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RESEARCH ARTICLE

Predicting Engine Emissions Using Eco-Friendly Fuels for Sustainable Transportation

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ABSTRACT

In recent years, increasing concerns about vehicle emissions' environmental and public health impacts have led to the desire to use eco-friendly fuels as alternatives to traditional fossil fuels. Biofuels, hydrogen, and electric power offer lower greenhouse gas emissions and improved air quality, resulting in their development and adoption globally. Predicting emissions using these fuels is crucial for assessing their environmental benefits. This study proposes using artificial neural networks (ANN), a machine learning technique, to accurately predict emissions associated with eco-friendly fuels across different compositions and engine speeds. The ANN model strongly correlates with predicted and observed emissions values, indicating its effectiveness. The training dataset had an R-value of 0.99928, the test dataset had an R-value of 0.99937, and the validation dataset had an R-value of 0.99904. When all datasets were combined, the overall R-value of 0.99927 confirmed the model's accuracy in capturing the data patterns. This study underscores the importance of adopting innovative approaches to address environmental challenges and promote sustainable transportation solutions. It contributes to reducing the adverse effects of vehicle emissions on air quality and public health by assisting policymakers, car manufacturers, and city planners in making effective decisions. Moreover, It promotes environmental sustainability by providing valuable insights into vehicle emissions prediction and guiding the development of eco-friendly fuels for a more efficient transportation system.

Keywords: Engine emissions prediction, Eco-friendly fuels, Artificial neural network, Environmental sustainability, Sustainable transportation

1. Introduction

In recent years, there has been a growing global concern about environmental pollution and its detrimental effects on human health. Pollution originating from various sources, including industrial emissions, vehicle exhaust, agricultural runoff, and improper waste disposal, has led to air, water, and soil contamination, posing serious risks to the environment and public health. Vehicular emissions, in particular, play a significant role in this issue, contributing substantially to the worsening levels of air pollution. The rising pollution, especially from vehicles on roads, presents a major challenge due to rapid urban growth and increased reliance on private transportation, further exacerbating air quality issues. As a result, the increasing number of vehicles with internal combustion engines is a primary concern for air quality today. A significant portion of urban air pollution comes from vehicles with these engines, and the type of pollutants and their concentrations depend on factors like engine type, tuning, driving habits, fuel makeup, and weather conditions. When fossil fuels are burned in vehicle engines, they release various pollutants into the air, including carbon monoxide (CO), nitrogen oxides (NOx), particulate matter (PM), and volatile organic compounds (VOCs) [1]. Achieving ideal conditions for complete combustion is practically impossible, leading to incomplete combustion and the creation of additional pollutants. Vehicle exhaust gases, responsible for 75% of total pollutants, contain a mixture of unburned hydrocarbons like kinds of paraffin, olefins, and aromatics, as well as partially burned hydrocarbons such as aldehydes, ketones, and carboxylic acids. They also contain CO, NOx, lead compounds, and particulate matter. What makes emissions from combustion noteworthy is their polluting properties and their immediate and significantly harmful toxic effects, distinguishing them from emissions originating from other sources. These emissions, which substantially negatively impact human health and environmental quality, can be classified into six main categories: carbon oxides, nitrogen oxides, sulfur compounds, hydrocarbons, aldehydes, and particulates [2]. These pollutants deteriorate air quality and present significant health hazards to people, resulting in respiratory illnesses, cardiovascular issues, and other harmful health outcomes [3], [4]. Alternative fuels are crucial for reducing vehicle emissions because they emit fewer pollutants, support climate change mitigation, vary energy sources, and often have lower lifecycle emissions than fossil fuels. Using environmentally friendly fuels like biofuels, natural gas, electricity, and propane in vehicles has led to substantial

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reductions in emissions. In contrast to fossil-based (FB) fuels, biohydrogen, biomethane, biodiesel, and bioethanol have shown considerable emission reductions of 70%, 63%, 41%, and 54%, respectively, when utilized in vehicles [5]. As urbanization and industrialization expand globally, vehicle emissions and resulting air pollution are increasing, highlighting the urgent need for measures to reduce their impact, as controlling these pollutants has become essential due to their direct or indirect endangerment to human health and the environment. Challenges in predicting engine emissions when using eco-friendly fuels include the need for significant modifications to motor vehicles to accommodate biomethane as a fuel, alongside the potential increase in emissions of certain pollutants. Predicting engine emissions is crucial for several reasons: it aids in effective air quality management by identifying sources of pollution and implementing targeted control measures, allows health professionals to assess potential health risks associated with pollutants emitted from vehicles, enabling the development of appropriate mitigation strategies. Additionally, predicting emissions helps environmental scientists evaluate their impact on ecosystems and biodiversity, contributing to conservation efforts, while also facilitating regulatory compliance by assisting vehicle manufacturers and regulatory agencies in meeting emission standards and developing more efficient emission control technologies. Lastly, predicting emissions is crucial for addressing climate change, allowing policymakers to assess contributions to global warming and develop strategies for mitigation.

In the literature, Chadha et al. [6] underscore the significant contribution of the transportation sector to global CO_2 emissions, amounting to approximately 16.2% of the total. Their study explores the prediction of CO_2 emissions by vehicles using various machine learning (ML) techniques. Through methods such as Lasso Regression, Multiple Linear Regression, XGBoost, Support Vector Regressor (SVR), Random Forest, and Ridge Regression, they achieve promising results with an RMSLE of 0.71 and an accuracy of around 99.8%. This highlights the potential of ML approaches in aiding local authorities in planning effective public transportation infrastructure to mitigate CO_2 emissions. The study conducted by Xu, Kang, and Lv [7] proposes a three-layer artificial neural network model for predicting vehicle exhaust emissions based on remote sensing data. Their approach employs an adaptive lasso algorithm to identify principal factors and establishes the Backpropagation neural network model as the optimal method. Their research aims to reduce inspection costs and establish a prediction model for total pollutant discharge, thereby supporting motor vehicle pollution regulation. Azeez et al. [8] present a hybrid model for predicting vehicular carbon monoxide (CO) emissions in urban areas of Kuala Lumpur, Malaysia. Their model combines correlation-based feature selection (CFS), support vector regression (SVR), and Geographic Information Systems (GIS). Through CFS, they identify seven road traffic CO predictors, and SVR is utilized for emission prediction. The model achieves impressive validation accuracy, correlation coefficient, mean absolute error, and root mean square error, highlighting its effectiveness in assessing traffic-related CO emissions on roads. Singh and Dubey [9] propose a deep-learning model using vehicle telematics sensor data to predict CO_2 emissions. With climate change a significant concern, their scalable model utilizes real-time vehicle sensor data and a Recurrent Neural Network (RNN)-based Long Short-Term Memory (LSTM) model to estimate CO_2 emissions. The system, utilizing On-Board Diagnostics (OBD-II) port data, offers an efficient approach to monitor emissions at the vehicular level, facilitating easy transmission of data to the cloud for analysis. Shobana Bai [10] explores ways to decrease emissions in a low-carbon biofuel-hydrogen dual-fuel engine. They test lemon peel oil, camphor oil, hydrogen induction, and a zeolite-based after-treatment system. Machine learning methods like XGBoost, LGBM, CatBoost, and Random Forest are used to predict engine emissions and performance, with CatBoost showing high accuracy. This research highlights the potential of machine learning in predicting emissions and improving engine efficiency in low-carbon fuel systems. In their study, Hananto et al. [11] explore ways to decrease emissions in a low-carbon biofuel-hydrogen dual-fuel engine. They test lemon peel oil, camphor oil, hydrogen induction, and a zeolite-based after-treatment system. Machine learning methods like XGBoost, LGBM, CatBoost, and Random Forest are used to predict engine emissions and performance, with CatBoost showing high accuracy. This research highlights the potential of machine learning in predicting emissions and improving engine efficiency in low-carbon fuel systems. Ramalingam et al. [12] employ artificial neural network (ANN) modeling to predict the behavior of a non-modified diesel engine fueled by blends of two low viscous biofuels. They find that the B20 blend exhibits improved efficiency, while the B50 blend shows minimal emissions compared to other blends. The trained ANN models demonstrate high accuracy, emphasizing the potential of the B20 blend as an effective alternative fuel for diesel engines.

The aim of this study is to systematically optimize the architecture of the artificial neural network (ANN) and employ data normalization techniques to enhance the accuracy and reliability of predictions for engine emissions. The originality of this study lies in its innovative application of machine learning techniques to predict engine emissions using eco-friendly fuels. While previous research has explored various methods for emissions prediction, this study uniquely focuses on ANN to accurately forecast emissions across different fuel compositions and engine speeds. Integrating ANN-based prediction models into emission control strategies can facilitate the development of cleaner and more sustainable transportation systems, thereby reducing the adverse impacts of emissions on the environment and public health.

2. Material and Methods

2.1. Artificial Neural Networks (ANN)

This section presents the methodology employed in utilizing Artificial Neural Networks (ANN) to predict engine emissions associated with eco-friendly fuels. The Artificial Neural Network (ANN) is a computational model inspired by the human 'brain's information processing mechanism. Structurally, it comprises distinct layers: an input layer, an output layer, and several hidden layers. Each layer consists of neurons, the fundamental processing units interconnected through communication links governed by connection weights. Signal transmission within the network occurs via these weighted connections [13], [14]. The structure of a neuron and Artificial Neural Network (ANN) is depicted in Figure 1. This illustration highlights the organizational framework of a neuron, along with the interconnected layers and nodes within an ANN.

Development of the ANN model involves two pivotal stages: training/learning and testing/verification. The network is enhanced during training to produce output estimations based on input data. Subsequently, experimental data is compared with predicted outcomes in the testing phase, and training terminates once the test error meets the specified tolerance level. The ""backpropagation algorithm"" (BPA) is the predominant technique in ANN model development. It operates in two phases: forward feed and feedback. In the forward feed phase, information flows from the input layer to the output layer. During the feedback phase, the discrepancy between the achieved output and the target output is evaluated, and this discrepancy is subsequently utilized to update the connection weights, thus improving the model [15], [16]. During the development of the ANN model, 'it's common practice to use metrics like Mean Squared Error (MSE) and coefficient of determination (R^2) to measure the 'model's ability to predict outputs accurately.

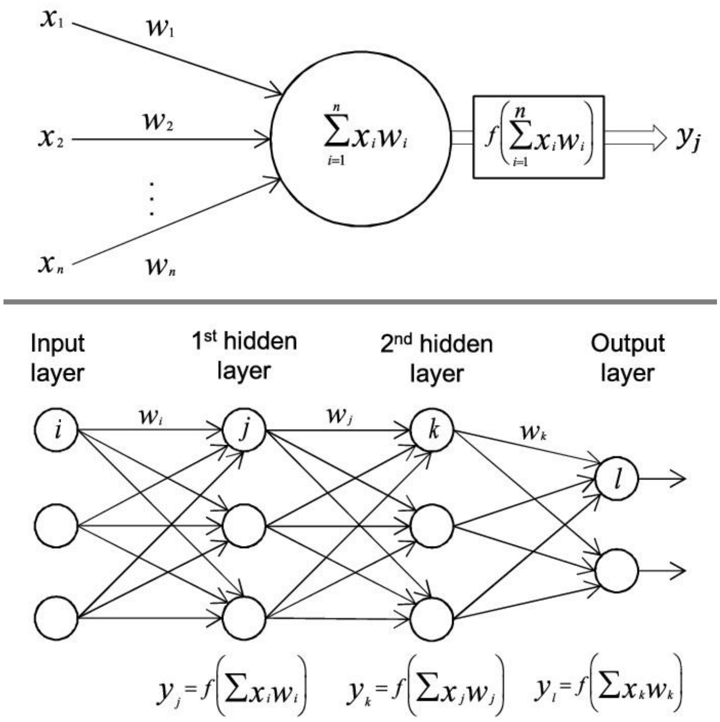

Figure 1 Structure of a Neuron and ANN [17]

Artificial neural network modeling involves several key steps, each crucial for developing an effective model. Firstly, data collection, where relevant data is gathered to train and test the neural network, is essential. This data should accurately represent the problem being addressed, such as historical stock prices for stock prediction tasks. Following data collection, the next step is data preparation, involving tasks like cleaning, outlier removal, and normalization to ensure the data is suitable for use by the neural network. Once the data is prepared, the appropriate neural network architecture is chosen based on the specific requirements of the problem. With the architecture selected, the network is trained using the prepared data, allowing it to learn and recognize patterns. Subsequently, the trained network is tested using a separate dataset to evaluate its accuracy and generalization capability. Finally, upon satisfactory testing results, the neural network can be deployed for real-world use, enabling it to make predictions or decisions in production environments. Each step in this methodology is essential for developing a robust and reliable artificial neural network model [18], [19].

2.2. Dataset

The dataset utilized in this study was acquired through a series of experiments to determine engine emissions. These experiments were conducted under varying conditions, including adjustments to fuel compositions (gasoline and ethanol ratios) and engine speeds (rpm). The primary objective was to develop an ANN model to predict emissions such as NOx (ppm), HC (ppm), and CO (%) levels. The emission concentrations were derived from the experimental data collected during these trials, resulting in a dataset comprising 90 observations. Statistical summaries of this dataset are presented in Table 1. In the model, the input variables include fuel ratio (gasoline and ethanol) and engine speeds, while the output variables consist of NOx, HC, and CO emissions. The dataset reflects a comprehensive evaluation of engine emissions under varying fuel ratios and engine speeds, providing valuable insights into the 'engine's behavior and environmental impact. Gasoline was predominantly used as fuel, with occasional ethanol additives. Engine speeds varied from 1400 to 3400 rpm, indicating experimentation across different operating conditions. Nitrogen oxide (NOx) emissions ranged from 1328 to 2330 ppm, while hydrocarbon (HC) emissions varied from 176 to 295 ppm. Carbon monoxide (CO) emissions ranged from 1.12% to 1.68%.

Table 1 Statistical information related to the dataset utilized in this study.

	Features		Unit	Minimum	Maximum	Average
Input	Fuel Ratio	Gasoline	-	0.8	1	0.9
		Ethanol	-	0	0.2	0.1
	Engine Speeds		rpm	1400	3400	2400
Output	NOx		ppm	1328	2330	1877
	HC		ppm	176	295	232
	CO		%	1.12	1.68	1.36

2.3. Data Normalization and Model Performance Evaluation

Data normalization is a critical process in preparing datasets for analysis, particularly in machine learning. This technique involves adjusting the scale of data values to bring them within a standardized range. By doing so, we can mitigate the influence of outliers and ensure that different features contribute equally to the analysis. Data normalization is especially crucial for algorithms like artificial neural networks (ANNs), where consistent input ranges can significantly improve model performance. Various methods, such as min-max scaling or z-score normalization, are employed depending on the specific requirements of the dataset and the algorithm being used. In this study, we employ the min-max normalization technique, as outlined in Equation 1 [20].

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}(u - l) + l \tag{1}$$

where:

- x represents the original data.
- x' represents the normalized data.
- x_{max}, x_{min} refer to the maximum and minimum values of the original data vector.
- u, l represent the upper and lower bounds of the new range for the normalized data.

The performance of ANN models has been evaluated based on the utilization of two metrics. Mean Squared Error (MSE) is commonly employed due to its simplicity and effectiveness in measuring the squared difference between actual and predicted values. This metric provides insight into the 'model's overall accuracy by quantifying the average squared distance between predicted and actual values. Utilizing squared differences helps prevent the cancellation of negative terms, contributing to the robustness of MSE as a performance metric. On the other hand, R Squared (R^2) serves as a metric to assess the 'model's performance relative to a baseline model. Unlike MSE, which depends on the context, the R^2 score offers a standardized measure of goodness of fit independent of the specific problem context. It provides a means to compare the performance of the regression model against a simple baseline model, typically represented by the mean line. R^2, also known as the Coefficient of Determination or Goodness of Fit, quantifies how much better the regression line fits the data than a mean line, thereby providing valuable insights into the overall explanatory power of the model. The equations for R^2 and MSE are provided below:

R Squared (R^2) [21]:

$$R^2 = 1 - \frac{x_{res}}{x_{tot}} \tag{2}$$

- x_{res} represents the sum of squared residuals (the squared differences between actual and predicted values).
- x_{tot} represents the total sum of squares (the squared differences between each data point and the mean of the dependent variable).

Mean Squared Error (MSE) [21]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_{act} - x_{pre})^2 \tag{3}$$

Where:

- n is the number of data points.
- x_{act} is the actual value of the dependent variable for the i_{th} data point.
- x_{pre} is the predicted value of the dependent variable for the i_{th} data point.

3. Results and Discussion

In this study, we acquired the dataset through experiments aimed at assessing engine emissions. The dataset consists of three independent variables and three dependent variables. A comprehensive overview of the dataset is presented in Table 1, containing a total of 90 row data records. Subsequently, the dataset was normalized using Equation 1, following which it was randomly partitioned into training (75%, 67 data), validation (15%, 14 data), and testing (10%, 9 data) subsets.

To determine the optimal configuration of the neural network architecture, a single-hidden-layer artificial neural network (ANN) was employed. The number of neurons within the hidden layer was systematically varied from 10 to 50 in increments of 5. Training of the network was performed utilizing the Scaled Conjugate Gradient algorithm, with the sigmoid activation function implemented in the hidden layer and the pure-line function employed in the output layer.

During the training phase, engine parameters were utilized as inputs, while corresponding emission levels served as outputs. Through iterative backpropagation, the network iteratively adjusted its internal weights and biases to minimize the discrepancy between predicted and actual emission values. At the end of the training process, the neural network demonstrated proficient predictive capabilities for unseen input data. Evaluation of the 'network's performance, conducted using the mean square error (MSE) index, revealed that the optimal number of neurons in the hidden layer for predicting engine performance was 50, as delineated in Figure 2.

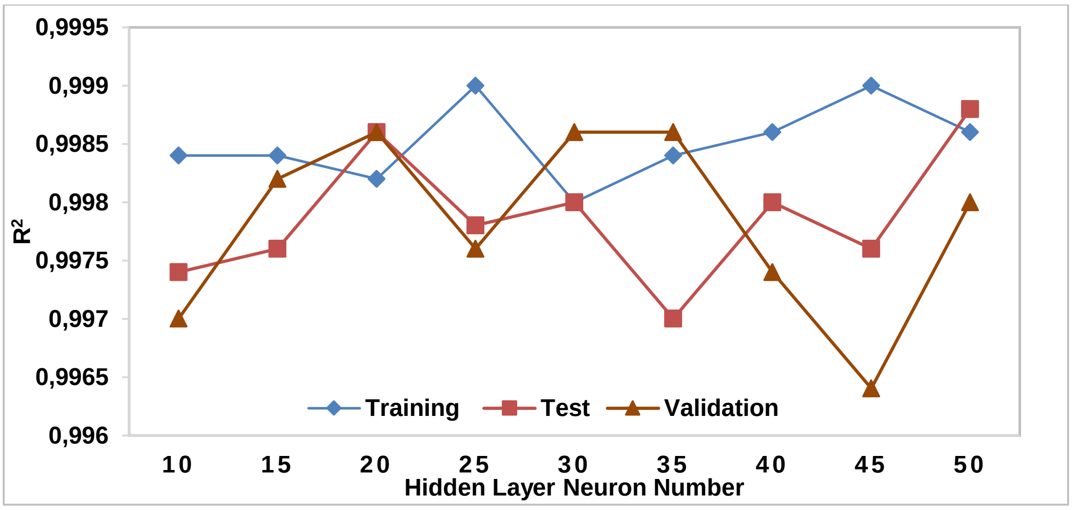

Figure 2 Determination of Neuron Number at the Hidden Layer

Figure 3 depicts an Artificial Neural Network (ANN) architecture comprising three input and output variables. The network includes a hidden layer containing 50 neurons. The schematic representation of the proposed ANN model is presented in Figure 4.

Figure 5 depicts the mean square error (MSE) values corresponding to varying numbers of hidden neurons within an artificial neural network (ANN). These MSE values are computed across training, testing, and validation datasets, offering insights into the ANN's performance across different hidden neuron configurations. This underscores the importance of selecting an optimal number of hidden neurons to attain superior model performance and generalization capability. According to Figure 5, the most suitable number of neurons in the hidden layer appears to be 50, exhibiting the lowest MSE values across all three datasets.

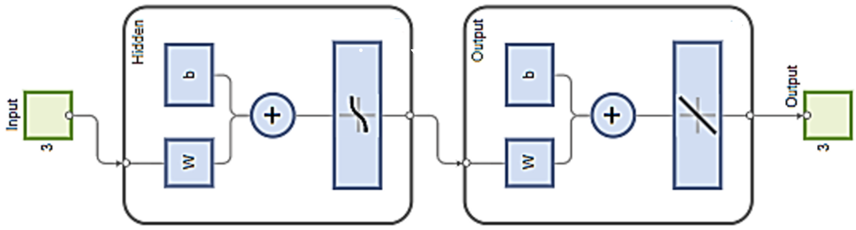

Figure 3 ANN Architecture Utilized for Prediction of the Effective Efficiency of the Engine

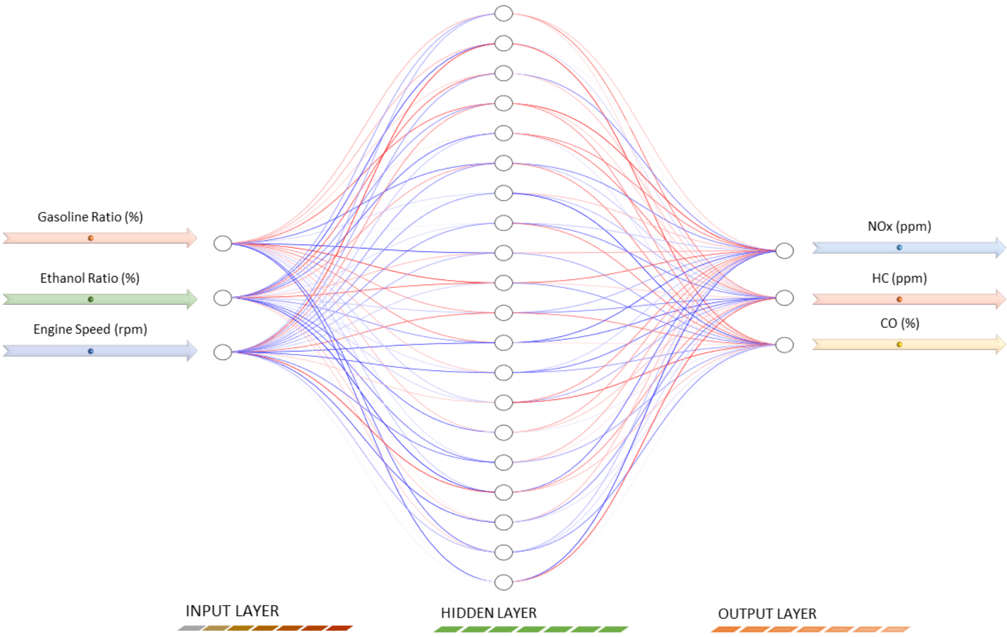

Figure 4 The schematic representation of the proposed ANN model.

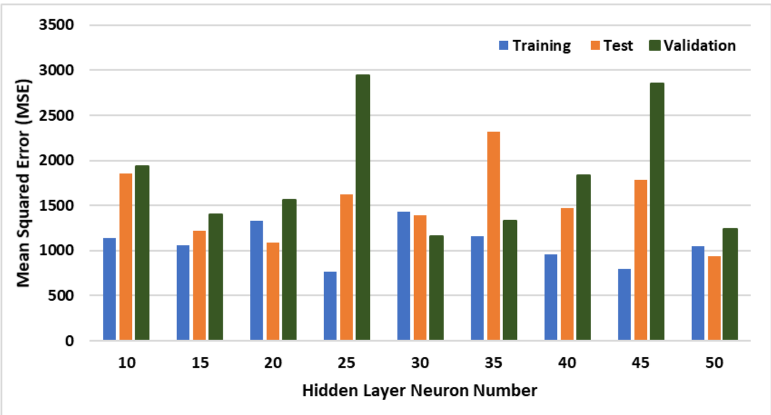

Figure 5 The Mean Squared Error (MSE) Values of the Neural Network

Figure 6 displays a scatter plot comparing predicted data against observed data. This visualization provides insights into the relationship between the predicted values generated by the model and the actual observed values in the dataset. The high R values observed for the training (0.99928), test (0.99937), and validation (0.99904) datasets indicate strong correlations between predicted and observed values, showcasing the 'model's accuracy in predicting engine emissions. When considering all datasets combined, the overall R-value of 0.99927 further reinforces the 'model's effectiveness in accurately capturing the underlying patterns in the data. This suggests that the 'model's predictions closely align with the observed data across various scenarios, highlighting its reliability and robustness in predicting engine emissions.

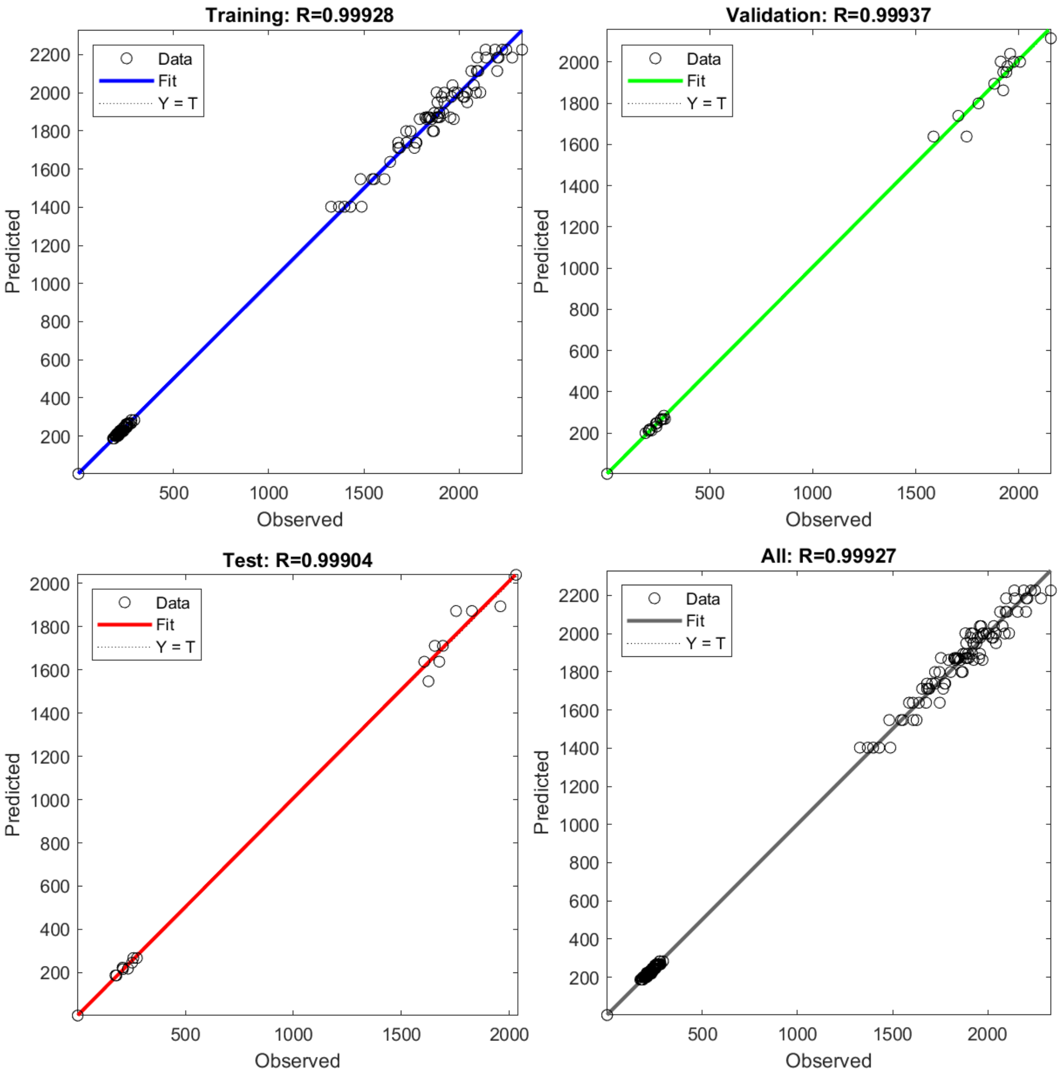

Figure 6 Scatter Plot Representing the Relationship Between Predicted and Observed Data Points.

In our study, we have evaluated the performance of a machine learning model in predicting engine emissions for eco-friendly fuels. The results presented in the Results section showcase strong correlations between predicted and observed emissions values, with high R values across different datasets indicating the accuracy and reliability of our model. This aligns with similar studies conducted in the literature, such as Chadha et al. [6], Xu, Kang, and Lv [7], Azeez et al. [8], Singh and Dubey [9], Shobana Bai [10], and Hananto et al. [11], which also employ various predictive modeling techniques to address emissions prediction in the transportation sector. However, our study stands out due to its focus on predicting emissions specifically for eco-friendly fuels and its utilization of a single-hidden-layer artificial neural network (ANN) architecture optimized through data normalization techniques. This unique approach contributes to the advancement of sustainable transportation solutions by providing accurate predictions for engine emissions under varying fuel compositions and engine speeds.

4.Conclusions

This study employed machine learning techniques to predict engine emissions for eco-friendly fuels. The dataset utilized in this research, acquired through experimental trials, provided valuable insights into engine emissions under varying fuel compositions and engine speeds. The dataset was prepared for analysis through data normalization techniques, such as min-max scaling, facilitating the training of a single-hidden-layer artificial neural network (ANN). The ANN architecture was optimized to determine the optimal number of neurons in the hidden layer. The results indicated that 50 neurons yielded the lowest mean square error (MSE) values across all datasets. Additionally, the scatter plot visualization demonstrated strong correlations between predicted and observed emissions values, further validating the effectiveness of the ANN model. Overall, the findings underscore the potential of machine learning approaches in predicting engine emissions and guiding the development of eco-friendly fuels, contributing to advancing our understanding of sustainable transportation solutions. In future studies, it would be valuable to explore the application of more advanced machine learning techniques or hybrid models for predicting engine emissions with eco-friendly fuels. Additionally, investigating the impact of other factors, such as ambient temperature, humidity, and driving conditions on emission levels could enhance the predictive accuracy of the models. Furthermore, conducting field experiments or real-world validations to assess the performance of the developed models under diverse operating conditions and vehicle types would provide valuable insights for practical applications. This study has practical implications for multiple fields involved in environmental sustainability and transportation management. By offering a reliable method for predicting engine emissions, the research enables policymakers to make informed decisions about emission control strategies and regulations. Furthermore, automotive manufacturers can control the findings to develop more efficient emission control technologies and create engines that are environmentally friendly. Urban planners and transportation authorities can also benefit by using the predictions to optimize public transportation routes and infrastructure, leading to reduced emissions from engines. Briefly, this research could significantly influence real-world efforts to reduce the environmental impact of transportation systems.

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Conflict of Interest Notice
The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Approval and Informed Consent
It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material
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