GUASNR

Biosystems Engineering and Renewable Energies

Journal homepage: https://bere.gau.ac.ir

ISAMEM

Original Research Paper

Developing an algorithm to detect the ratio of the blend of biodiesel-fusel oil with diesel fuel using an e-nose system

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Biosystems Engineering and Renewable Energies 2025, 1 (2): 115-120

KEYWORDS

Fuel blends
Machine learning
Quadratic discriminant analysis
Support vector machine

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Article history
Received: 2025-09-12
Revised: 2025-10-25
Accepted: 2025-11-2

ABSTRACT

In this study, diesel, biodiesel, and fusel oil blends were meticulously prepared in various ratios. Subsequently, an electronic nose (e-nose) system equipped with eight metal oxide semiconductor sensors was employed to analyze these fuel mixtures. Quadratic discriminant analysis (QDA) and support vector machine with polynomial kernel (SVM1), as well as support vector machine with radial basis function kernel (SVM2), were utilized to classify the fuel blends having their characteristics. Notably, e-nose sensors MQ2, MQ5, MQ138, MQ8, and MQ135 demonstrated significant sensitivity in detecting the fuel compositions. The average accuracy, sensitivity, specificity, and accuracy values for the QDA model performance on different fuels in the test data were 0.95, 0.57, 0.97, and 0.69, respectively. These values for the SVM1 model were 95%, 64%, 97%, and 69%, respectively, and for SVM2 were determined to be 95%, 59%, 97%, and 65%, respectively. Results show the acceptable performance of all three models, with slightly better performance of the SVM1 in the classification task.

1. Introduction

The global push towards industrialization and mechanization has driven an increased reliance on fossil fuels, constituting a significant portion of global energy needs, particularly in transportation (Uyumaz, 2017). This dependence has led to substantial greenhouse gas emissions, impacting climate patterns and sea levels. In response to diminishing fossil fuel reserves and environmental concerns, a shift towards sustainable renewable energy sources like biofuels, hydrogen, and synthetic gases is underway. Biofuels, i.e., biodiesel and ethanol, are highlighted as key sustainable alternatives due to their renewability and reduced pollution levels (Kelanic, 2016; Ren and Sovacool, 2015). In the contemporary world, reliance on fossil fuels as the primary energy source in transportation and industrial sectors has engendered significant environmental and economic challenges. The escalation of greenhouse gas emissions, air pollution, and depletion of petroleum resources underscores the imperative for exploring renewable and sustainable fuel alternatives (Ardebili et al., 2020a). Among them, higher alcohols derived from fusel oil—a byproduct of alcohol fermentation processes—emerge as a promising renewable fuel for internal combustion engines.

Fusel oil, sourced from agricultural and industrial wastes, exhibits substantial potential for applications in diesel and gasoline engines, albeit accompanied by challenges such as combustion instability and pollutant emissions (Ardebili et al., 2020a). Recent studies demonstrate that blending fusel oil with diesel fuels can enhance engine performance and mitigate harmful emissions. For instance, the incorporation of nano-biochar into the fusel oil-diesel mixtures has been shown to improve thermal efficiency and reduce carbon monoxide (CO) and unburned hydrocarbon (HC) emissions, achieved through enhanced combustion processes and diminished particulate matter formation (Ardebili et al., 2020b). Multi-objective optimization of diesel engine performance and emissions using response surface methodology (RSM) in diesel-biodiesel-fusel oil blends enables the attainment of an optimal balance among parameters such as power output, fuel consumption, and nitrogen oxide (NOx) emissions (Hassan Pour et al., 2018). Approaches such as thus technique not only diminish dependence on fossil fuels but also align with principles of sustainable development.

Despite these advancements, challenges persist, including limited global accessibility to fusel oil and the necessity for technical engine modifications (Ardebili et al., 2020a). The current study aims to delve deeper into this renewable fuel, proposing strategies to overcome barriers and harness its potential. This introduction provides a foundational context for a comprehensive analysis of fusel oil applications in internal combustion engines. Biodiesel, derived from biodegradable raw materials through transesterification, and ethanol, with its high octane number, are key players in the biofuel sector. Biofuels are broadly categorized into primary and secondary types. Primary biofuels, in their raw form, can be used for either heating, cooking, or electricity generation, while secondary biofuels are processed from biomass like ethanol and biodiesel for use in vehicles and industry. Biodiesel, a methyl ester of long-chain fatty acids, is produced from renewable raw materials and shares properties with diesel fuel. Ethanol, widely used in transportation for its efficiency, is a favorable fuel due to its non-toxic nature and abundance from renewable sources (Cabaneros Lopez et al., 2019; Cinar et al., 2015). Additionally, fusel oil, a byproduct of fermentation, is being explored as a potential alternative fuel (Calam et al., 2015). It has a high research octane

https://doi.org/10.22069/bere.2025.24064.1029

number similar to ethanol and has been utilized in various applications like biodiesel production.

The assessment of fuel quality to determine the presence and levels of impurities is critical in various applications (Panoutsou et al., 2021). An effective and non-destructive approach for evaluating fuel quality involves the use of electronic nose (e-nose) systems (Beurey et al., 2021). These systems mimic human olfactory perception and analyze sample characteristics based on their scent profile (Khorramifar et al., 2022). Researchers have extensively studied these alternatives, focusing on biofuels for their renewability and potential to reduce reliance on crude oil (Li et al., 2019). A typical e-nose system comprises two main components: software and hardware (Loutfi et al., 2015). In an e-nose setup, gases released are absorbed by an array of sensors that generate signals (Hu et al., 2023). These signals can be differentiated using various statistical tools, but with the advent of artificial intelligence, machine learning algorithms are utilized for quality assessment based on the signals (Wojnowski et al., 2017).

This study aims to develop a robust, non-destructive algorithm using an e-nose and advanced machine learning techniques to accurately detect and classify blends of diesel, biodiesel, and fusel oil, facilitating quality control in biofuel production and reducing reliance on invasive analytical methods.

2. Materials and Methods

Mixtures of diesel-biodiesel-fusel oil with gasoline at levels of 10, 15, 20, 25, and 30 volumetric percent were blended together. The compositions and fuels used in this project were obtained from Razi Alcohol Production Company, a subsidiary affiliated with the sugar industry. The physical and chemical specifications of the fuels are presented in Table 1. The experimental matrix and various levels of fuel mixtures are shown in Table 2. The raw diesel fuel was considered the control.

The e-nose system consists of several key components, including a sampling unit for collecting air samples, an electronic unit for processing sensor signals, a sensor array chamber containing metal oxide semiconductor sensors, a hydrop-neumatic unit for maintaining moisture balance, and a computer for system control. The system involves a three-stage data acquisition process: baseline correction, sample injection, and sensor chamber purging. Selected sensors are arranged in a parallel reaction space within the sensor chamber. The sensors MQ2, MQ3, MQ5, MQ8, MQ9, MQ135, MQ137, MQ138, used in this work, are known for their longevity, sensitivity, chemical stability, and broad applicability (Table 3). The data acquisition process includes cleaning the sensor chamber, injecting the sample odor, and purging the chamber. The experiment involves repeated measurements and data collection for analysis and evaluation. The system's timing and operation are crucial for accurate data acquisition and analysis. In the data acquisition phase, sensor signals are transferred to the computer via a USB interface with a one-second interval and stored. Subsequently, to enhance efficiency and optimize array outputs, signal preprocessing is performed using various methods such as the differential method, relative method, and fractional method. In the differential method, the difference between adjacent signal samples is calculated to capture relatively rapid changes in the signal. This method is utilized to extract information regarding rapid changes in the signal. The relative method compares the signal to a reference point to infer relative information and differences between signals. The fractional method normalizes the obtained response in addition to being dimensionless. It is employed to eliminate noise and enhance sensor detection capabilities and can be used for both small and large signals. The fractional method was applied in the mentioned research to eliminate noise and enhance sensor detection capabilities. Furthermore, this method is suitable for complementing the other two methods (Arshak et al., 2004).

In this study, quadratic discriminant analysis (QDA) and support vector machine (SVM) were employed for the classification of blended fuels by having their characteristics obtained by the e-nose system. QDA is a statistical method used to find second-degree combinations of features that separate objects into two or more distinct groups. This method is commonly used in machine learning to identify a combination of desired features and recognize patterns. Typically, in research, two-thirds of the data are used to train models, and the remaining one-third is used for testing. SVM is a supervised learning algorithm that predicts which group each sample belongs to. It utilizes a hyperplane to separate two groups in a way that maximizes the distance from the hyperplane to both groups. The closest training samples to this hyperplane are called support vectors. These samples essentially define the boundary of their respective groups. SVM can use different kernels, like polynomial and Gaussian kernels, we called them SVM1 and SVM2, respectively, in this work.

The classification of fuels was conducted using the models with 15 repetitions for each fuel combination. Ten repetitions were randomly selected for model training, and five were used for testing, resulting in 150 data points for training and 75 for testing. All eight sensors were given equal weights of 1 in the input. For model evaluation, after conducting experiments and designing various classification models, their performance was evaluated based on statistical criteria based on true negative (TN), false negative (FN), true positive (TP), and false positive (FP), including accuracy, precision, specificity, and sensitivity (Eqs. 1-4) (Mahmodi et al., 2019).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (3)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (4)$$

3. Results and Discussion

3.1. The results of e-nose sensors

The radar chart plotted for diesel, biodiesel, and fusel oil odors based on normalized average sensor responses at a 5% volume ratio revealed significant impacts on various sensors (Figure 1). The diesel odor notably affected the MQ2 sensor, associated with detecting multiple odors like natural gas, butane, propane, and more. Biodiesel odor had a significant impact on the MQ138 sensor, detecting odors like alcohol, benzene, and carbon monoxide. The MQ5 sensor, crucial for detecting natural gas and fusel oil odors, influenced the MQ138 sensor, which detects alcohol, benzene, and other compounds. Sensors like MQ8 and MQ135, detecting gases like natural gas and benzene, played essential roles. Eliminating less influential sensors can optimize olfactory machine costs, improve efficiency, and prevent overfitting during analysis (Rasekh et al., 2021).

Table 1. Physical and chemical properties of diesel, biodiesel, and fusel oil fuels

Component	Density (kg/cm^3)	Viscosity (mm^2/s)	Pouring point	Calorific value (MJ/kg)	Cetane number	Flash point
Diesel	837	2.5	-9	42.72	52.2	65
Biodiesel	894	5.5	3	39.76	57.2	150
Fusel oil	840	3.88	5	29.5	42	26

Table 2. Fuel mixture characteristics used in this work

Treatment	Diesel fuel (volumetric percent)	Biodiesel fuel (volumetric percent)	Fusel fuel (volumetric percent)
D100	100	0	0
B100	0	100	0
F100	0	0	100
D95B5	95	5	0
D90B10	90	10	0
D80B20	80	20	0
D70B30	70	30	0
D95F5	95	0	5
D90F10	90	0	10
D80F20	80	0	20
D70F30	70	0	30
D90B5F5	90	5	5
D80B10F10	80	10	10
D70B10F20	70	10	20
D70B20F10	70	20	10

Table 3. Specifications of selected sensors in the e-nose system

Sensor	Applications in diagnosing gases
MQ2	Natural gas, butane, propane, methane, alcohol, hydrogen, and smoke
MQ3	Alcohol and benzene
MQ5	Natural gas, alcohol, cooking steam, and carbon monoxide
MQ8	Natural gas, alcohol, and carbon monoxide
MQ9	Methane, carbon monoxide, and natural gas
MQ135	Benzene, ammonia, carbon dioxide, carbon monoxide, and alcohol
MQ137	Ammonia
MQ138	Alcohol, benzene, ammonia, dioxide, and carbon monoxide

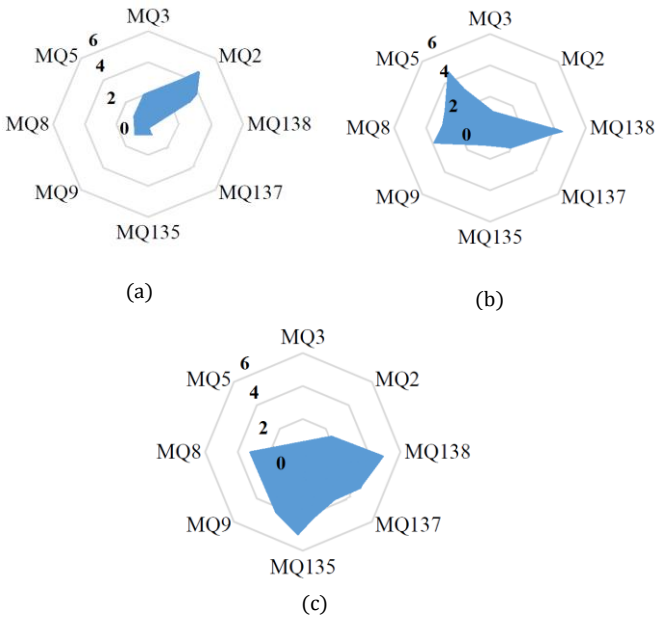

Figure 1. Average response of e-nose sensors (a) diesel, (b) biodiesel, and (c) fusel oil

3.2. Results of blended fuel classification using QDA

The performance evaluation results of the QDA model for classifying diesel, biodiesel, and fusel oil fuels are outlined in Table 4. With 100% training data, the QDA model successfully differentiated between various fuel blends based on accuracy, sensitivity, and specificity values. In the test data, fuels like D100, D95B5, D90B10, D80F20, D80B10F10, and D70B10F20 achieved a perfect classification accuracy of 100%, while fuels F100 and D70F30 showed a precision of 0.2. The average accuracy, sensitivity, specificity, and accuracy values for the QDA model performance on different fuels in the test data were 0.95, 0.57, 0.97, and 0.69, respectively, reflecting the model's effectiveness in classification. The training data demonstrated an average value of 1 for all four performance criteria, indicating efficient training model performance.

In a study by Mahmodi et al. (2022), the classification accuracy of pure diesel and biodiesel fuels using QDA and LDA methods was reported as 94% and 87%, respectively. Another research focused on classifying apples based on storage time, achieving accuracies of 80.56% and 83.33% with LDA and QDA models, respectively (Lashgari & Mohammadigol, 2016). Moreover, in the detection of fraud in extra virgin olive oil using an e-nose system, Cerrato Oliveros et al. (2002) obtained a prediction accuracy exceeding 95% with QDA, LDA, and ANN methods. Similarly, Anwar et al. (2023) evaluated an e-nose system for classifying tea quality, with artificial neural networks outperforming LDA and SVM methods, achieving an 88% classification accuracy. The studies collectively highlight the effectiveness of various classification methods in different domains, emphasizing the importance of accurate and efficient classification techniques in scientific research (Anwar et al., 2023). In a study focusing on detecting impure olive oil and sunflower oil using an e-nose system with 12 metal oxide sensors, LDA, QDA, and ANN methods were employed for data analysis. The models displayed very satisfactory results, with prediction rates exceeding 95% and, in certain cases, reaching 100% accuracy in differentiation and classification tasks. While the ANN models showed slightly weaker performance compared to other methods, overall, the differentiation and classification capabilities were highly effective (Balabin and Lomakina, 2011).

The performance criteria of the QDA method for classifying all data of fuel blends are summarized in Table 5. The accuracy results indicate that fuel blends D100, D95B5, D90B10, D80F20, D80B10F10, and D70B10F20 achieved a separation accuracy of 1, representing a perfect 100% separation. The average sensitivity, specificity, and accuracy indices for the overall data of fuel blends were calculated as 0.85, 0.99, and 0.87, respectively. These values suggest that the QDA method demonstrates acceptable performance in effectively classifying fuel blends based on the provided data.

3.3. Results of blended fuel classification using SVM1

The SVM method is a significant model in data mining, leveraging statistical learning theory and mathematical optimization principles to provide an optimal solution by minimizing structural errors efficiently. In this study, two SVM models, SVM1 and SVM2, based on polynomial and radial basis function kernels, respectively, were utilized for classifying diesel, biodiesel, and fusel oil fuels. For the classification of various fuel mixtures, the SVM method employed normalized data from eight sensors of an e-nose system as input, with different fuel percentages serving as output groups. The performance criteria of the SVM1 method for various fuel blends based on training and test data are presented in Table 6. In this approach, using the training data, all fuels except B100 were accurately separated from other types of fuels with 100% precision. Furthermore, the performance indicator results of the test data demonstrated a 100% accuracy in distinguishing fuel blends D95B5, D80F20, D70B10F20, and D70B20F10. The lowest performance was associated with the F100 fuel blend, with a precision of 37%, indicating a lesser degree of differentiation compared to other fuel blends. The overall average performance indices, comprising accuracy, sensitivity, specificity, and precision for the test data, were 95%, 64%, 97%, and 69%, respectively. Correspondingly, for the training data, these indices were determined to be 100%, 97%, 100%, and 98%, respectively. The results of the performance indices of the SVM1 method for the classification of all fuel blend data are presented in Table 7. Based on the results, the precision for fuel blends D95B5, D80F20, D70B10F20, and D70B20F10 was 100%. The average accuracy, sensitivity, specificity, and accuracy indices for the overall fuel blend data were determined to be 98%, 86%, 99%, and 87%, respectively, indicating an acceptable performance of the SVM1 method.

Table 4. The performance criteria of the QDA method for classifying training and test data

	Train				Test			
Fuel blends	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**
D100	1.000	1.000	1.000	1.000	0.974	1.000	1.000	0.600
B100	1.000	1.000	1.000	1.000	0.926	0.400	0.961	0.400
F100	1.000	1.000	1.000	1.000	0.904	0.200	0.949	0.200
D95B5	1.000	1.000	1.000	1.000	0.987	1.000	1.000	0.800
D90B10	1.000	1.000	1.000	1.000	0.949	1.000	1.000	0.200
D80B20	1.000	1.000	1.000	1.000	0.949	0.556	0.946	1.000
D70B30	1.000	1.000	1.000	1.000	0.962	0.750	0.986	0.600
D95F5	1.000	1.000	1.000	1.000	0.915	0.417	0.909	1.000
D90F10	1.000	1.000	1.000	1.000	0.938	0.500	0.973	0.400
D80F20	1.000	1.000	1.000	1.000	0.987	1.000	1.000	0.800
D70F30	1.000	1.000	1.000	1.000	0.882	0.222	0.913	0.400
D90B5F5	1.000	1.000	1.000	1.000	0.962	0.750	0.986	0.600
D80B10F10	1.000	1.000	1.000	1.000	0.987	1.000	1.000	0.800
D70B10F20	1.000	1.000	1.000	1.000	0.949	1.000	1.000	0.200
D70B20F10	1.000	1.000	1.000	1.000	0.938	0.500	0.960	0.600
Average	1.000	1.000	1.000	1.000	0.947	0.686	0.972	0.573

Table 5. The performance criteria of the QDA method for classifying all data

Fuel blends	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**
D100	0.991	1.000	1.000	0.867
B100	0.974	0.800	0.986	0.800
F100	0.966	0.733	0.982	0.733
D95B5	0.996	1.000	1.000	0.933
D90B10	0.983	1.000	1.000	0.733
D80B20	0.983	0.789	0.981	1.000
D70B30	0.987	0.929	0.995	0.867
D95F5	0.970	0.682	0.968	1.000
D90F10	0.978	0.857	0.991	0.800
D80F20	0.996	1.000	1.000	0.933
D70F30	0.957	0.632	0.968	0.800
D90B5F5	0.987	0.929	0.995	0.867
D80B10F10	0.996	1.000	1.000	0.933
D70B10F20	0.983	1.000	1.000	0.733
D70B20F10	0.978	0.813	0.986	0.867
Average	0.982	0.878	0.990	0.858

Table 6. The performance criteria of the SVM1 method for classifying training and test data

	Train				Test			
Fuel blends	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**
D100	1.000	1.000	1.000	1.000	0.974	0.800	0.986	0.800
B100	0.974	0.714	0.972	1.000	0.938	0.500	0.973	0.400
F100	0.974	1.000	1.000	0.600	0.915	0.375	0.935	0.600
D95B5	1.000	1.000	1.000	1.000	0.974	1.000	1.000	0.600
D90B10	1.000	1.000	1.000	1.000	0.938	0.500	0.973	0.400
D80B20	1.000	1.000	1.000	1.000	0.938	0.500	0.933	1.000
D70B30	1.000	1.000	1.000	1.000	0.974	0.800	0.986	0.800
D95F5	1.000	1.000	1.000	1.000	0.949	0.556	0.946	1.000
D90F10	1.000	1.000	1.000	1.000	0.938	0.500	0.947	0.800
D80F20	1.000	1.000	1.000	1.000	0.974	1.000	1.000	0.600
D70F30	1.000	1.000	1.000	1.000	0.938	0.500	0.987	0.200
D90B5F5	1.000	1.000	1.000	1.000	0.938	0.500	0.973	0.400
D80B10F10	1.000	1.000	1.000	1.000	0.974	0.800	0.986	0.800
D70B10F20	1.000	1.000	1.000	1.000	0.957	1.000	1.000	0.333
D70B20F10	1.000	1.000	1.000	1.000	0.987	1.000	1.000	0.800
Average	0.997	0.981	0.998	0.973	0.954	0.688	0.975	0.636

Table 7. The performance criteria of the SVM1 method for classifying all data

Fuel blends	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**
D100	0.991	0.933	0.995	0.933
B100	0.962	0.667	0.973	0.800
F100	0.953	0.643	0.977	0.600
D95B5	0.991	1.000	1.000	0.867
D90B10	0.978	0.857	0.991	0.800
D80B20	0.978	0.750	0.977	1.000
D70B30	0.991	0.933	0.995	0.933
D95F5	0.983	0.789	0.981	1.000
D90F10	0.978	0.778	0.981	0.933
D80F20	0.991	1.000	1.000	0.867
D70F30	0.978	0.917	0.995	0.733
D90B5F5	0.978	0.857	0.991	0.800
D80B10F10	0.991	0.933	0.995	0.933
D70B10F20	0.984	1.000	1.000	0.750
D70B20F10	0.996	1.000	1.000	0.933
Average	0.982	0.871	0.990	0.859

3.4. Results of blended fuel classification using SVM2

Based on the values shown in Table 8, the SVM2 model was able to classify fuel blends D80B10F10, D70B10F20, and D70B20F10 with 100% precision from other fuel types. The lowest accuracy in classification was observed for fuel blends D70B30, D90F10, and D90B5F5, with precisions of 42%, 37%, and 33%, respectively. The average performance indices of accuracy, sensitivity, specificity, and precision for the test data were determined to be 95%, 59%, 97%, and 65%, respectively. In Table 9, the results of the performance indices of the SVM2 method for the classification of all fuel blend data are presented. The precision of distinguishing fuel blends D80B10F10, D70B10F20, and D70B20F10 was 100%. The average accuracy, sensitivity, specificity, and precision indices for the classification of fuel blends were found to be 98%, 86%, 99%, and 87%, respectively. In a study, various percentages of biodiesel produced from corn oil, peanut oil, and canola oil were investigated using near-infrared spectroscopy (NIR). Hierarchical cluster analysis (HCA), principal component analysis (PCA), and SVM approaches were employed for classifying and identifying different biodiesel blends. The results indicated a higher predictive capability of the SVM method compared to the other two methods (Cunha et al., 2017). In another study, the relationship between near-infrared spectra and the biodiesel source in 10 different samples was examined. Biodiesel classification based on their origins using regularized discriminant analysis (RDA), partial least squares discriminant analysis (PLS-DA), k-nearest neighbors (kNN) technique, and SVM was conducted. The results showed that kNN and SVM techniques were more effective in classifying biodiesel based on their oil types (Xu et al., 2023).

4. Conclusion

The classification accuracy of all three QDA, SVM1, and SVM2 methods on test data was 95%, showing their acceptable fuel blend classification efficiency. Additionally, based on precision results on test data, in the QDA method, fuels such as D100, D95B5, D90B10, D80F20, D80B10F10, and D70B10F20 achieved 100% classification precision, while fuels like D95B5, D80F20, D70B10F20, and D70B20F10 were perfectly classified using SVM1, and fuels like D80B10F10, D70B10F20, and D70B20F10 were classified effectively using SVM2 across all classes.

Funding: This work was supported by Shahid Chamran University of Ahvaz [grant number: SCU.AA1403.29840].

Table 8. The performance criteria of the SVM2 method for classifying training and test data

	Train				Test			
Fuel blends	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**
D100	1.000	1.000	1.000	1.000	0.962	0.750	0.986	0.600
B100	1.000	1.000	1.000	1.000	0.938	0.500	0.987	0.200
F100	1.000	1.000	1.000	1.000	0.962	0.750	0.986	0.600
D95B5	1.000	1.000	1.000	1.000	0.949	0.571	0.959	0.800
D90B10	1.000	1.000	1.000	1.000	0.947	0.600	0.978	0.500
D80B20	1.000	1.000	1.000	1.000	0.949	0.571	0.959	0.800
D70B30	1.000	1.000	1.000	1.000	0.915	0.417	0.909	1.000
D95F5	1.000	1.000	1.000	1.000	0.938	0.500	0.947	0.800
D90F10	1.000	1.000	1.000	1.000	0.915	0.375	0.935	0.600
D80F20	1.000	1.000	1.000	1.000	0.949	0.667	0.986	0.400
D70F30	1.000	1.000	1.000	1.000	0.962	0.667	0.973	0.800
D90B5F5	1.000	1.000	1.000	1.000	0.926	0.333	0.974	0.200
D80B10F10	1.000	1.000	1.000	1.000	0.962	1.000	1.000	0.400
D70B10F20	1.000	1.000	1.000	1.000	0.957	1.000	1.000	0.333
D70B20F10	1.000	1.000	1.000	1.000	0.987	1.000	1.000	0.800
Average	1.000	1.000	1.000	1.000	0.948	0.647	0.972	0.589

Table 9. The performance criteria of the SVM2 method for classifying all data

Fuel blends	**Accuracy**	**Precision**	**Specificity**	**Sensitivity**
D100	0.987	0.929	0.995	0.867
B100	0.978	0.917	0.995	0.733
F100	0.987	0.929	0.995	0.867
D95B5	0.983	0.824	0.986	0.933
D90B10	0.980	0.867	0.991	0.813
D80B20	0.983	0.824	0.986	0.933
D70B30	0.970	0.682	0.968	1.000
D95F5	0.978	0.778	0.981	0.933
D90F10	0.970	0.722	0.977	0.867
D80F20	0.983	0.923	0.995	0.800
D70F30	0.987	0.875	0.991	0.933
D90B5F5	0.974	0.846	0.991	0.733
D80B10F10	0.987	1.000	1.000	0.800
D70B10F20	0.984	1.000	1.000	0.750
D70B20F10	0.996	1.000	1.000	0.933
Average	0.982	0.874	0.990	0.860

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