A Data-Driven Machine Learning Approach to Identify End-of-Life Vehicles in Indonesia

Fajar, Rizqon
Research Center for Transportation Technology, National Research and Innovation Agency

Kurnia Fajar Adhi Sukra
Research Center for Transportation Technology, National Research and Innovation Agency

Hidiyanto, Fitra
Research Center for Transportation Technology, National Research and Innovation Agency

Nilam Sari Octaviani
Research Center for Transportation Technology, National Research and Innovation Agency

他

https://doi.org/10.5109/7236891

出版情報：Evergreen. 11 (3), pp.2504-2514, 2024-09. Interdisciplinary Graduate School of Engineering Sciences, Kyushu University, Japan
バージョン：

EVERGREEN Joint Journal of Novel Carbon Resource Sciences & Green Asia Strategy, Vol. 11, Issue 03, pp2504-2514, September, 2024

A Data-Driven Machine Learning Approach to Identify End-of-Life Vehicles in Indonesia

Rizqon Fajar[1,*], Kurnia Fajar Adhi Sukra[1,3], Fitra Hidiyanto[1,*], Nilam Sari Octaviani[1], Dhani Avianto Sugeng[2]

[1]Research Center for Transportation Technology, National Research and Innovation Agency, Indonesia

[2]Research Center for Energy Conversion and Conservation, National Research and Innovation Agency, Indonesia

[3]Faculty of Malaysia-Japan International Institute of Technology, University Teknologi Malaysia, Malaysia

*Author to whom correspondence should be addressed:
E-mail: rizq001@brin.go.id, fitr009@brin.go.id

(Received May 22, 2024: Revised July 9, 2024: Accepted August 1, 2024).

Abstract: This research addresses the issues of traffic congestion, economic losses, and air pollution in major Indonesian cities by focusing on End-of-Life Vehicles (ELVs) and emission standards. The study highlights the impact of rapid population growth and increased vehicle ownership on road infrastructure, resulting in prolonged commuting times and elevated air pollution levels. The research predicts emission thresholds and identifies non-compliant vehicles by mapping vehicles aged 10 to 30 years and employing machine learning techniques. Key findings reveal that 15-80% of gasoline vehicles and 40-70% of diesel vehicles fail to meet the 2023 emission standards. The study proposes emission thresholds of 245 ppm for hydrocarbons, 1.8% for carbon monoxide, and 70% for opacity in diesel vehicles, with a minimum age of 10 years for ELVs. Machine learning models, particularly XGBoost for gasoline vehicles and Gradient Boosting for diesel vehicles, demonstrated high accuracy in predicting non-compliant vehicles. Policy recommendations include stricter emission testing, financial incentives for retiring old vehicles, and establishing low-emission zones. Implementing these policies, supported by robust public awareness campaigns and stakeholder engagement, is expected to significantly reduce air pollution, improve public health, and enhance urban transportation systems. The research provides valuable insights for policymakers to develop sustainable transportation strategies and effectively manage ELVs, contributing to Indonesian cities' overall quality of life.

Keywords: sustainable transportation; emission test; gasoline & diesel vehicle; air pollution; End-of-Life Vehicles; machine learning

1. Introduction

Major Indonesian cities, including Jakarta, Surabaya, and Bandung, face significant challenges from escalating traffic congestion and air pollution[1)]. Jakarta, the capital, faces severe jams due to population growth and more vehicles. Surabaya and Bandung also have less intense congestion with their own urban traffic issues[2)]. The main cause is road infrastructure overcapacity[3)], leading to longer commutes[4)], economic losses[5)], higher fuel use[6)], and more pollution[7)]. Sustainable transportation is crucial, involving reducing older vehicles that fail emission tests[8)]. In 2023, the Indonesian government tightened motor vehicle emission standards to address these issues[9)]. Controlling unfit vehicles, implemented gradually, can reduce congestion, fuel use, and pollution while minimizing social and economic disruptions[10)].

In 2024, Indonesia granted Jakarta special authority to regulate the age and ownership of private motor vehicles[11)]. This policy will lead to guidelines on the maximum vehicle age allowed and its implementation. Existing emission rules will advance with age-based End-of-Life Vehicle (ELV) policies. ELV enforcement in Jakarta should be gradual to avoid economic and social disruptions. This study uses a machine learning model to propose ELV based on vehicle age and emission tests. Inputs include vehicle age and engine capacity; the output is whether the vehicle meets emission standards.

Table 1 illustrates the emission regulations for vehicles categorized by engine type (diesel and gasoline), carbon monoxide (CO) and hydrocarbon (HC) for gasoline, opacity for diesel, manufacturing year, and vehicle weight. This standard applies to two-wheeled and four-wheeled motor vehicles that are already in operation on the roads and is used to determine the amount of annual tax based on emission value from testing. Vehicles that fail the 2023 emission standards can still be operated after necessary repairs. Older vehicles, especially non-Euro and Euro 2, may not meet these standards[12,13]. Since 2022, new vehicles in Indonesia should comply with Euro 4 standards[14–16], but many older vehicles still struggle to pass emission tests. Non-Euro vehicles may permanently fail due to engine technology limitations. Using emission data, we can predict which vehicles will pass or fail the tests with machine learning based on parameters like manufacturing year and engine capacity[17]. Like Indonesian regulations, other developing countries have tightened vehicle emission standards to reduce pollution. For instance, India and China have implemented stringent Bharat Stage and China VI emission standards, respectively, aiming to reduce vehicular pollution significantly[18,19].

Table 1. The 2023 Emission standard[9].

Gasoline			Diesel	
Year Made	**CO [%]**	**HC. [ppm]**	**Year Made**	**Opacity [%HSU]**
<2007	4	1000	<2010	65
2007-2018	1	150	2010-2021	40
>2018	0.5	100	>2021	30

This research proposes an innovative solution aligning with Indonesia's stringent 2023 motor vehicle emission regulations and the 2024 law on vehicle age restrictions in Jakarta. It suggests using machine learning to predict vehicle compliance with emission limits based on age and engine capacity data from the state police database. Depending on city policies, a vehicle can be classified as an ELV at 10 years or older. This method is applicable in Jakarta and other major cities, especially in developing countries with similar social and economic conditions, to save costs and resources. The machine learning-based ELV model can predict vehicles likely to fail emission tests, allowing authorities to target inspections more effectively. Additionally, it provides valuable data to policymakers for developing better emission standards, helps prioritize enforcement against the most polluting vehicles, and ensures effective resource use.

2. Literature Review

2.1 Enhancing Vehicle Emission Control in Jakarta: Strategies and Challenges

According to the World's Air Quality Report 2023, Jakarta ranks 14th among the most polluted cities[20]. The primary sources of pollution in Jakarta are emissions from motor vehicles running on diesel and gasoline. In 2022, the number of motor vehicles in Jakarta was approximately 26.37 million, with an annual increase of 4.39%[21]. The high pollution levels are attributed to the uncontrolled number of motor vehicles and traffic congestion, which leads to inefficient fuel combustion in engines. Effective strategies to control the number of motor vehicles with minimal socio-economic impact need to be implemented promptly. There are two strategies to control vehicle pollution: implementing new technologies like Euro 3 and Euro 4 standards, CNG vehicles, and electric vehicles, and traffic management interventions accompanied by vehicle scrapping[22].

Evaluations of various emission control strategies for Jakarta have been conducted through simulations. The results indicate that a combination of implementing Electronic Road Pricing (ERP), using electric vehicles, and scrapping old vehicles (ELV) is most effective in reducing pollution[22]. ERP has been trialled, while electric vehicles are being promoted with tax incentives at purchase. The technical procedures for ELV scrapping are currently being developed. The ELV implementation must be gradual and cautious to prevent social and economic upheaval[23]. Public awareness and studies on societal responses should begin now, especially concerning determining ELV age, vehicle types, and financing and management[24].

The implementation of End-of-Life Vehicles (ELV) in developing countries like Malaysia and Indonesia faces challenges related to vehicle age limits, financing, and management, leading to the proliferation of aged and unsafe vehicle[25]. Public awareness and acceptance of ELV management are also low, with regulations proving ineffective in reducing the number of old vehicles[24]. There is also a need to establish specific laws and regulations to ensure sustainable ELV management, which can contribute to environmental protection, job creation, and promoting a circular economy. Furthermore, studies suggest that introducing private vehicle inspections and age limits for passenger vehicles could be a potential strategy to enhance the implementation of ELV policy in these countries. Mapping the number of ELV vehicles is also necessary to prepare the financing required from the government, vehicle owners, and operators for dismantling and recycling these vehicles.

2.2 Methods for Determining the ELV-age

Determining the age of ELVs involves factors like government policies, public awareness, and regular inspections. This section explores various methods and studies on how different countries manage ELVs. Determining the age of motorized vehicles declared as ELV involves considering factors such as public perception, government policies, and vehicle roadworthiness inspections. Studies from Malaysia highlight the importance of implementing an ELV policy to manage aged and unsafe vehicles with determining the age at which a vehicle must be scrapped involves several factors, including regulatory age limits, emission and safety standards, mileage, and economic viability.

Table 2. Emission vehicle data of gasoline and diesel.

Parameter	Gasoline				Diesel		
	Manufacture year	CO [%]	HC [ppm]	Age [year]	Manufacture year	Opacity [HSU]	Age [year]
Min	1992	0	0	1	1992	0	1
Q1	2006	0.01	10	4	2003	29.1	5
Q2	2010	0.07	37	6	2008	51.6	8
Q3	2011	0.45	128	10	2011	80	13
Max	2012	10	10,000	30	2012	100	30
Average	2008	0.79	129	7	2006	54	9
Data	156,264				54,958		

Some countries set a fixed age limit for vehicles, beyond which they must be scrapped. For example, commercial vehicles might be retired after 15 years, while private cars could be scrapped after 20 years. This method is straightforward but does not account for the vehicle's condition. The European Union has directives that suggest age limits for scrapping vehicles, often tied to emission standards like Euro 3 and Euro 4. Furthermore, studies in Mexico estimate the current number of ELVs and predict future growth scenarios using statistical tools like the Weibull distribution, projecting around one million ELVs by 2020[27)]. Additionally, periodic inspections ensure vehicles comply with emission and safety standards[28)]. These findings underscore the significance of age limits, public awareness, and governmental initiatives in determining the age of motorized vehicles designated as ELVs.

Mileage and usage also play a crucial role in determining ELV. Vehicles that exceed certain mileage limits are considered to have reached the end of their useful life and must be scrapped. Research from various studies highlights the significant impact of vehicle wear and tear on emission performance and maintenance costs, influencing fleet replacement policies globally. Studies in Nanjing, China, and Delhi, India, demonstrate that vehicles aged 10 to 17 years or with over 120,000 km mileage are likelier to fail emission tests, emphasizing the importance of considering mileage over age in assessing vehicle deterioration[29)]. In conclusion, methods for determining ELV age vary by country and depend on specific national contexts. The most suitable approach for Indonesia includes setting age limits and adhering to emission standards, as these factors are outlined in the country's regulations.

2.3 Using Machine Learning for Modeling ELVs

Machine learning techniques can play a crucial role in predicting the ELVs of motorized vehicles. Machine learning methods such as deep learning, decision trees, neural networks, support vector machines, and regression analysis have enhanced the efficiency of modelling ageing processes and vehicle failure predictions. Machine learning models have also been developed to determine the remaining useful life (RUL) of critical components of electric vehicles, such as batteries[30)]. Generally, machine learning is still rarely used for ELV modelling, especially for classifying motor vehicles as ELVs in developing countries like Indonesia, Malaysia, and Vietnam, due to limited and varied data.

Automated Machine Learning (AutoML) offers a promising solution for ELV modelling by reducing complexity and enhancing usability for end-domain users and practitioners. AutoML, as highlighted in the provided research papers[31)], plays a crucial role in simplifying the binary, multiclass and multilabel classification problems by automating intricate processes like data preprocessing, model selection, and hyperparameter tuning. This automation empowers domain experts without machine learning expertise to create accurate and efficient ELV models, ensuring consistent and reproducible results while enabling continuous improvement by integrating new data. This research uses this technique to determine ELVs for old vehicles that do not pass emissions tests.

3. Methodology

3.1 Dataset preparation

The Indonesian Ministry of Environment and Forestry collected the dataset from emission test results in 2022. They conducted idle emission tests for gasoline vehicles and free acceleration tests for diesel vehicles. The dataset encompasses variables such as the year of testing, vehicle manufacturing year, fuel type, engine capacity, emission test outcomes, CO and HC levels for gasoline vehicles, and opacity measurements for diesel ones. Table 2 shows the emission distribution of both gasoline and diesel vehicles, utilizing information from vehicles manufactured post-1992.

Consequently, a substantial portion of the vehicles in this dataset is relatively recent. Conversely, diesel-fueled vehicles exhibit a comparatively elevated average opacity, measuring 57.6 % HSU. The high opacity is attributed to the older average age of diesel vehicles, standing at eight years compared to gasoline counterparts. Furthermore, the subsequent section will explore the technological distinctions between gasoline and diesel vehicles.

The emission data was categorized based on the Ministry of Environment and Forestry Regulation No. 8 of 2023[32)], which set the emission limit for vehicles operated on the road. Table 1 shows a detailed explanation of the gasoline and diesel vehicle emission limits. The gasoline vehicles were based on the vehicle year of manufacture, CO, and HC, and the diesel vehicles were based on the year of manufacture and opacity. The emission limit is a threshold for determining whether a vehicle has passed or failed. The emission was one of the parameters for the engine, which could show the quality of engine combustion.

3.2 Classification Modeling

The dataset initially comprises 54,958 entries for diesel vehicles and 156,264 for gasoline vehicles. Through feature engineering, invalid ELVs, such as vehicles aged only 10-30 years, and outliers in emission test data were filtered out. After rebalancing, the final dataset used in this research consisted of 8,143 entries for diesel and 6,574 entries for gasoline.

For preprocessing, modelling, and evaluation, the author applied AutoML techniques to determine the most accurate algorithms. Specifically, the author used the PyCaret library[33,34], an open-source Python-based machine learning tool that streamlines the entire machine learning workflow from beginning to end.

The machine learning algorithms employed in this study encompass a variety of techniques, including extreme gradient boosting (XGB), light gradient boosting (LGB), gradient boost (GB), random forest (RF), decision tree (DT), extra tree (ET), and others, totalling approximately 15 algorithms executed by the PyCaret auto ML library which are renowned for their reliability in classification. Meanwhile, a confusion matrix[35] was employed to conduct classification analysis and identify which data area contributed to the most errors.

3.3 Performance Evaluation

Table 3 shows the confusion matrix of the classification model. We could calculate the model's accuracy, precision, recall, and F1 score.

Table 3. Confusion matrix evaluation

Predicted	Actual	
	True	False
True	True Positive (TP)	False Positive (FP)
False	False Negative(FN)	True Negative (TN)

Accuracy indicates how well the model correctly predicts the true class or label[35–37]. Precision represents the proportion of true positive results among all positive predictions made by the model, which is especially important for imbalanced classification problems[37]. Recall, also known as sensitivity, denotes the proportion of true positive results among all actual positive instances in the dataset[37]. The F1-score integrates precision and recall into a single measure by calculating their harmonic mean. The Area Under the Curve[38] (AUC) assesses the model's capacity to differentiate between positive and negative classes in binary classification, with a higher AUC signifying superior performance. The formulas are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2 \times TP}{2 \times TP + FP + FN} \tag{4}$$

4. Results and Discussion

4.1 Emission Test for Gasoline Vehicles

Fig. 1 displays the distribution of conditions of gasoline vehicles (pass or fail) after undergoing an emissions test for vehicles aged ten and over (max. 30 years) from 2013 to 2022.

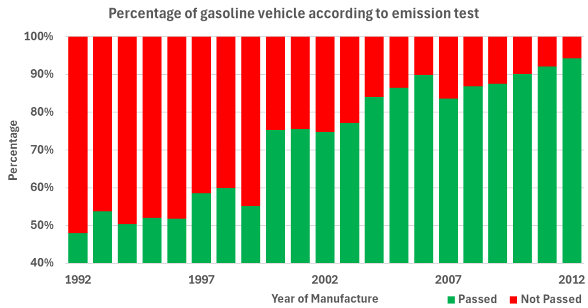


Fig. 1: Percentage of pass and fail results by gasoline vehicle according to year of manufacture.

Generally, as vehicle age increases, the proportion of vehicles passing the emission test tends to decrease. The percentage of vehicles that fail emissions tests varies from 6% to a maximum of 52% in older vehicles. This trend suggests that older vehicles are more likely to fail emissions tests, which could be due to factors such as wear and tear, lack of modern emission control systems, and outdated technology. Those older vehicles can be proposed as ELVs, covering vehicles with non-Euro and Euro 2 technology.

Fig. 2 illustrates how mean CO and HC emissions increase with vehicle age from 10 to 30 years, aligning with the expected trend of older vehicles emitting more. The red line indicates the emission test failure threshold for these gases. CO emissions for failing gasoline vehicles range from 1.8% to 6% annually, while HC emissions range from 245 ppm to 900 ppm. Using the average emissions at ten years of age as a benchmark, these values—1.8% for CO and 245 ppm for HC—could serve as a threshold for potential ELVs. Compared to the EURO

IV type II emission standard, the limit for CO emission is stricter than the emission threshold of the model. However, EURO IV does not set an emission limit for HC emission.

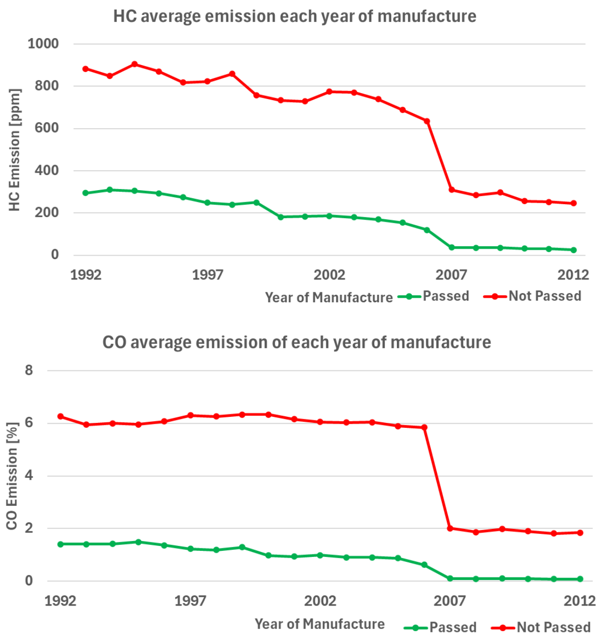


Fig. 2: Average CO and HC emissions of a gasoline vehicle.

Fig. 3 presents a scatter plot of vehicle age versus engine capacity for gasoline vehicles, categorized by emission test results. The plot shows a mix of pass and fail outcomes across various engine capacities and ages, with no clear linear relationship between these factors. The distribution of results is spread out, suggesting that further analysis with additional variables or advanced modelling may be needed to identify potential patterns.

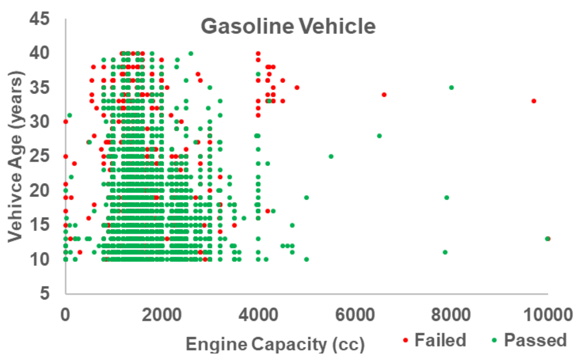


Fig. 3: Engine capacity and age of gasoline vehicle

4.2 Distribution Data of Failed Emission Test Gasoline Vehicle

Fig. 4 displays a cumulative histogram of gasoline vehicles failing emission tests, providing a detailed distribution overview. CO emissions are predominantly concentrated between 4% and 5%, encompassing about 20% of the dataset. In contrast, HC emissions are heavily concentrated above 1000 ppm. Excluding emissions exceeding 1000 ppm reveals a more even distribution, with peak values between 300 and 400 ppm. Regarding vehicle age, over a quarter of vehicles are under 12, tapering off towards 30 years. These statistical insights from the histogram guide the formulation of optimal ELV criteria for gasoline vehicles.

Table 4 presents statistical details for gasoline vehicles that did not pass emission tests, offering insights into their emissions (CO and HC) and ages. This data is crucial for regulators to establish appropriate criteria for ELVs, considering not only emissions and vehicle age but also the socio-economic circumstances of vehicle owners.

Table 4. Statistical properties of gasoline vehicles that do not pass emission tests.

	CO [%]	HC [ppm]	Age [years]
Min	0.00	0	10
Q1	4.40	312	12
Q2	5.79	518	17
Q3	7.64	945	21
Max	10.00	10 000	30
Mean	5.72	764	17

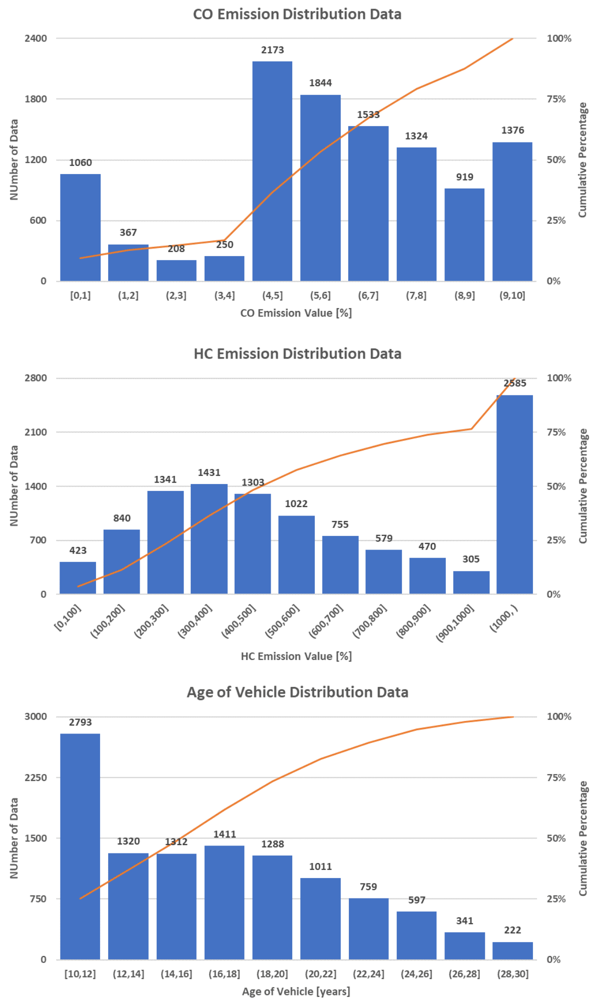


Fig. 4: Distribution data of CO, HC emissions and age of gasoline vehicles that failed the emissions test.

4.3 Emission Test for Diesel Vehicles

Fig. 5 indicates that vehicles failing emissions tests had mean opacity ranging from 70% to 98%, whereas passing vehicles showed opacity between 20% and 40%. These percentages suggest that older vehicles, particularly those failing emissions tests, often emit exhaust with higher opacity levels. Such findings could inform governments in setting criteria for identifying vehicles suitable for ELV designation. Additionally, vehicles failing emissions tests due to permanent engine damage or outdated emission technology may be considered for ELV status or restricted from road use.

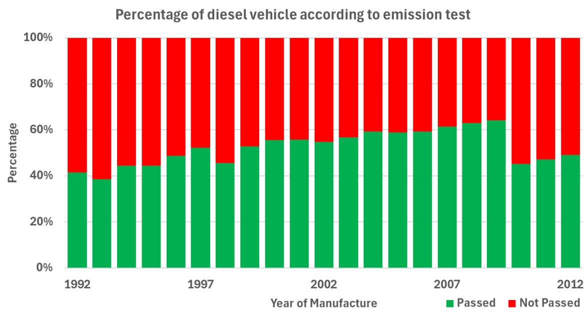


Fig. 5: Percentage of pass and fail results by diesel vehicle according to year of manufacture.

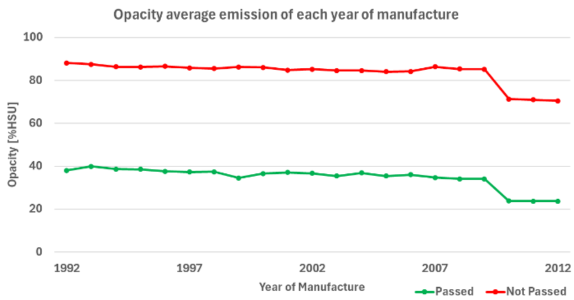


Fig. 6: Average opacity of diesel vehicles.

Based on the plot in Fig. 6, the mean opacity of the failed vehicles ranged from 70% to 98%, while the opacity of the vehicles that passed was between 20% and 40%. These values suggest that older vehicles, especially those not passing emission tests, tend to exhibit higher opacity levels in their exhaust emissions. Such insights could provide a basis for governments to establish thresholds for vehicles' ELVs.

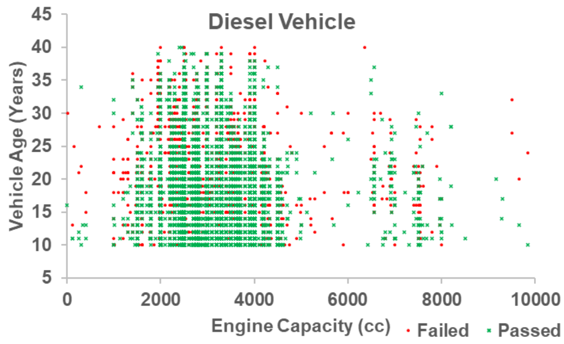
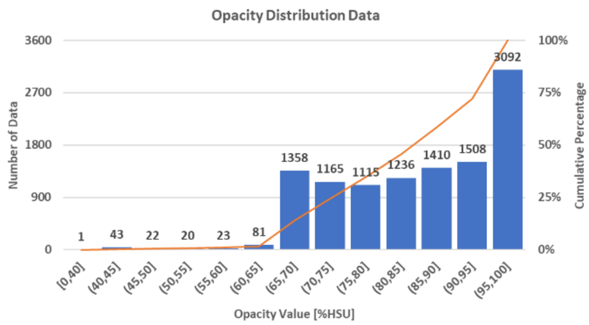


Fig. 7: Emission results scattered by engine capacity and age of diesel vehicle.

Fig. 7 illustrates the correlation between engine capacity and the age of diesel vehicles, categorized by emission test outcomes. Engine capacities vary widely, with most below 10,000 cc, and vehicle ages span the entire range of capacities, indicating a diverse dataset. Emission test results are scattered across different engine capacities and vehicle ages, without distinct separation between 'Pass' and 'Fail' outcomes based solely on these factors. Improved feature engineering could generate new variables to capture the relationship with emission test results better.

4.4 Distribution Data of Failed Emission Test Diesel Vehicle

Fig. 8 presents a cumulative histogram showing diesel vehicles failing emissions tests, with opacity levels between 95% and 100% and vehicle ages focused around 10% to 12%. These insights are crucial for developing criteria to designate diesel vehicles as ELVs based on their emissions and age characteristics.



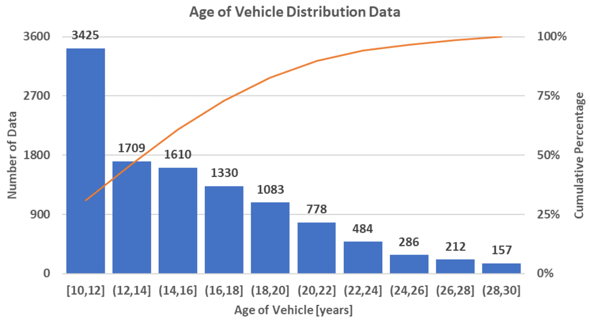


Fig. 8: Distribution data of opacity and age of diesel vehicles which failed the emissions test.

Table 5. Statistical details of diesel vehicles that failed the emission test.

	Opacity [%HSU]	Age [years]
Min	40.0	10
Q1	75.3	12
Q2	86.8	15
Q3	96.0	19
Max	100.0	30
Mean	85.1	15

Table 5 indicates that for four-wheeled diesel-powered vehicles that fail the emissions test and are recommended for ELV treatment, the minimum opacity value is 40% at an age of 10 years, exhibiting an upward trend towards 100% opacity at 30 years, with an average opacity of 85% at 15 years of age.

4.5 Machine Learning Modeling Result

Table 6. Performance metrics for ELV prediction of gasoline vehicles

Model	Acc	AUC	Rec	Prec	F1
XGB	0.9762	0.9975	0.9698	0.9960	0.9827
LGB	0.9757	0.9975	0.9698	0.9953	0.9824
RF	0.9753	0.9972	0.9693	0.9953	0.9821
DT	0.9752	0.9958	0.9681	0.9963	0.9820
ET	0.9752	0.9963	0.9683	0.9960	0.9820

The author employed a series of comprehensive evaluation metrics to evaluate the machine learning model's performance, including accuracy, precision, recall, F1-score, and AUC with F-fold cross-validation.

Table 6 compares models for classifying ELVs in gasoline vehicles using XGB, LGB, RF, DT, and ET algorithms. XGB stands out as the top performer with 97.62% accuracy, indicating strong capability in vehicle classification. Its high precision of 99.33% ensures accurate identification of non-ELVs, while an F1 score of 98.00% signifies a balanced performance in precision and recall, effectively minimizing false positives.

Table 7. Confusion matrix XGB model of ELV gasoline vehicle

Actual	Predicted	
	ELV	Non-ELV
ELV	195	3
Non-ELV	15	445

shows the confusion matrix for the XGB classifier of the gasoline ELV model. With only 3 false positives, the model rarely misclassifies ELVs as non-ELVs, minimizing the risk of non-compliant vehicles being allowed to continue operating. There are 15 false negatives, meaning some compliant vehicles are incorrectly classified as ELVs. While this number is relatively low, a few compliant vehicles might be unnecessarily targeted for removal or retrofit.

Table 8. Feature importance of gasoline vehicle

Feature	RF	GB
Age	0.749	0.827
CC	0.251	0.173

Table 8 presents the feature importance of models using Random Forest (RF) and Gradient Boosting (GB) algorithms. Age is highly significant, scoring 0.749 for RF and 0.827 for GB, indicating that older gasoline vehicles are more likely to be classified as ELVs. These values underscore the impact of ageing and outdated technology on compliance with emission standards. While less influential than age, engine capacity remains pivotal in emission determination, with larger engines potentially contributing to ELV classification if emissions exceed standards.

Fig. 9 shows the area under the ROC curve (AUC) for the XGB diesel engine ELV model. An AUC of 0.9975 indicates exceptional performance. The model almost perfectly distinguishes between ELVs and non-ELVs. This high AUC value reflects the model's ability to balance sensitivity (recall) and specificity (true negative rate). The ROC curve demonstrates a high true positive rate and a low false positive rate. The steep ascent towards the top-left corner of the ROC space indicates that the model is very effective at correctly identifying both compliant and non-compliant vehicles.

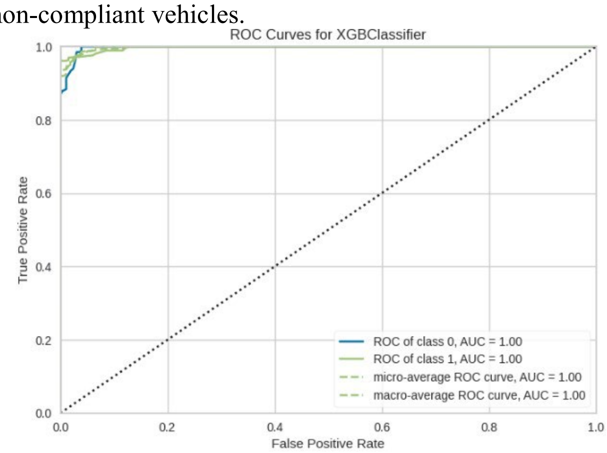


Fig. 9: ROC curve of XGB model for ELV gasoline

Several algorithms are used to model the ELV of diesel vehicles, with the best model shown in Table 9. RF gives the best accuracy of 96.74%, indicating strong performance in correctly classifying most vehicles. A precision of 98.75% suggests that nearly all identified non-ELVs are compliant. An F1 score of 97.94% reflects a good balance between precision and recall, demonstrating the model's effectiveness in correctly identifying compliant vehicles and minimizing false positives.

Table 9. Algorithm results for ELV diesel vehicle model.

Model	Acc	AUC	Rec	Prec	F1
RF	0.9674	0.9911	0.9651	0.9880	0.9764
LGB	0.9670	0.9928	0.9635	0.9890	0.9761
GB	0.9667	0.9928	0.9635	0.9886	0.9759
ET	0.9657	0.9873	0.9619	0.9888	0.9752
XGB	0.9656	0.9922	0.9629	0.9876	0.9751

Table 10. Confusion matrix RF model of ELV diesel vehicle

	Predicted	
Actual	ELV	Non-ELV
ELV	238	7
Non-ELV	18	552

Table 10 shows the confusion matrix RF of ELV diesel vehicles. With only 7 false positives, the model maintains a low rate of misclassifying ELVs as non-ELVs, ensuring minimal risk of high-emission vehicles being allowed to operate. The model has 18 false negatives, indicating a few more compliant vehicles are misclassified as ELVs compared to the gasoline model. These vehicles might be unnecessarily targeted for removal or retrofit.

Table 11. Feature importance of diesel vehicle

Feature	RF	GB
Age	0.749	0.827
CC	0.251	0.173

Table 11 shows the importance of features of diesel vehicles using RF and GB algorithms. Both algorithms show that age was the main factor in determining the ELV group. The older vehicles tend to have an ELV than those with higher engine capacity. Older vehicles had technology that could not perform better than newer ones.

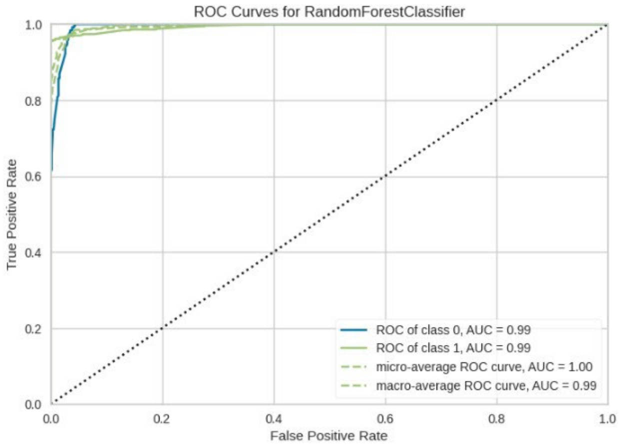


Fig. 10: ROC curve RF model ELV diesel

Fig. 10 This shows the AUC of the RF model for diesel vehicles. An AUC value of 0.9911 indicates that the RF model for diesel vehicles is also highly effective in distinguishing between compliant and non-compliant vehicles. While slightly lower than the gasoline model, it still signifies a high level of accuracy in distinguishing between ELVs and non-ELVs. The ROC curve shows a strong ability to balance sensitivity and specificity, meaning the model accurately identifies non-compliant vehicles (high true positive rate) while maintaining a low rate of false positives.

The gasoline and diesel vehicle classification models exhibit strong performance in identifying ELVs, offering high accuracy, precision, and recall. These attributes enable efficient management of highly polluting vehicles, supporting effective emission control strategies and sustainable urban transportation initiatives for policymakers and regulatory authorities. However, the model's applicability is limited to vehicles with older technologies. It may not accurately predict those equipped with EURO IV and newer technologies due to the absence of relevant data. This limitation could lead to reduced accuracy and bias when assessing such vehicles.

5. Conclusion

The findings of this study provide critical insights into managing End-of-Life Vehicles (ELVs) in major Indonesian cities, particularly Jakarta, to combat urban traffic congestion and air pollution. Key findings and their implications for policy and practice include:

1. High Failure Rates in Older Vehicles: The study identifies that a significant percentage of older vehicles (10-30 years) fail to meet the 2023 emission standards
2. Proposed Emission Thresholds: The research proposes specific emission thresholds for defining ELVs, including 245 ppm for HC, 1.8% for CO, and 70% opacity for diesel vehicles
3. Machine Learning Model Efficacy: Using AutoML with XGB and RF models demonstrates high accuracy in predicting ELVs.

Future research should improve data collection by including variables like vehicle maintenance history and driving patterns to enhance emission prediction accuracy. Refining machine learning models with advanced algorithms will also improve robustness. Comprehensive impact assessments are needed to evaluate the socio-economic and environmental benefits of ELV regulations. Comparative studies with other countries can offer insights into best practices and potential pitfalls, aiding policy customization for Indonesian cities.

6. Public Awareness and Policy Recommendation

Tackling ELVs and enforcing emission standards is crucial for reducing traffic congestion, economic losses, and air pollution in Indonesian cities. Implementing educational campaigns, stakeholder workshops, stricter emission testing, vehicle inspections, incentives for retiring older vehicles, establishing scrapping and recycling infrastructure, and creating low-emission zones will significantly reduce pollution and enhance urban living conditions.

In implementing this ELV modelling research into policy, machine learning should set emission thresholds and identify non-compliant vehicles with regularly updated standards. Policies should include stricter annual emission testing focused on vehicles predicted to be non-compliant and incentives for retiring old vehicles. Designate and expand low-emission zones based on pollution and traffic patterns. Address challenges with public awareness campaigns, phased policies with financial aid, investment in testing infrastructure, advanced emission controls, robust monitoring, and coordinated efforts among government, manufacturers, NGOs, and the public.

Acknowledgements

The authors acknowledge the Ministry of Environment and Forestry for providing materials for this research.

References

1) S. Sugiarto, T. Miwa, and T. Morikawa, "The tendency of public's attitudes to evaluate urban congestion charging policy in asian megacity perspective: case a study in jakarta, indonesia," *Case Stud. Transp. Policy*, 8 (*1*) 143–152 (2020). doi:10.1016/j.cstp.2018.09.010.
2) A.F. Aritenang, "The crucial role of motorcycle-based ride-hailing among commuters: the case of jakarta and bandung in metropolitan areas," *J. Public Transp.*, 26 (*February*) (2024). doi:10.1016/j.jpubtr.2024.100082.
3) M. Saleem, S. Abbas, T.M. Ghazal, M. Adnan Khan, N. Sahawneh, and M. Ahmad, "Smart cities: fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques," *Egypt. Informatics J.*, 23 (*3*) 417–426 (2022). doi:10.1016/j.eij.2022.03.003.
4) A. Genser, and A. Kouvelas, "Dynamic optimal congestion pricing in multi-region urban networks by application of a multi-layer-neural network," *Transp. Res. Part C Emerg. Technol.*, 134 (*June 2021*) 103485 (2022). doi:10.1016/j.trc.2021.103485.
5) Y. Yuan, and D. Li, "Urban economic efficiency, environmental factors, and digital finance: impacts on sustainable development in chinese cities," *Sustainability*, 15 (*18*) 13319 (2023). doi:10.3390/su151813319.
6) B. Liu, C.-T. Lam, and B.K. Ng, "Improved Real-Time Traffic Congestion Detection with Automatic Image Cropping using Online Camera Images," in: 2021 IEEE 21st Int. Conf. Commun. Technol., IEEE, 2021: pp. 1117–1122. doi:10.1109/ICCT52962.2021.9657853.
7) M. Zareba, H. Dlugosz, T. Danek, and E. Weglinska, "Big-data-driven machine learning for enhancing spatiotemporal air pollution pattern analysis," *Atmosphere (Basel).*, 14 (*4*) (2023). doi:10.3390/atmos14040760.
8) C.M. Leite de Almeida, S. Silveira, E. Jeneulis, and F. Fuso-Nerini, "Using the sustainable development goals to evaluate possible transport policies for the city of curitiba," *Sustainability*, 13 (*21*) 12222 (2021). doi:10.3390/su132112222.
9) Menteri Lingkungan Hidup dan Kehutanan Republik Indonesia, "Peraturan Menteri Lingkungan Hidup dan Kehutanan Republik Indonesia Nomor 8 Tahun 2023 tentang Penerapan Baku Mutu Emisi Kendaraan Bermotor Kategori M, Kategori N, Kategori O, dan Kategori L.," Indonesia, 2023.
10) C. Sitinjak, R. Ismail, Z. Tahir, R. Fajar, W.F. Simanullang, E. Bantu, K. Samuel, R.A.C. Rose, M.R.M. Yazid, and Z. Harun, "Acceptance of elv management: the role of social influence, knowledge, attitude, institutional trust, and health issues," *Sustain.*, 14 (*16*) 1–17 (2022). doi:10.3390/su141610201.
11) W.P. Retnaningtyas, and I.R. Maksum, "Analysis of the implementation of garage ownership or control policy for motor vehicle owners: a case study in the dki jakarta province," *Eduvest - J. Univers. Stud.*, 4 (*2*) 584–592 (2024). doi:10.59188/eduvest.v4i2.1044.
12) Menteri Lingkungan Hidup dan Kehutanan Republik Indonesia, "Peraturan Menteri Lingkunagn Hidup dan Kehutanan Nomor P.20/MENLHK/SETJEN/KUM.1/3/2017 Tentang Baku Mutu Emisi Gas Buang Kendaraan Bermotor Tipe Baru Kategori M Katagori N dan Katagori O," Indonesia, 2017. https://ppkl.menlhk.go.id/website/filebox/734/190930171534KEPMENLH-141 TAHUN 2003.pdf.
13) A. Pratama, and A. Tokai, "Passenger vehicle emissions in indonesia: future projections," *J. Sustain.*

Dev., 11 (*6*) 222 (2018). doi:10.5539/jsd.v11n6p222.
14) S.S. Wirawan, M.D. Solikhah, H. Setiapraja, and A. Sugiyono, "Biodiesel implementation in indonesia: experiences and future perspectives," *Renew. Sustain. Energy Rev.*, 189 (*September 2023*) (2024). doi:10.1016/j.rser.2023.113911.
15) M. Mokhtar, A. Sukmono, H. Setiapraja, M. Ma'ruf, S. Yubaidah, I. Haryono, B. Rochmanto, R.T. Soewono, K.F. Adhi Sukra, A. Thahar, E. Manurung, C.S. Wibowo, S. Widodo, F. Supriyadi, R.Y. Abriyant, R.Y. Abriyant, D. Suntoro, F. Faridha, and I.K. Reksowardojo, "Towards nationwide implementation of 40% biodiesel blend fuel in indonesia: a comprehensive road test and laboratory evaluation," *Biofuel Res. J.*, 10 (*03*) 1876–1889 (2023). doi:10.18331/brj2023.10.3.2.
16) Y. Xie, and M. Harjono, "The retail fuels market in indonesia," *Icct*, (*36*) 1–13 (2020).
17) A.S. Chadha, Y. Shinde, N. Sharma, and P.K. De, "Predicting CO2 Emissions by Vehicles Using Machine Learning," in: S. Goswami, I.S. Barara, A. Goje, C. Mohan, A.M. Bruckstein (Eds.), Springer Nature Singapore, Singapore, 2023: pp. 197–207. doi:10.1007/978-981-19-2600-6_14.
18) M.D. Gajbhiye, S. Lakshmanan, N. Kumar, S. Bhattacharya, and S. Nishad, "Effectiveness of india's bharat stage mitigation measures in reducing vehicular emissions," *Transp. Res. Part D Transp. Environ.*, 115 103603 (2023). doi:10.1016/j.trd.2022.103603.
19) L. Xu, F. Zhao, H. Wei, P. Zhao, W. Qian, and M. Qian, "The Development of a Zeolite-Based Cold-Start Catalyst (CSC) for a Conventional China 6b Vehicle in Meeting the Next More Stringent Chinese Vehicle Emission Standards," in: SAE Tech. Pap. 2023-01-0233, 2023. doi:10.4271/2023-01-0233.
20) IQAir, "2023 World Air Quality Report," 2023. doi:https://doi.org/10.5194/egusphere-egu23-6686.
21) BPS, “Jumlah kendaraan bermotor menurut provinsi dan jenis kendaraan (unit), 2022,” (2022). https://www.bps.go.id/id/statistics-table/3/VjJ3NGRGa3dkRk5MTlU1bVNFOTVVbmQyVURSTVFUMDkjMw==/jumlah-kendaraan-bermotor-menurut-provinsi-dan-jenis-kendaraan-unit-.html?year=2022.
22) P. Lestari, M.K. Arrohman, S. Damayanti, and Z. Klimont, "Emissions Inventory of Air Pollutants from Anthropogenic Sources in Jakarta," in: EGU Gen. Assem. 2023, Vienna, Austria, 24–28 Apr 2023, EGU23-6686, EGU General Assembly, Vienna, 2023: p. 66866. doi:10.5194/egusphere-egu23-6686.
23) C. Sitinjak, R. Ismail, E. Bantu, R. Fajar, and W.F. Simanullang, "Study of public perception toward end-of-life vehicles (elv) management in indonesia," *Int. J. Sustain. Dev. Plan.*, 17 (*4*) 1341–1347 (2022). doi:10.18280/ijsdp.170431.
24) C. Sitinjak, R. Ismail, R. Fajar, E. Bantu, L. Shalahuddin, S. Yubaidah, W.F. Simanullang, and V. Simic, "An analysis of end-of-life vehicle management in indonesia from the perspectives of regulation and social opinion," *Int. J. Technol.*, 14 (*3*) 474–483 (2023). doi:10.14716/ijtech.v14i3.5639.
25) H.M. Ali, V. Simic, C. Sitinjak, J.Z. Hassim, M.H.M. Said, R.M. Khalid, G.E. Kaka, and R. Ismail, "Exploring public perceptions and disposal procedures in the development of a comprehensive end-of-life vehicle regulation in malaysia: a pilot study," *Sustainability*, 15 (*6*) 4786 (2023). doi:10.3390/su15064786.
26) H.M. Ali, C. Sitinjak, M.H. Md Said, J.Z. Hassim, R. Ismail, and V. Simic, "Model predicting social acceptance behavior to implement elv policy: exploring the role of knowledge toward elv policy on social acceptance in malaysia," *Front. Public Heal.*, 10 (2023). doi:10.3389/fpubh.2022.1093732.
27) Oxford Analytica, “Mexico’s Electric Car Sector Looks Ripe for Expansion,” in: Expert Brief., 2023. doi:https://doi.org/10.1108/OXAN-DB276039.
28) V. Jokubyniene, and J. Liebuviene, “Research in vehicle exhaust gas compliance with Euro standard,” in: 2023. doi:10.22616/ERDev.2023.22.TF048.
29) R. Tu, L. Xue, C. Meng, L. Xu, T. Li, and H. Chen, “Identifying specifications of in-use vehicles failing the inspection/maintenance emission test,” *Transp. Res. Part D Transp. Environ.*, 108 103327 (2022). doi:10.1016/j.trd.2022.103327.
30) X. Li, D. Yu, V. Søren Byg, and S. Daniel Ioan, “The development of machine learning-based remaining useful life prediction for lithium-ion batteries,” *J. Energy Chem.*, 82 103–121 (2023). doi:10.1016/j.jechem.2023.03.026.
31) H.J. Escalante, “Automated Machine Learning—A Brief Review at the End of the Early Years,” in: 2021: pp. 11–28. doi:10.1007/978-3-030-72069-8_2.
32) F. Hidiyanto, K. Fajar, A. Sukra, R. Fajar, N.S. Octaviani, and D.A. Sugeng, “Modeling indonesian motor vehicle tax coefficients based on machine learning emission data,” *J. Ind. Res. Innov.*, 17 (*1*) 16–23 (2023). doi:10.55981/mipi.2023.1734.
33) P. Whig, K. Gupta, N. Jiwani, H. Jupalle, S. Kouser, and N. Alam, “A novel method for diabetes classification and prediction with pycaret,” *Microsyst. Technol.*, 29 (*10*) 1479–1487 (2023). doi:10.1007/s00542-023-05473-2.
34) N. Sarangpure, V. Dhamde, A. Roge, J. Doye, S. Patle, and S. Tamboli, “Automating the machine learning process using pycaret and streamlit,” *2023 2nd Int. Conf. Innov. Technol. INOCON 2023*, 1–5 (2023). doi:10.1109/INOCON57975.2023.10101357.
35) A. Tharwat, “Classification assessment methods,” *Appl. Comput. Informatics*, 17 (*1*) 168–192 (2021). doi:10.1016/j.aci.2018.08.003.
36) D. Chicco, and G. Jurman, “The advantages of the matthews correlation coefficient (mcc) over f1 score

and accuracy in binary classification evaluation," *BMC Genomics*, 21 (*1*) 1–13 (2020). doi:10.1186/s12864-019-6413-7.

37) F. Hidiyanto, and A. Halim, "KNN Methods with Varied K, Distance and Training Data to Disaggregate NILM with Similar Load Characteristic," in: Proc. 3rd Asia Pacific Conf. Res. Ind. Syst. Eng. 2020, ACM, New York, NY, USA, 2020: pp. 93–99. doi:10.1145/3400934.3400953.
38) M. Gong, "A novel performance measure for machine learning classification," *Int. J. Manag. Inf. Technol.*, 13 (*1*) 11–19 (2021). doi:10.5121/ijmit.2021.13101.
39) R. Naveenkumar, S. Ramesh Kumar, G. Pushyanthkumar, and S. Senthil Kumaran, "NOx, co & hc control by adopting activated charcoal enriched filter in catalytic converter of diesel engine," *Mater. Today Proc.*, 22 2283–2290 (2020). doi:10.1016/j.matpr.2020.03.349.
40) Z. Zhang, R. Dong, G. Lan, T. Yuan, and D. Tan, "Diesel particulate filter regeneration mechanism of modern automobile engines and methods of reducing pm emissions: a review," *Environ. Sci. Pollut. Res.*, 30 (*14*) 39338–39376 (2023). doi:10.1007/s11356-023-25579-4.