 0.8622 g/cm³ at 10°C to 0.8522 g/cm³ at 40°C, and the viscosity decreased from 8.5 MPa to 7.2 MPa. For property prediction, the authors reported that Gaussian process regression (GPR) gave the most accurate results for the measured fuel-property data [22].

Several engine studies showed that nanoparticles and alcohol/oxygenated additives can improve combustion and reduce emissions, and most papers used machine learning to identify the best operating window. With Al₂O₃ nano-additives in a B30 castor biodiesel blend, tests on a Kirloskar diesel engine indicated better combustion, shorter ignition delay, lower CO, HC, and NOx, and improved fuel economy with reduced brake-specific fuel consumption (BSFC); XGBoost was selected as the strongest predictive tool for optimization [23]. For Abrus precatorius B20 with SiO₂ nanoparticles (50, 75, and 100 ppm), the reported best outcomes were BTE 34.98%, BSFC 0.297 kg/kWh, CO 0.0215%, UHC 35 ppm, and NOx 729 ppm, and the ML correlation strength ranged from R^2 0.93 to 0.99 [24]. In other non-edible biodiesel utilizing Momordica seed oil with blends of 10%, 20%, and 30% along with cerium oxide additives, the RFG model achieved $R^2 = 0.86$ for brake thermal efficiency and $R^2 = 0.62$ for carbon monoxide [25]. A separate fuel-blending study noted that increasing biodiesel content reduced thrust and increased TSFC, while hydrogen blending reduced those penalties; it also reported that an LSTM model produced R^2 above 0.9 for most emissions, but the CO₂ prediction remained comparatively weak [26]. For a diesel engine operated at 1500 rpm, the 90D5MO5H + 25 ppm ZrO₂ blend delivered an 8.63% higher BTE and 46.13% lower fuel consumption, and the ELM model reported $R^2 = 0.9604$ [27]. Engine optimization using neem oil biodiesel blends (B10, B20, B30) with alumina nanoparticles (100, 150, 200 ppm) reported an optimum of 89.85% diesel and 30% biodiesel, giving BSFC 0.45 kg/kWh and BTE 38.18%, with a Random Forest accuracy of $R^2 = 0.9620$ [28]. The 30% pongamia biodiesel work combined hydrogen, DTBP, and algae carbon nanoparticles (ACN) and proposed an adaptive fuel-control model for optimization [29].

The remaining studies extended the same theme to ternary mixtures, dual-fuel operation, and high-accuracy prediction tools, with the bracket numbers kept in order. In CRDi engines, DBMA20 (50% diesel, 30% Simmondsia chinensis biodiesel, and 20% methyl acetate) improved thermal efficiency and reduced NOx, and a neural network was used to predict optimal conditions [30]. A large property dataset for used frying oil biodiesel (UFOB) reported 2389 density measurements and compared models: GPM (R^2 99.68%, MAPE 0.17%), ANFIS (MAPE 0.25%), and DT (MAPE 0.72%), with GPM ranked best and SHAP used to identify key density factors [31]. In a modified diesel engine running ammonia (NH₃) as a dual fuel with JME20 as a pilot, tests at NH₃ flow rates of 8–16 lpm showed 12 lpm gave the highest HRR of 4.4 kW, and a 1D-CNN model achieved $R^2 = 0.99$ [32]. In comparative biodiesel blending

(from *Raphanus sativus*, *Jatropha*, and *Balanites aegyptiaca*), MB20 produced a 5.08% increase in BSFC and a 3.13% decrease in BTE, while CO and HC fell by 7.69% and 8.33%; adding 15% diethyl ether improved BTE by 1.87%, and the prediction models exceeded $R^2 > 0.93$ for BSFC, 0.97 for EGT, and 0.98 for NO_x and HC [33]. With *Momordica charantia* biodiesel and TiO₂ nanoparticles, the blend D90BG10 + 25 ppm TiO₂ showed a 7.25% rise in BTE, a 31.88% reduction in fuel consumption, and CO₂ of 3 g/kWh [34]. For estimating cylinder pressure under NP-enriched formulations, multiple ML options were compared, and polynomial regression (PR) was reported as the best performer [35]. In diesel–biodiesel–ethanol ternary blends, the study reported 3.76% higher BTE, 5.62% higher exergy efficiency for binary blends, a ternary-blend peak sustainability index of 1.28, and XG Boost desirability of 0.777 [36]. Finally, gene expression programming (GEP) applied to linseed oil methyl ester blends reported $R = 0.9926$ – 0.9999 , $R^2 = 0.9854$ – 0.9998 , RMSE = 0.0048–2.597, and MSE = 0.0037–4.386 [37]. Machine learning applications in internal combustion engine as shown in Figure 1,

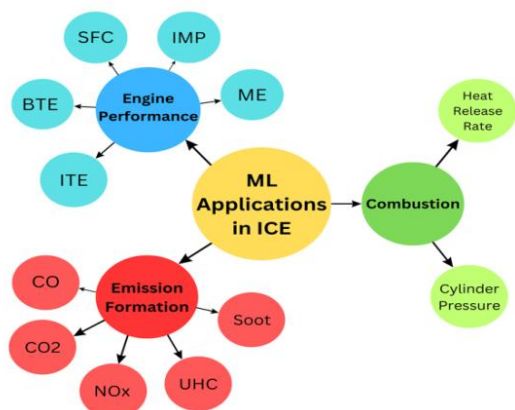


Figure1. Machine Learning Applications in IC engines

In summary, machine learning has transformed the study and optimization of internal combustion engines by delivering precise, data-oriented, and computationally efficient solutions. It not only improves performance prediction but also enhances diagnostic capabilities, fuel optimization, emission control, and system design. These developments bridge the gap between experimental studies and real-time engine control supporting the advancement of sustainable automotive technologies.

This work is novel because it applies machine learning methods to improve the study and optimization of internal combustion engines in a simple and effective way. Instead of depending only on traditional experiments, this approach uses data-driven models to predict engine performance, fuel consumption, and emissions with better accuracy and less time. It also helps in identifying faults and optimizing engine operation under different conditions. By connecting experimental results with real-time analysis, this method supports better engine design and control, contributing to improved efficiency and reduced environmental impact.

The main objective of this manuscript is to experimentally investigate the performance and emission characteristics of a single-cylinder four-stroke diesel engine fuelled with different blends of American saffron oil biodiesel (B10, B20, and B30) and to compare them with conventional diesel fuel. The study aims to identify the optimal blend that provides better efficiency and lower emissions under varying load conditions. In addition, the work focuses on developing predictive models to analyze engine behavior and establish relationships between operating parameters and output responses, thereby supporting improved engine performance and sustainable fuel utilization.

2. Materials and Methods:

2.1 Production of American Saffron Biodiesel

The production of biodiesel from American saffron oil begins with extracting the oil from crushed seeds, followed by filtration and drying to remove impurities and moisture. A catalyst solution is prepared by dissolving sodium hydroxide (NaOH) in methanol, forming sodium methoxide. The pretreated oil is then heated to around 60°C, and the methoxide solution is added under continuous stirring. During this process, known as transesterification, the triglycerides present in the oil react with methanol to produce fatty acid methyl esters (biodiesel) and glycerol as a by-product.

After the reaction, the mixture is allowed to settle so that the heavier glycerol separates at the bottom while biodiesel forms the upper layer. The biodiesel is carefully separated and purified through repeated water washing to remove residual catalyst, methanol, and impurities until it becomes neutral and clear. Finally, it is heated to remove any remaining moisture, resulting in a clean and stable biodiesel that can be used in diesel engines either in pure form or as a blend with conventional diesel fuel.

2.2 Experimental Setup:

The experiment was conducted on a 5.2 kW, four-stroke, water-cooled, single-cylinder DI diesel engine (Figure 2). The engine's shaft was connected to an eddy current dynamometer with varied loads at a constant speed. The temperatures and pressures of the combustion chamber were measured by thermocouples and a pressure transducer. The sensors were all connected to a data acquisition system. The fuels used were diesel fuel and mixtures of diesel fuel with concentrated American Saffron Biodiesel at a constant 1500 rpm engine speed, with the brake power varied to assess performance parameters. Emissions of CO₂, CO, hydrocarbons, and NO_x were measured by a five-gas Mars analyzer; a gas analyzer and smoke meter are shown in Figure 3. The fuel properties are shown in Table 1. The specifications of the engine are shown in Table 2.

Table 1. Fuel properties

Property	American saffron			B0	Test Method
	B10	B20	B30		
Flash Point (°C)	67	74	77	61	ASTMD93
Gross Calorific	10050	10000	9767	10090	IS 1448 (p-6)
Cloud Point (°C)	-10	-9	-9	-12	IS 1448 (P-10/Sec-1)
Pour Point (°C)	-13	-12	-12	-15	
Cetane Number	49	49	50	47	ASTMD613
Density (kg/m ³)	845	852	868	840	ASTMD792
Kinematic Viscosity (cSt)	3.18	3.28	3.4	2.6	ASTM D445

Table 2. Engine Specifications

Parameter	Specification
Make	Kirloskar
Number of Cylinders	1
Piston Shape	Cylindrical
Piston Dimensions	87.5 mm – 87.6 mm
Stroke Length	110 mm
CR Range	12:1 to 18:1
Rated Speed	1500 rpm
Dynamometer Arm Length	185 mm
Orifice Diameter	20 mm
Dynamometer Type	Eddy Current Dynamometer



Figure 2. Experimental Setup



Figure 3. Gas analyser and Smoke meter

2.3 uncertainty analysis

Uncertainty represents the possible errors that may occur during measurement and indicates the reliability or quality of the obtained data. Uncertainty analysis is carried out in experiments to ensure that the accuracy of different measurements remains within acceptable limits for the final results. The variation in experimental data is evaluated using the Gaussian distribution method. In the present study, the maximum uncertainty was found to be $\pm 2.05\%$. The uncertainties associated with the instruments used are listed in Table 3.

Table 3. Measurement Uncertainty and Instrument Accuracy

Instruments	Accuracy	Range	Uncertainty (%)
Fuel Flow meter	2 mm WC	0–500 mm WC	0.1
Air Flow meter	1 mm WC	0–250 mm WC	0.1
Temperature indicator	$\pm 1^\circ\text{C}$	0–1200 $^\circ\text{C}$	0.1
Exhaust gas analyzer			
Smoke	$\pm 1\%$	0–100%	1
CO	$\pm 3\%$	0–9.99%	0.5
NOx	± 25 ppm	0–500 ppm	1
HC	± 10 ppm	0–20,000 ppm	1

3. Work Methodology

The experiments were carried out at a constant engine speed of 1500 rpm under different brake power (BP) conditions. BP was varied from zero to the maximum at constant speed, and all performance and emission parameters were recorded and tabulated. The same procedure was repeated for diesel and all biodiesel blends. Finally, the results were combined into a single table so that every parameter could be compared against BP for all blends in one place. Graphs were then plotted with BP as the independent variable and outputs such as SFC, BTE, ME, etc., as dependent variables. Principal component analysis also confirmed BP as the independent variable. Before applying machine learning, the dataset was checked for noisy entries. Any row affected by speed fluctuations (1500 rpm) or issues such as fuse loss and abnormal signal variation was treated as noise and removed. After cleaning, the data were prepared for ML. Supervised learning uses labelled input–output data [38], while unsupervised learning works with unlabeled data [39]. For this work, supervised regression was selected because the target variables are continuous [40]. Several regression models were considered, including Linear Regression, Multi Linear Regression, Polynomial

Regression, SVR, SVM, Random Forest, Gradient Boost, Ex-Gradient Boost, and others, with care taken to reduce overfitting and underfitting [41].

Since the experimental dataset was limited, additional “organic” data were generated within the engine’s maximum BP range by fitting a 6th degree polynomial to each parameter curve. Multiple models (including Lasso, Ridge, Elastic Net, XG Boost, Gradient Boost, Random Forest, Decision Tree and ANN) were evaluated [42]. While selecting the best regression model, issues like overfitting and underfitting were observed, mainly due to poor feature selection, high model complexity, outliers, and skewed target distribution. Overfitting can be reduced using simpler models or regularization. Outliers disturb variance and weaken fit. For skewed targets, data transformation helps; for small datasets, data augmentation can reduce errors. Various machine-learning models are used in internal combustion engines as shown in Figure 4.

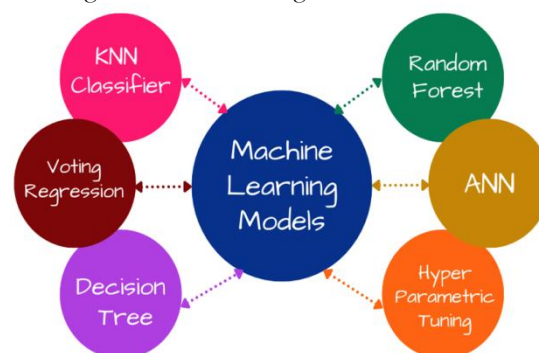


Figure 4. Common machine learning models for IC engines

3.1. Methodology of the presented System:

This section describes the machine learning approach. The variables in the dataset are engine performance and emissions: brake power, specific fuel consumption, brake thermal efficiency, NOx, and carbon monoxide. Data splitting: 80% for training and 20% for testing. Cross-validation was performed on the training set with 10 folds, where one fold was used for validation and the other nine for training. This was repeated for all the folds to obtain 10 values, the average of which was then calculated. Hyperparameter optimization was done to enhance accuracy and generalization. Hyperparameters were tuned using grid search, random search, and Bayesian optimization. This is an important step for models to be accurate and reliable, and it is illustrated in Figure 5.

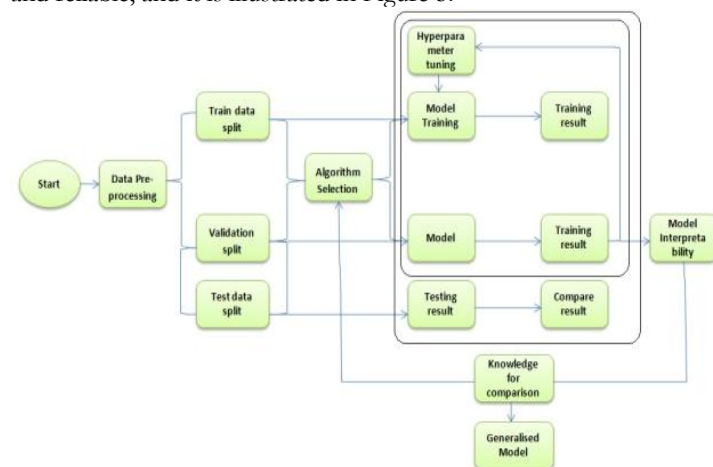


Figure 5. Methodology

4. Results and Discussion

The experiment above illustrates the relationships between the primary engine parameter, brake power, and various engine metrics

such as specific fuel consumption, brake thermal efficiency, HC, NO_x, smoke, and other emissions.

4.1. Specific fuel consumption:

Figure 6 compares SFC against brake power (BP) for B0 and the biodiesel blends. As BP increases from 0 to maximum load, SFC drops for all fuels. Relative to B0, B20 records about 30.30% lower SFC, while B10 and B30 show reductions of 24.24% and 9.09%, respectively. This kind of behavior is due to properties of fuel differences, mainly the lower heating value of biofuel, which changes the fuel quantity needed to produce the same power output [24]

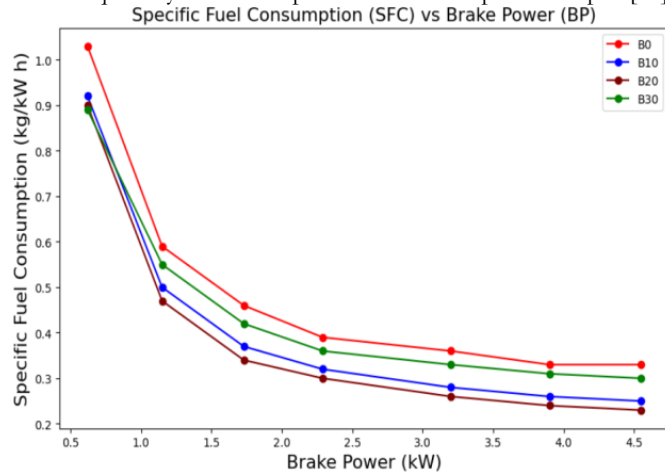


Figure 6. SFC Vs BP

4.2. Brake thermal efficiency:

Figure 7 shows BTE variation with brake power (BP) for B0, B10, B20, and B30. The BTE values are 26.01% (B0), 28.5% (B10), 29.5% (B20), and 26.94% (B30). Compared with B0, the BTE rise is highest for B20 (13.41%), followed by B10 (9.57%) and B30 (3.57%). For all blends, BTE gradually rises as BP increases. Among all blends, B20 indicates the strongest improvement and gives higher thermal efficiency than B0 under load. This enhancement is attributed to better oxygen content in biodiesel, which promotes efficient combustion and energy conversion.[28].

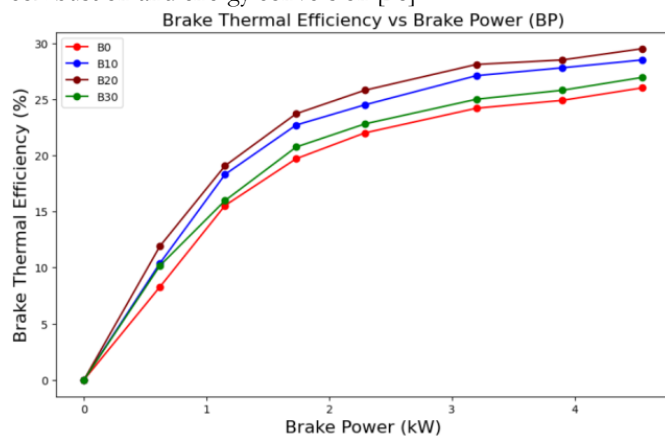


Figure 7. BTE Vs BP

4.3. Oxides of Nitrogen:

The variations in NO_x pollutant levels between a pure diesel (B0) and biodiesel blends (B10, B20, B30) are shown in Figure 8, plotted against brake power (BP). At high engine operating temperatures, nitrogen oxides are produced through the combination of oxygen and nitrogen. As brake power increases, so do NO_x levels for all blends, and NO_x levels were found to be 6.77%, 10.16%, and 13.55% greater than those of B0 for the B10, B20, and B30 blends. Higher oxygen content in biodiesel fuels results in better vaporization of the fuel and a larger role in the combustion process,

which leads to higher peak combustion temperatures resulting in increased production of nitrogen oxides[43].

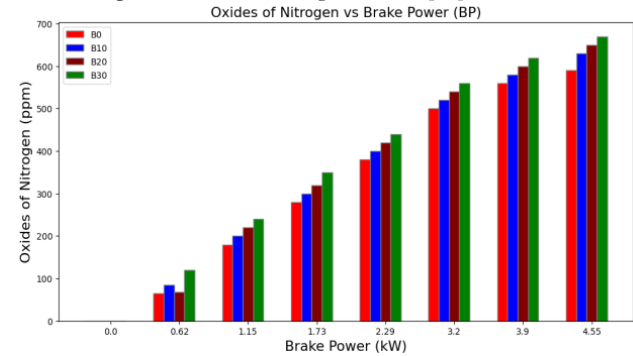


Figure 8. NO_x Vs BP

4.4. Hydrocarbons:

Figure 9 shows how the amount of hydrocarbon (HC) emissions changes for diesel (B0) and biodiesel blends (B10, B20, and B30) when the brake power (BP) is changed. The HC emissions for B10, B20, and B30 are 62 ppm, 60 ppm, and 64 ppm, respectively. Among these, the B20 blend produces the minimum HC emissions compared to diesel and the other biodiesel blends. At maximum load conditions, the HC emissions for B10, B20, and B30 are 8.8%, 11.76%, and 5.88%, respectively, less than the B0 blend. The primary reason for the reduced unburnt hydrocarbon pollutants in biodiesel blends is their higher ignition quality, which leads to more complete combustion[44].

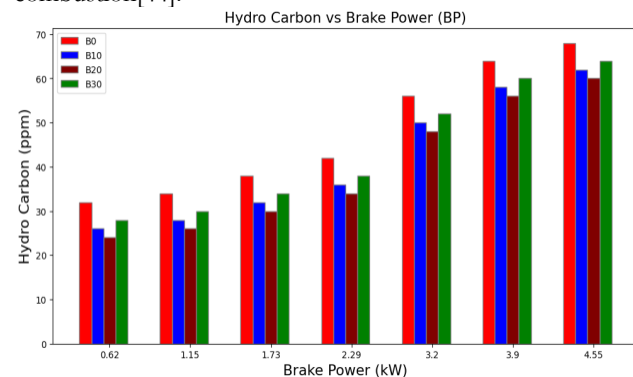


Figure 9. HC Vs BP

4.5. Carbon monoxide:

The carbon monoxide (CO) emissions for diesel (B0) and different Biodiesel blends (B0, B10, B20, and B30) are represented in Figure 10, based on brake power (BP). The blend B30 yields the least CO emissions than diesel and all other blend ratios. The amount of CO emissions for B10, B20 and B30 at the maximum load is respectively 8.51%, 14% and 18.09% less than the B0 blend. The main cause of reducing the unburnt of CO pollutants in the blends of biodiesel can be attributed to their higher ignition quality which causes more complete combustion [16].

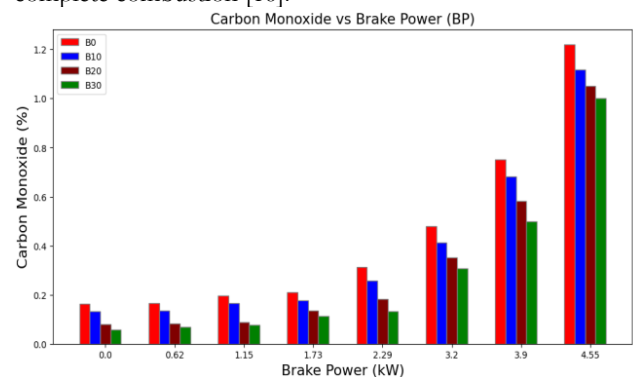


Figure 10. CO Vs BP

4.6. Smoke:

The smoke emissions for diesel (B0) and different biodiesel blends (B10, B20 and B30) are represented in figure 11, based on brake power (BP). The graph shows the variations in smoke emissions as brake power increases for the various fuel blends. The smoke emissions for B0, B10, B20 and B30 at maximum brake power are respectively about 45, 49, 52 and 55. Among these the minimum smoke emissions were produced with the B0 blend as compared to all other ratios of the blends. At the maximum load conditions the smoke emissions for B10, B20 and B30 were respectively 8.8%, 15.55% and 22.2% higher than the B0 blend. The main cause for the higher smoke pollutants in the blends of biodiesel is their high igniting characteristic which leads to more incomplete combustion [23].

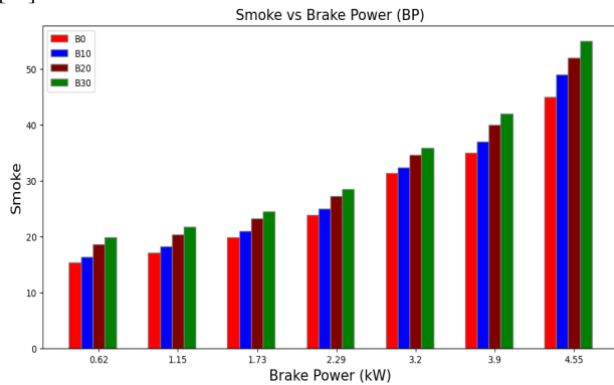


Figure. 11. Smoke Vs BP

5. ML Results and Discussions

A decision tree regression algorithm is used to test and train the datasets obtained from the above methodology.

5.1. Specific Fuel Consumption:

Figure 12 presents the average values of R^2 , R , RMSE, and SER for SFC prediction. The correlation coefficient (R) ranging from 0.88 to 0.91 indicates a strong positive relationship between experimental and predicted values, while R^2 values of 80–83 % confirm good model accuracy, with the best result for B0 and a slight reduction for B10–B30 due to increased combustion complexity. The RMSE shows a small rise from 0.12 for B0 to 0.15 for B30, indicating a marginal reduction in prediction accuracy at higher blend ratios.

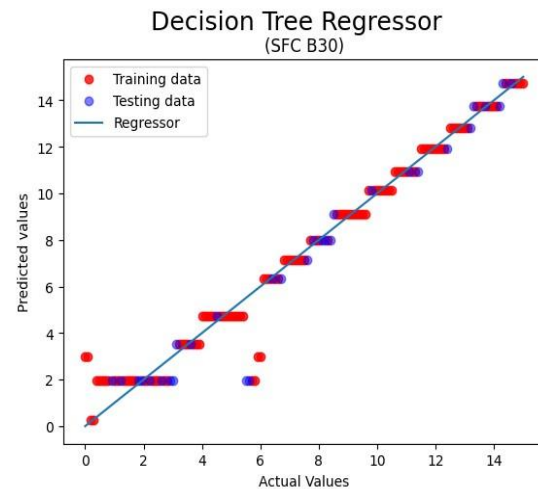
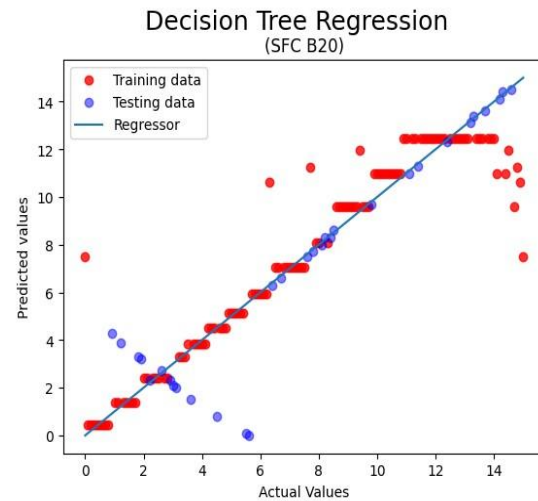
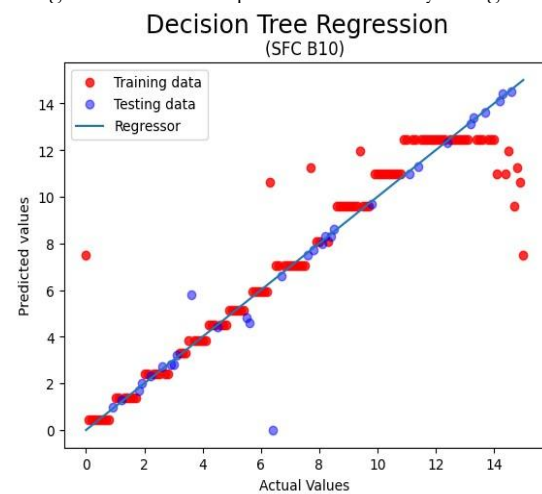


Figure. 12. Comparison of SFC across various blends

5.2. Brake Thermal Efficiency:

Figure 13 presents the correlation metrics for BTE prediction using different fuel blends. For B0, the model shows strong agreement with $R = 0.88$, $R^2 = 0.77$, and $RMSE = 0.15$, indicating high accuracy and stable combustion behaviour. A gradual reduction in model performance is observed for B10 ($R = 0.87$, $R^2 = 0.76$, $RMSE = 0.16$), B20 ($R = 0.86$, $R^2 = 0.75$, $RMSE = 0.17$), and B30 ($R = 0.85$, $R^2 = 0.74$, $RMSE = 0.18$), mainly due to increased variability in combustion characteristics at higher biodiesel concentrations.



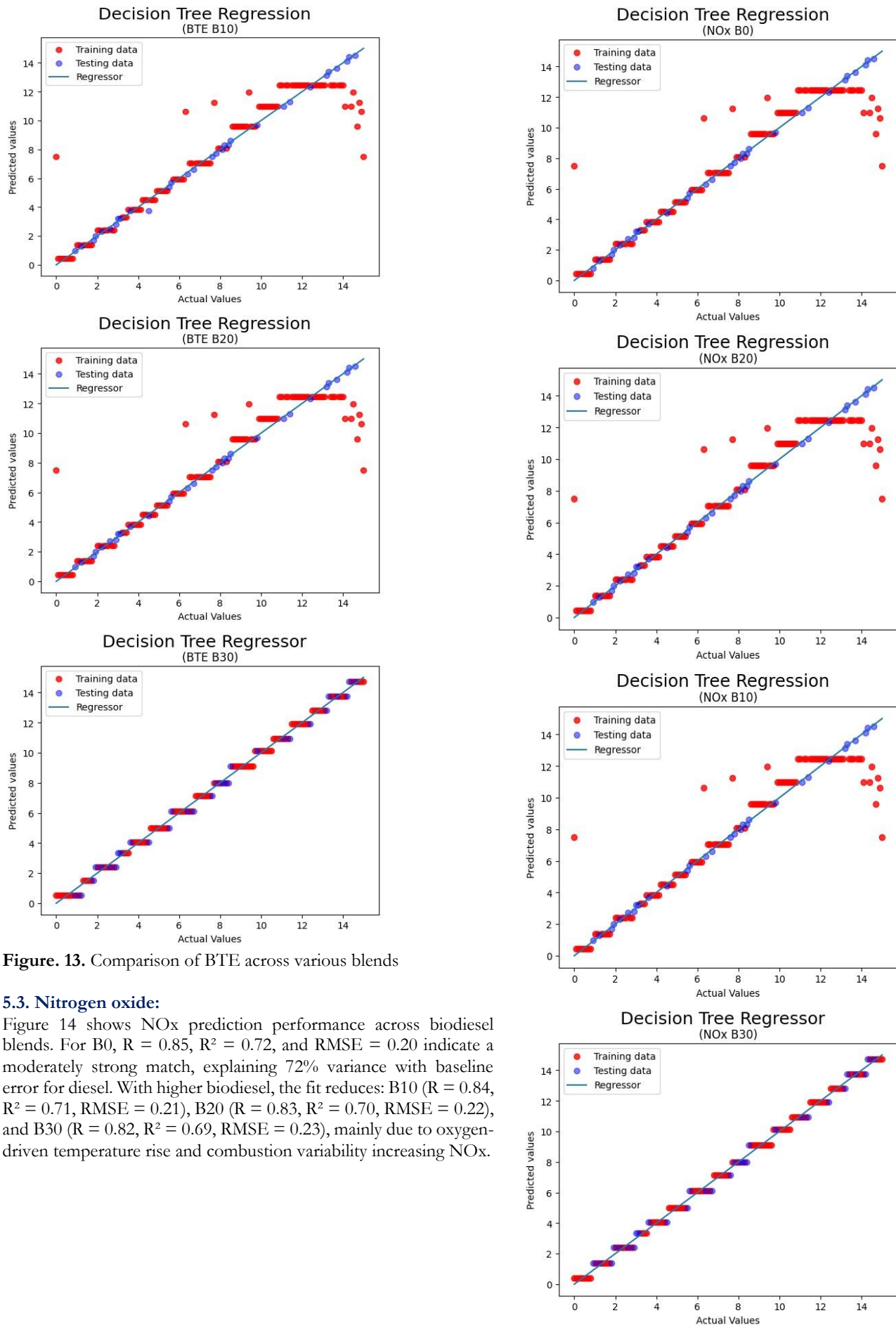


Figure. 13. Comparison of BTE across various blends

5.3. Nitrogen oxide:

Figure 14 shows NO_x prediction performance across biodiesel blends. For B0, $R = 0.85$, $R^2 = 0.72$, and $RMSE = 0.20$ indicate a moderately strong match, explaining 72% variance with baseline error for diesel. With higher biodiesel, the fit reduces: B10 ($R = 0.84$, $R^2 = 0.71$, $RMSE = 0.21$), B20 ($R = 0.83$, $R^2 = 0.70$, $RMSE = 0.22$), and B30 ($R = 0.82$, $R^2 = 0.69$, $RMSE = 0.23$), mainly due to oxygen-driven temperature rise and combustion variability increasing NO_x.

Figure. 14. Comparison of NO_x across various blends

5.4. Hydro Carbon:

Figure 15 indicates strong HC prediction for diesel, with B0 showing $R = 0.89$, $R^2 = 0.79$, and $RMSE = 0.18$, meaning 79% of HC variation is explained with low error. Model fit reduces slightly with higher biodiesel: B10 ($R = 0.88$, $R^2 = 0.78$, $RMSE = 0.19$), B20 ($R = 0.87$, $R^2 = 0.77$, $RMSE = 0.20$), and B30 ($R = 0.86$, $R^2 = 0.76$, $RMSE = 0.21$), due to changing combustion behavior and higher variability in HC trends.

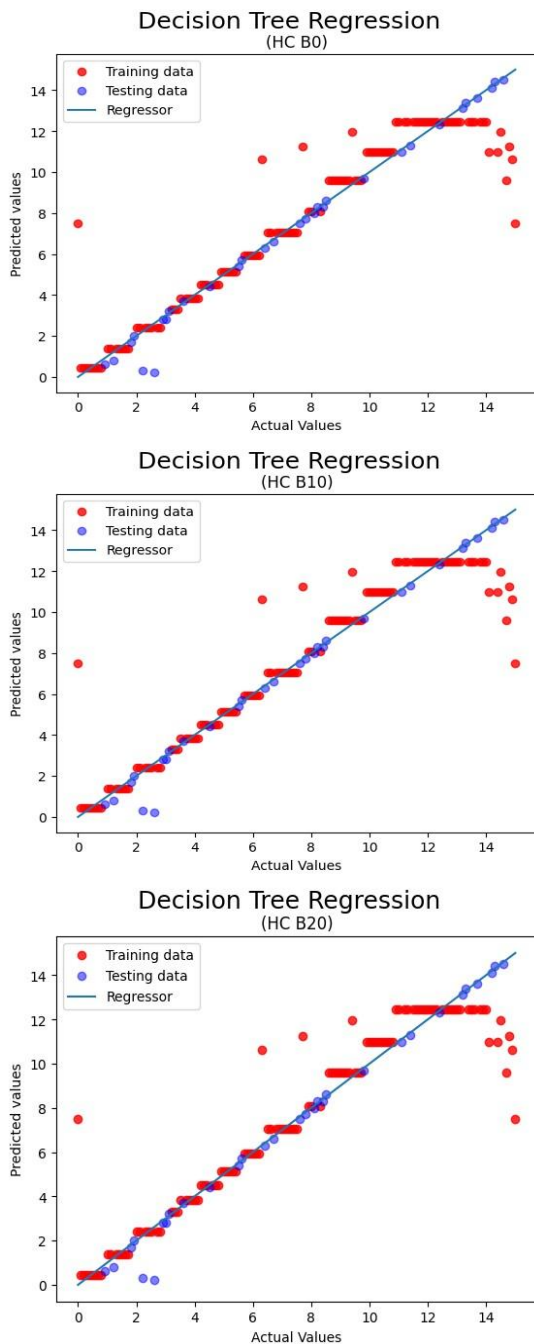
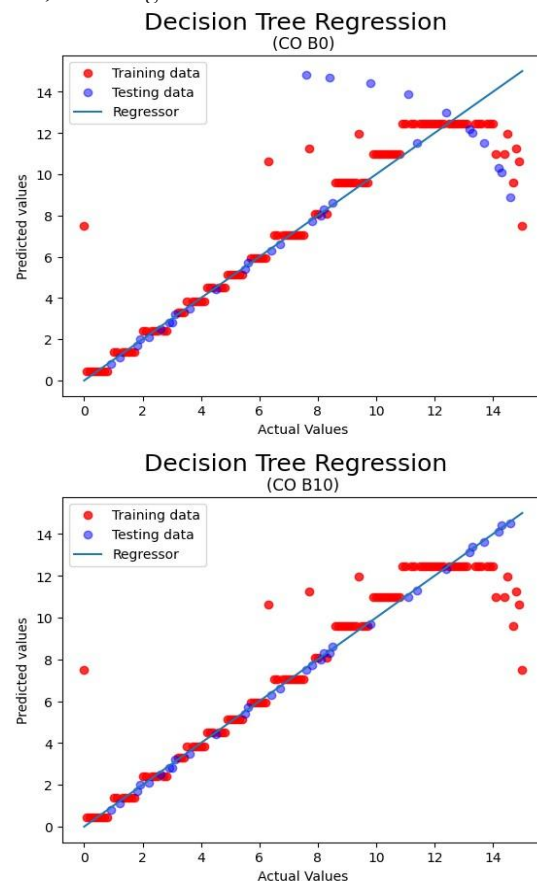


Figure 15. Comparison of HC across various blends

5.5. Carbon Monoxide:

Figure 16 compares Decision Tree predictions of CO for different blends using predicted vs actual plots. For B0, the fit is weaker ($R = 0.55$, $R^2 = 0.15$, $RMSE = 4.22$) because several points, especially at higher CO values, fall away from the ideal line. With B10, the match improves slightly ($R = 0.65$, $R^2 = 0.25$, $RMSE = 3.90$), but noticeable scatter remains at the upper range. For B20, the agreement drops again ($R = 0.55$, $R^2 = 0.10$, $RMSE = 4.22$), showing higher spread and less consistent prediction. B30 gives the best behavior ($R = 0.79$, $R^2 = 0.50$, $RMSE = 2.85$) as most points stay close to the diagonal line, indicating more stable CO estimation.



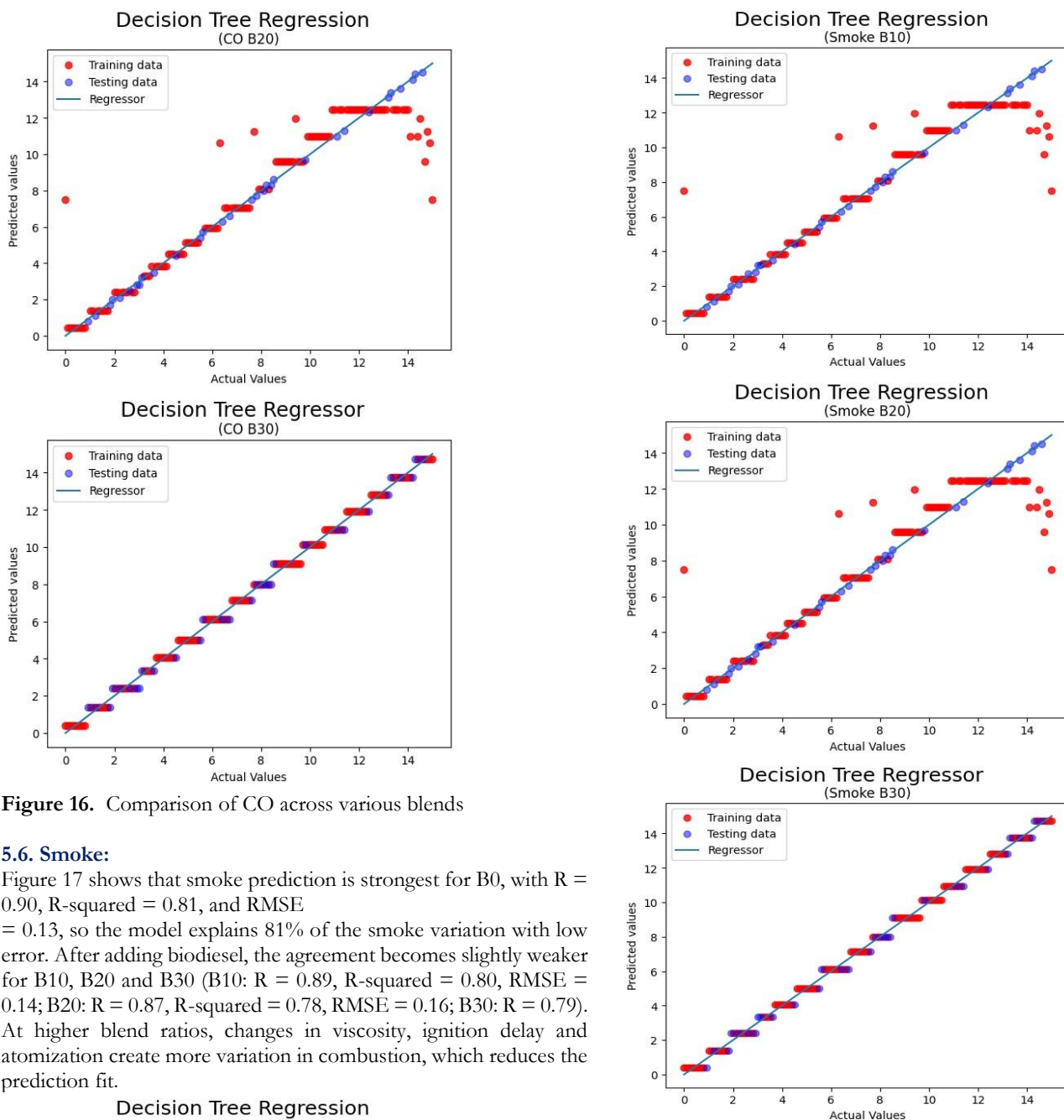


Figure 16. Comparison of CO across various blends

5.6. Smoke:

Figure 17 shows that smoke prediction is strongest for B0, with $R = 0.90$, $R\text{-squared} = 0.81$, and $RMSE = 0.13$, so the model explains 81% of the smoke variation with low error. After adding biodiesel, the agreement becomes slightly weaker for B10, B20 and B30 (B10: $R = 0.89$, $R\text{-squared} = 0.80$, $RMSE = 0.14$; B20: $R = 0.87$, $R\text{-squared} = 0.78$, $RMSE = 0.16$; B30: $R = 0.79$). At higher blend ratios, changes in viscosity, ignition delay and atomization create more variation in combustion, which reduces the prediction fit.

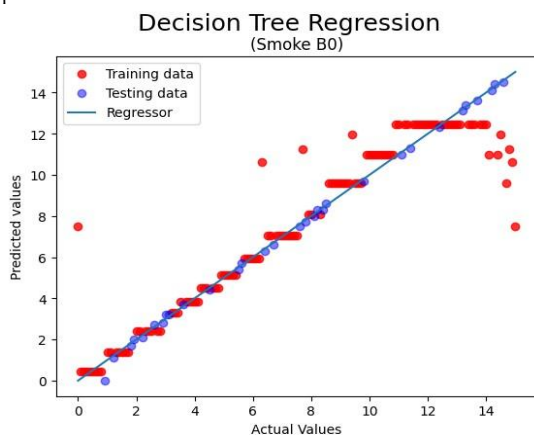


Figure 17. Comparison of smoke across various blends

6. Conclusions:

Engine tests were conducted on a compression ignition engine fueled with American Saffron Biodiesel–diesel blends to examine variations in performance and emission behaviour. In parallel, a machine learning model was implemented using 80% of the dataset for training and 20% for testing, where fuel type and engine load served as inputs, and specific fuel consumption, brake thermal efficiency, nitrogen oxides, hydrocarbons, carbon monoxide, and smoke emissions were considered as output parameters.

In comparison to pure diesel fuel (B0), biodiesel blends lower specific fuel consumption by 30.30% for B20, 24.24% for B10, and 9.09% for B30. The brake thermal efficiency increases by 13.41% for B20, 9.57% for B10, and 3.57%.

Hydrocarbon emissions were lowest for B20, while nitrogen oxide emissions increased with biodiesel content, rising by 6.77% for B10, 10.16% for B20, and 13.55% for B30 relative to B0 due to enhanced oxygen availability and higher combustion temperatures.

The decision tree model reliably represented the influence of blend variation, with predicted specific fuel consumption closely matching experimental values ($R = 0.88\text{--}0.91$), confirming the effectiveness of combining experimental analysis with machine learning for evaluating alternative fuels aimed at sustainable and cleaner energy use.

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