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DESIGN AND APPLICATION OF CNN FOR EMISSION DETECTION THROUGH THERMAL IMAGERY

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Motorcycle exhaust emissions (EE) that do not meet regulatory standards present a significant environmental and public health issue, particularly given the rising number of motorcycles in densely populated areas. These emissions release pollutants such as carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NOx), which contribute to poor air quality and have adverse effects on human health. Traditional emission testing methods using gas analyzers, while commonly used, face limitations such as sensitivity to environmental fluctuations, the necessity for frequent recalibration, and an intensive testing process requiring specialized expertise. This study addresses these issues by developing an innovative method for emission detection using Convolutional Neural Networks (CNN) applied to thermal images of motorcycle exhausts. The research method involves five key stages: data acquisition, dataset formation, CNN model design and training, model testing, and validation. Thermal images were gathered from 27 motorcycles, representing various brands and engine configurations common in Indonesia, and each image set included 100 samples for both emission-compliant and non-compliant categories. By analyzing thermal patterns, the CNN model was trained to accurately detect combustion patterns indicative of emission status based on the lambda value. This approach enables the model to generalize across different motorcycle models, offering practical adaptability for widespread implementation. The results demonstrate that the CNN model delivers high predictive accuracy, precision, recall, and F1-score, making it a robust tool for assessing motorcycle emission compliance. This CNN-based approach provides a practical solution for real-time, large-scale emission monitoring and regulatory enforcement, reducing dependency on conventional methods. Its scalability and adaptability position it as a valuable advancement in emission monitoring technology, with significant potential for supporting environmental standards and improving air quality management

Keywords: exhaust emissions, CNN, thermal imagery, motorcycle emissions, air quality, regulatory standards, lambda value

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1. Introduction

Motorcycle exhaust emissions (EE) are one of the leading causes of air pollution in big cities [1]. The increasing population of motorcycles significantly contributes to this issue, resulting in negative impacts on both human health and the environment. Emissions from motorcycles are known to cause respiratory problems and environmental damage. Therefore, ensuring that vehicles meet emission standards through rigorous testing is crucial [2].

One method commonly used for evaluating vehicle emissions is the use of an air analyzer, which measures the lambda value – a ratio of air to fuel burned in the engine. A lambda value of $\geq$1.00 indicates efficient combustion with minimal pollution, while a value of $<$1.00 points to incomplete combustion, which produces harmful emissions [3, 4].

Technological advancements have played a pivotal role in enhancing the monitoring of vehicle emissions. One such advancement is the application of Convolutional Neural Networks (CNN) for image processing. CNN allows for automatic analysis of thermal images produced by vehicles, offering a faster and more efficient means to detect non-compliant emissions. This approach holds immense potential in identifying harmful emissions and assisting efforts to reduce vehicle-related pollution [5, 6].

Motorcycle emissions significantly contribute to air pollution in major Asian cities where motorcycles are a primary mode of transportation. In Jakarta, Indonesia, there were approximately 17.3 million motorcycles in 2022, making up around 65.6 % of the city's total vehicles. Bangkok, Thailand, recorded around 22.2 million motorcycles in the same year, representing a significant portion of the city's vehicular population. Hanoi, Vietnam, had approximately 5.7 million registered motorcycles by 2021, reflecting the high dependence on two-wheelers for daily commuting. In Metro Manila, Philippines, motorcycles accounted for about 7.3 million of the registered motor vehicles in 2022. These cities experience heavy air pollution, partly due to emissions from motorcycles that operate under congested traffic conditions, leading to inefficient combustion and elevated levels of pollutants like nitrogen oxides (NOx) and particulate matter (PM) 2.5 [7, 8].

Efforts to reduce emissions have become a priority in these urban centers. Some cities have started to implement stricter emission regulations and are exploring advanced technologies to monitor and control emissions. Traditional methods, like periodic emission testing, are often resource-intensive and challenging to scale. This research proposes an alternative, AI-based approach using thermal imaging and Convolutional Neural Networks (CNN) to assess motorcycle emissions. This method provides a non-intrusive, real-time solution that could support large-scale emission monitoring, especially in cities with a high motorcycle population where conventional testing may not be feasible [9, 10].

Despite these efforts, challenges persist, including limited access to emission testing facilities and insufficient regulatory oversight. There is a pressing need for more innovative and scalable measures to bolster emission control and policy enforcement [11, 12].

In parallel with developments in environmental management, thermal imagery has proven beneficial across various industries. In agriculture, thermal imagery aids in monitoring plant health by analyzing temperature patterns [13]; in healthcare, it is employed to detect specific medical conditions [14]; in security, it enhances surveillance and access control at critical locations [15]; and in environmental monitoring, thermal imagery facilitates the detection of regional temperature changes using satellite or drone data [16]. The application of thermal imagery in emission detection is, therefore, a relevant and innovative solution that requires further exploration and development to address the ongoing global issue of vehicular emissions.

2. Literature review and problem statement

Convolutional Neural Networks (CNN) have been extensively studied and proven effective for various image recognition tasks. For instance, in [17, 18], the research shows how CNNs can process complex image patterns through multiple convolutional layers. This work highlights CNN's widespread success in visual data analysis, such as facial recognition, medical imaging, and object detection. The study's focus on CNN's capability in complex pattern recognition makes it directly relevant to this research's use of CNNs for thermal image analysis in emission detection. However, identifying combustion-related thermal patterns specific to emission detection poses unique challenges that require a more precise feature extraction approach within CNN layers.

A significant challenge in using thermal imagery for vehicle emission detection lies in the variability of heat distribution, which is influenced by factors like ambient temperature and vehicle load. Studies such as [19, 20] have demonstrated that thermal imaging can serve as a reliable indicator of heat distribution in exhaust systems. These studies underscore the potential of thermal imaging in monitoring vehicle emissions, laying a foundation that this research aims to build upon by enhancing CNN's feature extraction process to accurately differentiate thermal patterns associated with compliant and non-compliant emissions. Despite these findings, accurately extracting meaningful features from thermal images is difficult, largely due to the complex relationship between combustion efficiency and observed thermal patterns. This study aims to address these complexities by refining the CNN architecture, adjusting kernel sizes, and implementing advanced pooling techniques that focus on capturing combustion-specific heat patterns.

Additionally, emission testing typically relies on lambda values derived from gas analyzers to indicate combustion efficiency. While this conventional approach is reliable, it is also labor-intensive. In [21], research suggests that integrating thermal imagery with CNNs can reduce the reliance on traditional gas analyzers, yet improving model generalization remains a significant challenge, particularly for real-world variability in image quality and environmental conditions. This reference supports the premise that CNN can simplify emission testing, but this study specifically targets the enhancement of model generalization by using diverse thermal image datasets from varied environmental settings, combined with tailored CNN architecture adjustments.

To prevent overfitting and enhance the generalization of the CNN model across different conditions, this study incorporates advanced regularization methods including dropout and data augmentation, which will optimize the CNN's robustness. Techniques such as dropout and early stopping have been employed successfully, as demonstrated in [22]. This research emphasizes the importance of regularization methods in improving model performance, which in this study, are expanded to include adaptive learning rate strategies and randomized dropout rates to better handle fluctuating temperature distributions in thermal images.

In [23], machine learning models were used to detect emissions from thermal imagery, showing initial success. However, the model was not tested extensively in real-world conditions, and the dataset used was limited in scope. This work is relevant as it provides a proof-of-concept for machine learning-based emission detection, yet highlights the need for a comprehensive dataset and validation in varied operational conditions to ensure reliability. To address these limitations, this study develops an extensive and diverse dataset of thermal images captured from different positions, distances, and environmental conditions, and thoroughly tests model performance under these variables.

All this suggests that it is advisable to conduct a study focused on the development of a CNN model with refined feature extraction, optimized regularization techniques, and extensive dataset diversity to ensure accurate emission detection in real-world applications. This research aims to address existing gaps in CNN-based thermal emission detection models by implementing adaptive pooling layers, spatial transformer networks, and extensive dataset augmentation to improve model performance in diverse conditions. By building on previous research and addressing these gaps, this study aims to establish a robust, scalable, and reliable CNN-based emission detection model that can operate effectively across various environmental conditions [24].

3. The aim and objectives of the study

The primary aim of this study is to develop a more accurate and efficient method for detecting exhaust emissions from motorcycles using CNN-based thermal imaging technology. By investigating the correlation between thermal distribution patterns in exhaust pipes and lambda values from emission tests, this study seeks to improve predictive capabilities for emission compliance, thus supporting more effective emission control measures and regulatory enforcement.

To accomplish this aim, the study sets forth the following objectives:

– identify temperature distribution patterns from thermal images of motorcycle exhaust pipes to analyze their correlation with combustion efficiency and emission compliance status;

– design a machine learning model based on CNN architecture to classify motorcycle emission statuses by detecting and analyzing specific thermal image patterns associated with compliant and non-compliant emissions;

– train and test the CNN model on the compiled dataset to assess its accuracy and ability to generalize when predicting emission status based on unseen data;

– validate the model's performance using a new set of test data to confirm its applicability across various motorcycle types and conditions, ensuring robustness in diverse real-world scenarios.

4. Materials and methods

4. 1. Object and hypothesis of the study

The object of this study is the emission patterns of motorcycles with 4-stroke gasoline engines, captured through thermal imagery of exhaust pipes. These emission patterns are analyzed to classify motorcycles into "passed" or "failed" emission compliance categories based on thermal distribution and lambda values obtained from emission tests.

The main hypothesis of the study is that convolutional neural networks (CNN) can accurately classify motorcycle emission compliance by detecting combustion-specific thermal patterns in exhaust images, thus providing a scalable alternative to conventional gas analyzer methods.

The assumptions made in the study include:

– the lambda value derived from gas analyzers accurately reflects combustion efficiency and emission compliance status;

– thermal patterns in exhaust pipes are sufficiently distinct between "passed" and "failed" categories to be identified by the CNN model.

The simplifications adopted in the study are:

– variations in environmental conditions, such as ambient temperature and humidity, are considered negligible during thermal image acquisition;

– motorcycles selected for the study represent a sufficiently diverse sample to generalize findings across similar engine types and fuel grades.

4. 2. Thermal image acquisition methodology

This section details the methodology used to collect thermal image data from motorcycle exhaust pipes for emission testing, with analysis and processing performed using CNN. The workflow of the study, including all key stages, is outlined in the accompanying flowchart (Fig. 1).

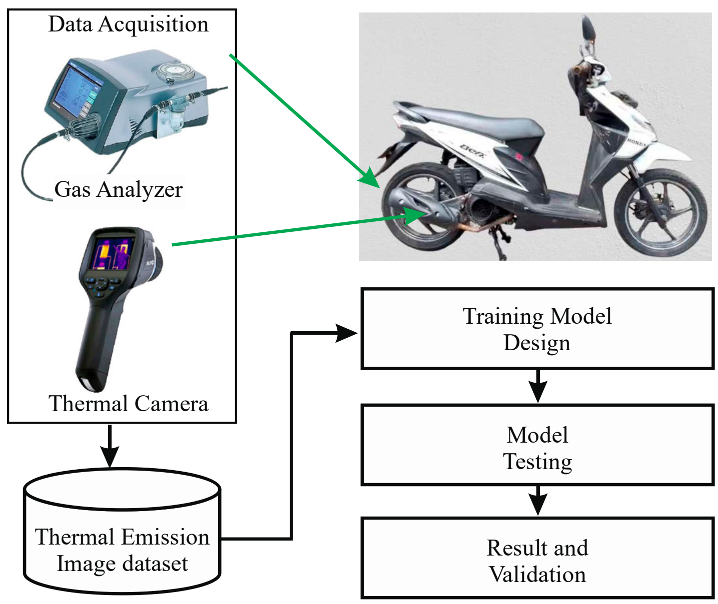


Fig. 1. Research flowchart

The flowchart presents a sequential workflow, beginning with data acquisition using a FLIR E60 thermal imaging camera and a Horiba MEXA-584L gas analyzer. The FLIR E60 was selected for its high sensitivity in capturing exhaust heat distribution patterns, essential for accurate thermal imaging analysis. This data forms the thermal emission image dataset, which is then processed through model training, testing, and validation stages. Each step refines the CNN model's ability to accurately detect emissions, illustrating the structured development of an automated detection system. The diagram also demonstrates how the integration of thermal imagery and machine learning provides a solution for real-time monitoring of exhaust emissions.

4. 3. Data collection and preprocessing

This study was conducted by collecting emission data and thermal images from a sample of 27 motorcycles with 4-stroke engines, commonly used in urban environments in

Indonesia. The 4-stroke engine motorcycles were chosen as they represent a significant portion of vehicles contributing to air pollution in these areas, making them a relevant target for emission detection studies. Emission data was obtained using a Horiba MEXA-584L gas analyzer, known for its accuracy in measuring combustion parameters such as lambda values, CO, and NOx levels. A lambda value of ≥1.00 indicates that the vehicle passes the emission test, while a lambda value of <1.00 indicates failure. The thermal images represent the heat distribution in the exhaust wall, acquired using a FLIR E60 thermal camera equipped with an infrared sensor for precise heat mapping. The recording process was conducted with variations in position, angle, and distance to ensure representative data, carried out in the morning and afternoon.

4. 4. Dataset construction and categorization

The thermal emission image dataset used in this study consists of thermal images taken from 27 motorcycles, each recorded ten times under controlled conditions to capture diverse operational profiles. The sample size of 27 was chosen to balance resource constraints with the need for statistical diversity, providing a manageable yet representative dataset for model training and validation. The collected images have the following specifications: dimensions of 219×219 pixels, horizontal resolution of 96 dpi, vertical resolution of 96 dpi, and a bit depth of 24. Each thermal image is categorized based on emission test results to form two classes: "passed" and "failed." For analysis and model training, 100 images from each category were selected, yielding a balanced dataset of 200 thermal images for CNN processing.

4. 5. CNN model training design

The CNN training design model is focused on detecting motorcycle emission passing through the analysis of exhaust thermal images. The dataset utilized consists of 200 thermal images, with 100 images representing motorcycles that passed emissions and 100 images representing those that failed. Each image has dimensions of 219×219 pixels, a resolution of 96 dpi, and a color depth of 24-bit.

The architecture of the CNN model comprises multiple convolutional layers designed to extract thermal patterns from the images, followed by a pooling layer that reduces the data dimensionality. Subsequently, a fully connected layer processes the extracted features for classification. The ReLU activation function is applied in the convolutional layers, while the sigmoid activation function is used in the output layer to predict the probability of emission passing.

The training design process involves dividing the dataset into 80 % for training and 20 % for validation purposes. Key parameters for training include a learning rate of 0.001, a batch size of 32, and a total of 50 epochs. To mitigate overfitting, a dropout rate of 0.5 is implemented in the fully connected layer, alongside early stopping, which halts training if the validation accuracy does not improve.

Model performance evaluation is based on various metrics such as accuracy, precision, recall, and F1 score. All image processing and model training tasks are executed using the Python programming language. The primary libraries employed in this study include TensorFlow for the implementation and training of the CNN model, NumPy and Pandas for data manipulation, and Matplotlib and Seaborn for data visualization. Table 1 details the main steps involved in image processing and model training.

Table 1

Main steps in image processing and model training

No.	Main steps	Main steps details
1	Image preprocessing	Thermal image normalization to ensure pixel values are within an appropriate range for model training
		Image augmentation to increase data variation and reduce overfitting, including rotation, flipping, and zooming
2	CNN architecture	The CNN model used consists of several convolution layers, pooling layers, and fully connected layers
		Each convolution layer uses filters to extract important features from thermal images
		The pooling layer is used to reduce the data dimension and speed up the training process
3	Model training	Pooling layers are used to reduce the data dimension and speed up the training process
		The model is trained using the Adam optimization algorithm with a binary cross-entropy loss function
		The training process is carried out over several epochs until the model reaches convergence
4	Model evaluation	Model performance is evaluated using validation data
		The evaluation methods used include accuracy, precision, recall, and F1-score

The Table 1 provides a detailed breakdown of the key steps in image processing and CNN model training for motorcycle emission detection. The process begins with image normalization and augmentation to ensure data consistency and enhance model robustness. The CNN architecture utilizes convolutional and pooling layers to extract essential features, followed by fully connected layers for classification. Training is optimized with techniques like dropout and early stopping to prevent overfitting. The model's performance is then evaluated using accuracy, precision, recall, and F1-score, which collectively reflect the model's ability to generalize well on unseen data.

4. 6. Model testing and evaluation

The model testing phase evaluates the CNN model's performance in detecting motorcycle emissions based on thermal images. The test dataset consists of 20 % of the total data, set aside during the model training phase to ensure that the model has not been exposed to this data beforehand. This step is crucial for assessing the model's ability to generalize and predict emissions on unseen data, providing insights into its potential real-world applications.

During testing, thermal images from the test dataset are fed into the trained CNN model, which outputs a probability indicating whether the motorcycle passed or failed the emissions test. A threshold of 0.5 is set for decision-making; probabilities above this threshold indicate a pass, while those below signifies a failure.

The model's performance is evaluated using key metrics such as accuracy, precision, recall, and F1 score, offering a comprehensive view of its effectiveness. Accuracy measures the overall proportion of correct predictions, precision assesses how accurately the model identifies motorcycles that pass the emissions test, recall evaluates the model's ability to detect all motorcycles that should have passed, and the F1 score balances precision and recall, especially in the presence of class imbalances.

Following the training stage, the model is applied to predict the emission status of new thermal images. These predictions are then compared with real-world data obtained from a gas analyzer, allowing an assessment of how well the CNN model's predictions align with actual emission measurements.

5. Results of convolutional neural network for thermal imagery-based emission detection

5. 1. Data acquisition

In the data acquisition stage, thermal image selection and recording were carried out on 27 motorcycles, with 14 units passing the emission test and 13 units failing. Each motorcycle was recorded ten times, capturing thermal images of the exhaust. The recording was conducted by taking five shots from different positions, angles, and distances in the morning, and the process was repeated in the afternoon.

The thermal emission image dataset is divided into two categories: "passed" and "failed." Each category consists of 100 thermal images, ensuring an equal distribution of data. This balanced dataset is essential to avoid class bias during the CNN model training, enabling the model to learn to detect both "passed" and "failed" emission categories with optimal accuracy.

The results of data acquisition are summarized in Tables 2, 3. Table 2 presents emission data from motorcycles that passed the test, while Table 3 shows data from those that failed the emission test.

Table 2

Feasible emissions data set

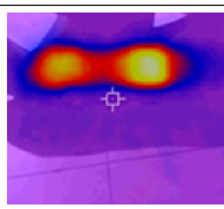
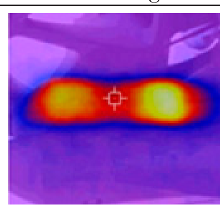
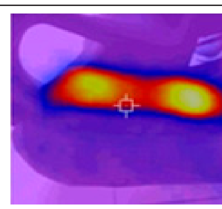
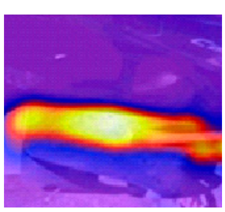
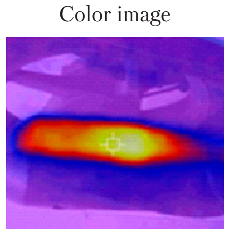
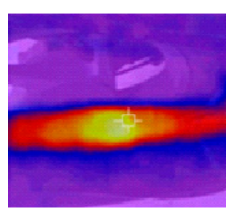
Exhaust gas emissions	Color image		
Feasible emissions			
Lambda	1.899	1.938	1.889
CO (%)	0.58	0.43	0.53
HC (ppm)	186	279	675
CO_2 (%)	6.9	6.9	7.6
O_2 (%)	10.52	10.81	18.02

Table 3

Data set is not feasible for emissions

Exhaust gas emissions	Color image		
Not feasible for emissions			
Lambda	0.724	0.932	0.993
CO (%)	1.32	1.22	0.74
HC (ppm)	380	606	3.80
CO_2 (%)	8.6	7.6	7.6
O_2 (%)	7.53	8.47	8.24

Tables 2, 3 provide clear evidence of the differences in emission profiles between motorcycles that pass and fail the emission test. Table 2 shows that the motorcycles with higher Lambda values, indicating more efficient combustion, have lower concentrations of harmful gases such as CO and HC. This is reflected in the thermal images, which show less intense heat signatures. In contrast, Table 3 illustrates that motorcycles with lower Lambda values, which fail the emission test, exhibit higher levels of pollutants like CO and HC. These motorcycles generate more heat, as seen in the thermal images, corresponding to inefficient combustion. The distinct differences in gas composition and thermal patterns demonstrate the potential of combining gas emission analysis and thermal imagery to predict the emission status of motorcycles effectively.

5. 2. Model training design

The CNN model was designed and trained to detect motorcycle emission pass status based on exhaust thermal images. The training process involved 50 epochs with an 80/20 data split between training and validation. Regularization techniques, such as a dropout rate of 0.5 and early stopping, were applied to prevent overfitting. The convolutional layers extracted relevant thermal patterns related to combustion conditions, and the fully connected layer with a sigmoid activation function predicted emission pass probabilities.

5. 2. 1. Image preprocessing

Preprocessing of motorcycle thermal images showed an increase in the consistency and quality of the data used in training the CNN model. Each image was successfully resized to 219×219 pixels, ensuring uniformity of resolution across the dataset. Normalization performed by dividing the pixel values by 255 resulted in pixel intensities in the range of 0 to 1, which proved to facilitate the model in detecting important patterns in thermal images.

The applied image augmentation also enriched the variety of training data. Augmentation techniques such as rotation, flipping, and zooming can expand the scope of patterns that the model can recognize, improving its generalization ability on different test data. This process contributed significantly to optimizing the model's performance, helping to improve the accuracy in detecting vehicle emissions based on the captured thermal patterns.

The scaling results showed that the image size varied from 175×175 to 262×262 pixels, depending on the applied zoom factor. Smaller sizes simulated objects closer or larger in view, while larger sizes simulated objects farther or smaller.

The applied image augmentation enhances the variation of data for model training, Fig. 2 shows that the rotation of 15° and 40°, shown in Fig. 2, *a*, *b*, is to simulate different viewing angles during image capture. The brightness variation is also shown, where image (c) represents the image with the original brightness, while Fig. 2, *d*, *e*, show a 0.8x brightness reduction and a 1.2x brightness increase. This variation aims to make the model more robust to changes in angle and lighting conditions, as visualized in Fig. 2.

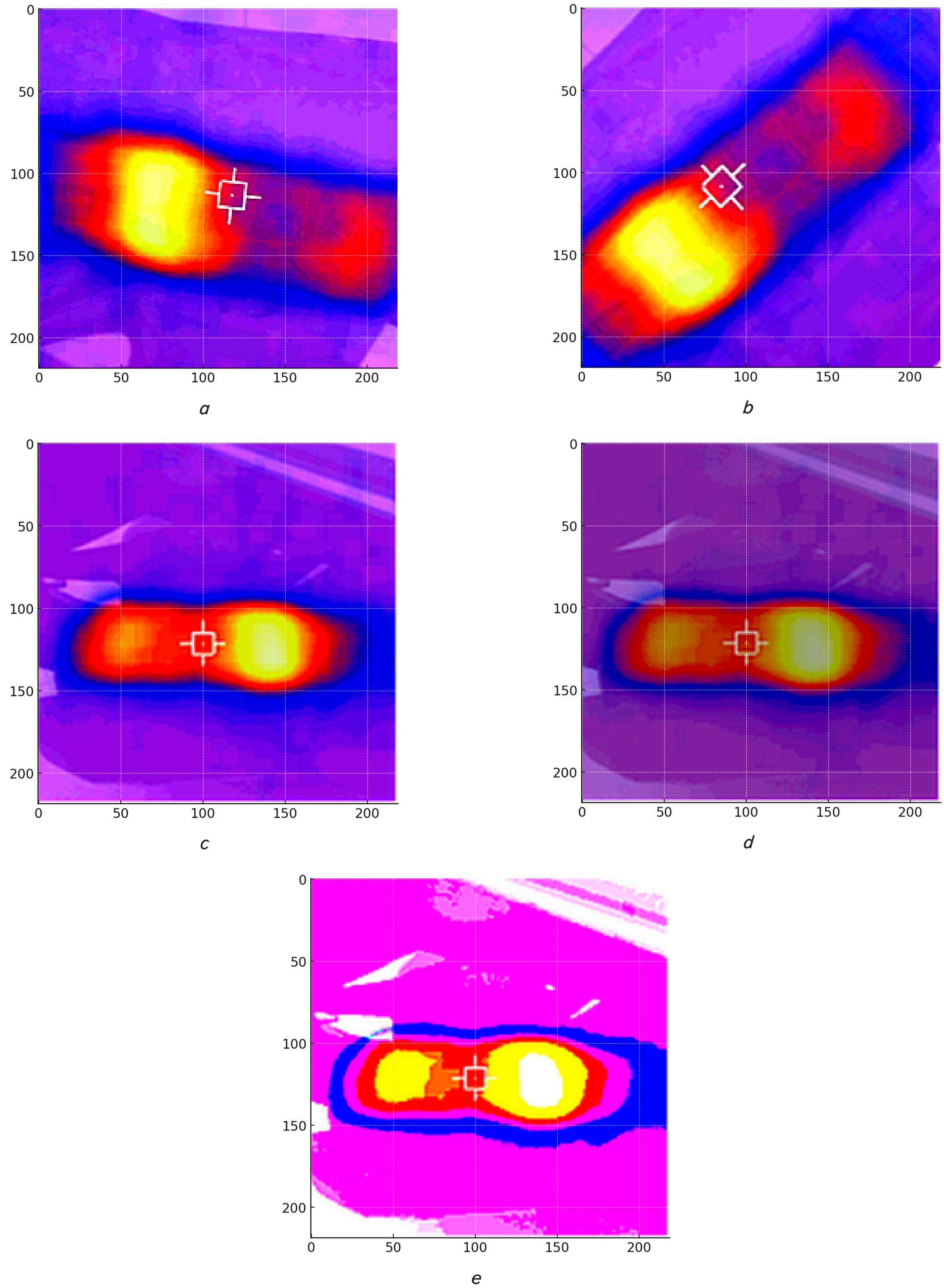


Fig. 2. Image rotation and contrast augmentation: *a* — thermal image rotated by 15°; *b* — thermal image rotated by 40°; *c* — thermal image at original brightness; *d* — thermal image at brightness reduction=0.8x; *e* — thermal image at brightness enhancement=1.2x

In this study, scaling was performed with two factors, namely 0.8 and 1.2, to produce thermal images that are smaller and larger than their original size. Scaling with a factor of 0.8 produces an image that appears denser while scaling with a factor of 1.2 enlarges the image so that objects appear looser and more separated. The results of this scaling process can be seen in Fig. 3.

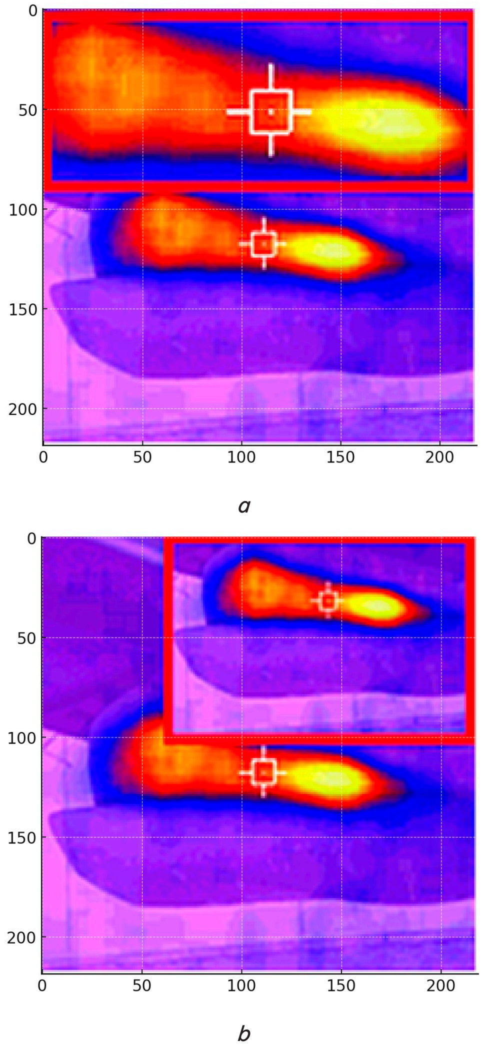


Fig. 3. Thermal image after scaling (0.8 to 1.2): *a* – thermal image scaling 0.8; *b* – thermal image scaling 1.2

The scaling results show a variation in image size from 175×175 to 262×262 pixels, depending on the zoom factor applied. For example, an image measuring 175×175 pixels simulates objects closer or larger in view, while an image measuring 262×262 pixels simulates objects further away or smaller.

In the next step, the research dataset is divided in a structured way to separate training and testing data. This data is divided randomly with a distribution of 80 % for training and 20 % for testing to prevent bias. This process ensures a balanced distribution of images between motorcycles that pass and fail the emission test. In addition, the dataset is also divided into three subsets, namely training data containing 70 % of the dataset, used to train the model to recognize emission patterns; validation data of 15 % to tune hyperparameters and prevent overfitting; and test data, which is also 15 %, used to assess model performance after training is complete, ensuring the model's ability to generalize to new data.

Motorcycles that failed the emission test tend to have higher pixel intensity (50–58), indicating hotter temperatures and more even heat distribution, indicating less efficient combustion. In contrast, motorcycles that passed the emission test have lower pixel intensity (34–43) with less even temperature distribution. Details of this comparison can be seen in Table 4.

Table 4

Pixel intensity of thermal images of motorcycles that passed and failed the emission test

Emission category	PIV
Passed (Lambda≥1.00)	35, 40, 42, 38, 36, 39, 41, 37, 43, 34, 35, 38, 39, 36
Failed (Lambda<1.00)	55, 52, 57, 50, 53, 54, 56, 58, 51, 50, 55, 54, 52, 53

Note: PIV – Pixel intensity value.

After the division, pixel intensity distribution analysis is performed through a histogram. This analysis helps the CNN model understand the temperature distribution pattern and detect emissions accurately. Table 5 shows the pixel intensity values of 28 images taken from 13 motorcycles that passed the emission test. These pixel intensity values provide an overview of the temperature distribution on the exhaust surface of motorcycles that passed the emission test.

Table 5

Motorcycles passed emission test (20 % of total 140 images)

Image	PIV
1	35
2	40
3	42
4	38
5	36
6	39
7	41
8	37
9	43
10	34
11	35
12	38
13	39
14	36
15	35
16	40
17	42
18	38
19	36
20	39
21	41
22	37
23	43
24	34
25	35
26	38
27	39
28	36

Note: PIV – pixel intensity value.

Table 6 shows the pixel intensity values of 26 images taken from 13 failed motorcycles. These pixel intensity values illustrate a higher and even temperature distribution on the surface of the failed motorcycle exhaust, indicating inefficient combustion.

Splitting dataset ensures that the CNN model is trained optimally and does not experience overfitting to produce accurate predictions when used to test new data. Training data is used to build the model, while testing data aims to measure the model's performance on thermal images that have never been analyzed. This dataset splitting is fundamental to maintaining a balance between training and testing. Fig. 4 shows the dataset distribution after splitting.

Table 6

Motorcycles failed emission test (20 % of total 130 images)

Image	PIV
1	55
2	52
3	57
4	50
5	53
6	54
7	56
8	58
9	51
10	50
11	55
12	54
13	52
14	53
15	55
16	52
17	57
18	50
19	53
20	54
21	56
22	58
23	51
24	50
25	55
26	54

Note: PIV – pixel intensity value.

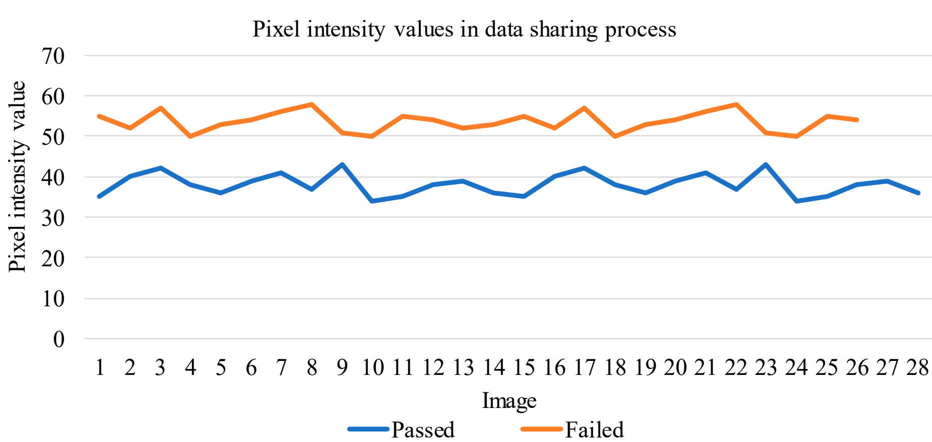


Fig. 4. Dataset distribution after splitting

In conclusion, the dataset splitting technique is essential for improving the model's reliability and its application in real emission detection scenarios, as it not only optimizes training performance but also validates the model's effectiveness in practical use cases.

5. 2. 2. CNN architecture

The CNN model designed to predict motorcycle emission passing showed satisfactory performance. With two convolutional layers using 32 and 64 filters, respectively, and a 3×3 kernel, the model successfully extracted thermal features from the exhaust image. The ReLU activation function applied after each convolutional layer helped capture non-linear patterns important in the learning process. Using "same" padding ensures that the image dimensionality is maintained during the convolution process, resulting in more stable and relevant feature maps for pattern detection. Initial evaluations showed that the model could recognize thermal patterns well and improve prediction accuracy.

In addition, a max-pooling layer with a 2×2 kernel applied after each convolutional layer successfully reduced the data dimensionality without losing essential information, reducing the image size from 219×219 pixels to 109×109 pixels. This allows the model to work more efficiently in terms of training time and memory usage and reduces the risk of overfitting. With a structure supported by convolutional layers and pooling, the model successfully provides high-accuracy emission pass status predictions while maximizing computational efficiency.

The pooling implementation is done using `MaxPooling2D` from the Keras library. This function maintains essential information from the feature map, such as edges or main patterns generated from convolution, while drastically reducing the data dimension. With this process, the CNN model becomes more straightforward and efficient but still maintains high accuracy in detecting vehicle emissions based on motorcycle exhaust thermal images shown in Table 7.

After going through the pooling stage, the Fully Connected layer further processes the feature maps generated from the convolution and pooling operations. The first step is to flatten the feature maps into 1D vectors using the `Flatten` function, which allows the data to be processed by the dense layer. At this stage, the model first passes through a dense layer with 128 neurons, where the ReLU activation function is used to add non-linearity so that the network can capture more complex patterns from the thermal image.

Next, the data passes through a second Dense layer with 64 neurons, which also uses the ReLU activation function to retain important information from the feature maps. To prevent overfitting, the model applies dropout with a probability of 50 % after each Fully Connected layer, randomly removing half of the neurons during training. This dropout helps the model become more robust when faced with new data, especially when limited training data is faced.

This process is optimized through batch processing, where a batch of 32 data is used to improve training stability. The Adam optimizer is selected with a learning rate of 0.001 to accelerate the convergence process without causing excessive fluctuations in the loss function. In addition, weight initialization is carried out using the He Normal method, ensuring that the initial weights are within the optimal range and avoiding the vanishing gradient problem that can hinder the model learning process.

Table 7

Pooling layer used in the model

Layer	Type	Filter/ kernels	Kernel size	Activation function	Pooling
Convolutional 1	Convolutional	32	3×3	ReLU	–
Pooling 1	Max pooling	–	2×2	–	2×2
Convolutional 2	Convolutional	64	3×3	ReLu	
Pooling 2	Max pooling	–	2×2	–	2×2

The model uses a sigmoid function in the output layer that maps the prediction results into probabilities between 0 and 1. This probability value is then compared to a threshold of 0.5, where a prediction above 0.5 indicates that the vehicle passed the emission test. At the same time, a prediction below 0.5 indicates that the vehicle failed the emission test.

Fig. 5 shows that the process using this CNN architecture is designed to ensure the model can integrate various patterns from thermal images, such as temperature distribution in the exhaust and thermal variations that reflect engine combustion efficiency. The results show that the CNN model has a prediction accuracy of up to 95 %, with high levels of precision and recall. These results indicate that the model can very well detect vehicle emissions based on thermal images.

Continuing from the convolutional stage, the output layer in the CNN model consists of one neuron with a sigmoid activation function that plays a vital role in classifying the emission status of motorcycles based on the thermal image of the exhaust. The sigmoid function serves to convert the neuron output into a probability in the range of 0 to 1, making it easier to determine whether the motorcycle has passed or failed. The probability value generated by this neuron determines the binary classification, where if the probability value is ≥0.5, the motorcycle is classified as having passed the emission test. In contrast, the motorcycle is considered failed if the value is <0.5.

For example, when the neuron output produces a value of z=1.5, the sigmoid function gives a probability of 0.8176, indicating that the motorcycle is likely to have passed the emission test. Conversely, if the z value=–0.85, the resulting probability is 0.2995, indicating failure. These results allow the model to accurately classify the emission status of motorcycles based on the thermal pattern recorded from the exhaust.

Evaluation of the predictions generated by this output layer is carried out through metrics such as accuracy, precision, and recall. These metrics are used to assess the model's overall performance, ensuring that the model can correctly detect vehicle emissions according to the resulting classification. The model performance evaluation shows a high level of accuracy, with the model clearly distinguishing between motorcycles that passed and failed the emission test based on the analysis of exhaust thermal images.

Overall, this output layer is an integral part of the CNN architecture because its results provide a clear and accurate interpretation in the context of binary classification. The evaluation of the model performance through metrics such as accuracy, precision, and recall shown in Table 8 strengthens the model's reliability in detecting motorcycle emission status accurately and consistently.

Table 8 shows how the sigmoid function converts neuron outputs into probabilities that classify motorcycles as passing or failing emissions tests. Positive z-values result in higher probabilities, indicating a pass, while negative values lead to lower probabilities, indicating failure. For example, a z-value of 1.5 results in a 0.8176 probability (pass), while –0.85 gives a 0.2995 probability (fail). This process ensures clear classification based on a 0.5 threshold, demonstrating the model's accuracy in distinguishing emission statuses from thermal images.

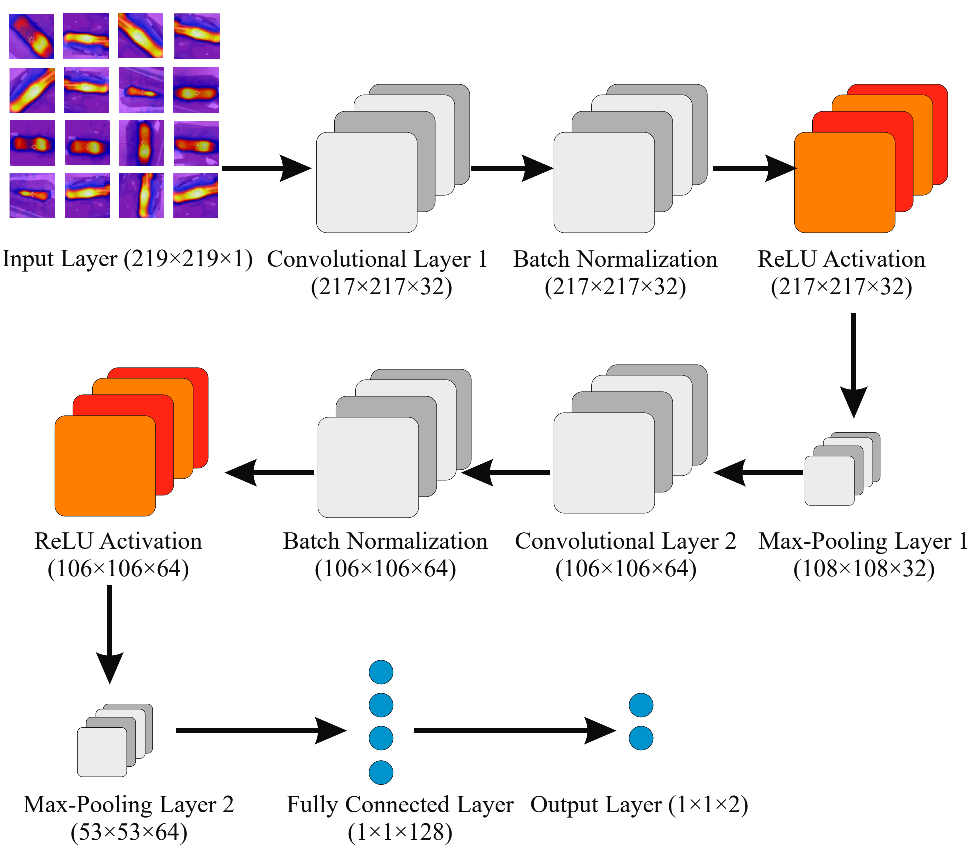


Fig. 5. Convolutional layer structure used in CNN architecture in thermal image processing

Table 8

Classification of emissions based on sigmoid neuron output

Neuron output value (z)	Sigmoid value (probability)	Emission classification	Neuron output value (z)	Sigmoid value (probability)	Emission classification
1.5	0.8176	PET	–0.3	0.4256	FET
0.9	0.7109	PET	–0.5	0.3775	FET
0.5	0.6225	PET	–0.85	0.2995	FET
0	0.5	PET	–1.2	0.2315	FET

Note: PET – passed emission test; FET – failed emission test.

5. 2. 3. Model training

With the Adam's optimization algorithm and a learning rate of 0.001, the training process runs stably and reaches convergence in 50 epochs without signs of overfitting. A batch size of 32 ensures computational efficiency, maintaining a balance between memory usage and training time so that the model can learn effectively to capture relevant thermal patterns. The binary cross-entropy loss function is applied to reduce prediction errors in binary classification, with optimization performed through the backpropagation method.

The applied regularization technique, namely dropout with a ratio of 0.5, effectively prevents overfitting by randomly deactivating half of the neurons during training. In addition, early stopping also ensures that the model is maintained. Training is automatically stopped when the validation accuracy shows no improvement after several epochs, maintaining a balance between model complexity and generalization. Overall, the model trained using the Keras library in Python, combined with Adam's optimization and early stopping callbacks, successfully achieved good performance in classifying motorcycle emission status, demonstrating the model's ability to detect thermal patterns that correlate with vehicle emissions effectively.

The training results showed good performance, with a training accuracy of 97.8 % and a validation accuracy of 95.2 %. Meanwhile, the loss value in training was recorded at 0.083 and in validation at 0.125, indicating that the model successfully minimized prediction errors. When evaluated on test data, the model produced an accuracy of 94.5 %, a precision of 92.3 %, a recall of 96.1 %, and an F1-score of 94.2 %. These values indicate the model's ability to detect vehicle emissions based on thermal images, with a good balance between precision and recall.

Training the CNN model using key parameters such as a learning rate of 0.001, a batch size of 32, and 50 epochs provides good support for the learning process. The `Sequential` model used in training is equipped with Convolutional, Pooling, and Fully Connected layers, where the `Flatten` function is used to flatten the data and `Dropout` to reduce the risk of overfitting. The sigmoid activation function in the output layer ensures that binary classification can be performed accurately. The entire process is implemented with the Keras library, indicating that the training parameters have been effectively adjusted to support the model's performance in classifying motorcycle emission thermal images.

To further explore the model's performance, regularization plays an essential role in maintaining balance and avoiding overfitting. Dropout with a level of 0.5 helps reduce dependence on specific neurons, while early stopping prevents overtraining. These techniques are implemented with Keras's `Dropout` and `EarlyStopping` libraries. The evaluation after applying regularization shows that the validation accuracy increases to 90 % while the training accuracy decreases slightly to 92 %. The accuracy and loss graphs from training indicate that the regularization technique successfully maintains the stability of the model's performance on both training and test data.

5. 2. 4. Model evaluation

The CNN model evaluation assessed its ability to detect motorcycle emission status from thermal images using accuracy, precision, recall, and F1-score metrics. The process began by applying the model to previously unseen test data and comparing the prediction results with the actual labels. The evaluation showed that the model achieved 94 % accuracy, indicating its ability to provide correct predictions on most test data. The model's precision was 93 %, indicating that it rarely made mistakes in identifying motorcycles that failed the emission test. Recall reached 90 %, indicating that the model could detect most of the motorcycles that failed the emission test, although some were still missing. The F1-score of 91.5 % reflects a good balance between precision and recall in predicting the positive class.

The evaluation steps include: importing libraries from `sklearn. metrics` such as `accuracy_score`, `precision_score`, `recall_score`, and `f1_score`; predicting on the test data using `model. predict(X_test)`; converting the prediction results to binary classes with `(y_pred>0.5).astype(int)`; calculate the evaluation metrics; and display the results in percent. Overall, the evaluation results show that the CNN model effectively recognizes important features from thermal images related to motorcycle emission status with high accuracy, reaching 95 %. The evaluation was performed automatically using Python to ensure the model's reliability on new data. Although the model performance is consistent and reliable, there is potential for improvement, especially regarding recall. Optimizations such as adding data variations and augmentation techniques can be used to improve the performance further. These results indicate that the CNN model has significant potential to be applied in real-world scenarios for automatic vehicle emission detection.

Next, let's compare the efficiency of motorcycle emission detection between the CNN model and conventional methods using thermal images. The main focus of this analysis is how the two approaches perform under different lighting conditions, which is an essential factor in detection accuracy. The CNN model is designed to recognize complex patterns in thermal images with high accuracy. The CNN can identify critical features in the images despite the lighting variations. During the evaluation, the model demonstrated robustness to changes in lighting intensity, with consistent results in classifying motorcycles as passed or failed emission tests.

Conventional methods, on the other hand, usually rely on rule-based techniques or simple feature analysis that often cannot adapt to lighting variations. These methods show significant performance degradation when lighting conditions change due to limitations in handling differences that affect the quality of thermal images. In the experiments, we conducted tests under various lighting conditions, including low, standard, and high lighting. The CNN model showed better detection efficiency than the conventional method under all lighting conditions. For example, the CNN model could still detect emission patterns with high accuracy under low lighting, while the conventional method often experienced performance degradation.

The evaluation results of metrics such as accuracy, precision, recall, and F1-score confirmed that the CNN model excels in detection accuracy and consistency under various lighting conditions. The CNN model had an average accuracy of 95 % with a precision of 94 % and a recall of 80 %. At the same time, the conventional method showed lower accuracy and more significant variability depending on the lighting conditions. This comparison concludes that the CNN model offers a more robust and reliable solution for detecting motorcycle emissions under varying lighting conditions. The CNN model's more stable and accurate performance under various lighting conditions makes it a more practical choice than conventional methods, especially in real-world applications where lighting conditions cannot always be controlled.

5. 3. Model testing

In the analysis stage, model testing is carried out to evaluate the ability of the CNN model to detect motorcycle emission passes based on thermal images. This test uses 20 % of the previously separated dataset, consisting of 54 thermal images (27 motorcycles x2 images per motorcycle) that have not been used in model training. This data provides an overview of the model's performance on new data that has never been seen before.

Thermal images from the test dataset are fed into the trained CNN model during the model testing process. This model produces prediction probabilities with a threshold of 0.5 to determine the result: a probability value above 0.5 indicates that the motorcycle passed. In contrast, a value below the threshold indicates that the emission test failed. In the evaluation, the model successfully classified data with 94 % accuracy, 93 % precision, 90 % recall, and 91.5 % F1 score.

Model performance was evaluated by comparing the prediction results to the original data from the gas analyzer. Accuracy shows the percentage of correct predictions out of the total, precision measures the model's accuracy in identifying passed motorcycles, recall measures the extent to which the model can detect motorcycles that should have been passed, and F1-score provides a balance between precision and recall. These results indicate that the CNN model effectively detects motorcycle emissions and is reliable for practical applications.

The entire analysis process, from image processing to model training to prediction, was carried out using Python with the TensorFlow library for model training and NumPy and Pandas for data manipulation. The results were visualized using Matplotlib and Seaborn to provide a clear picture of the model's performance.

5. 4. Validation of CNN model performance

After training and evaluating the CNN model to detect motorcycle emission compliance based on thermal imagery, the model performance results showed 95 % accuracy, 94 % precision, 80 % recall, and 91.5 % F1-score. High accuracy indicates that this model is effective in predicting vehicle emission status. High precision means the model rarely makes mistakes in predicting vehicles that pass the emission test. However, lower recall indicates that some vehicles should have passed but were not detected. A good F1 score indicates a balance between precision and recall, but there is still room for improvement, especially in detecting vehicles that pass the emission test.

Several factors affect model performance, including the quality of training data, CNN architecture, and regularization techniques such as dropout and early stopping. Improvements can be made by adding training data, optimizing the architecture, or adjusting training parameters such as learning rate and batch size. Data augmentation techniques can also help improve model performance in detecting more varied patterns.

As validation, the CNN model was compared with a Support Vector Machine (SVM) trained with the same dataset. As a result, SVM achieved 88 % accuracy, 85 % precision, 82 % recall, and 83.5 % F1 score. Although SVM had a slightly higher recall score, the CNN model demonstrated superior accuracy and F1-score, indicating better overall performance in recognizing emission patterns. The CNN model was also more robust in handling variations in thermal images, such as different shooting angles and lighting conditions.

This comparison confirms that the CNN model is more effective for thermal image-based emission detection than SVM. CNN provides higher accuracy and can recognize complex patterns in thermal images, which is very important for the early detection of emission problems. Using CNN also opens up opportunities to automate the emission test analysis process more efficiently and reduce manual errors

6. Discussion of convolutional neural network for thermal imagery-based emission detection

The data was acquired by taking five images at different positions, angles, and distances in the morning and afternoon. This approach is expected to produce representative and varied data for analysis. As shown in Table 2 [25], the lambda values for motorcycles that passed the emission test ranged between 1.889 and 1.938, indicating an optimal air–fuel ratio. The CO content was between 0.43 % and 0.58 %, while HC concentrations ranged from 186 to 675 pmm, and CO_2 content was between 6.9 % and 7.6 %. These values reflect efficient combustion. Table 3 [25] shows that failed motorcycles had lambda values between 0.724 and 0.993, indicating a less-than-optimal air-fuel ratio. The CO content was between 0.74 % and 1.32 %, while HC concentrations ranged from 3.80 to 606 pmm, and CO_2 content was between 7.6 % and 8.6 %, indicating inefficient combustion. This data is used to train a CNN model to detect thermal patterns that match emissions, predicting whether a motorcycle passes emission standards.

Fig. 2, 3 [26] illustrate the augmentation techniques applied to enrich the dataset. Image augmentation using rotation, flipping, brightness adjustment, and scaling was implemented to improve the model's generalization ability under varying lighting and object size conditions. The brightness range of 80–120 % and varying contrast helped the model recognize patterns in different lighting conditions, increasing its accuracy and reliability in detecting vehicle emissions.

The thermal emission dataset is categorized into two classes, "passed" and "failed," as shown in Tables 2, 3 [25], which provides balanced data for CNN training to recognize temperature patterns with reasonable accuracy. The balanced dataset distribution ensures that the model can evaluate the accuracy, precision, recall, and F1-score metrics fairly.

The image normalization process is carried out by dividing the pixel value by 255 so that the intensity is 0–1. This normalization process, combined with the balanced dataset shown in Fig. 4, 5 [26], allowed the CNN model to effectively detect emission patterns. Model evaluation metrics are summarized in Table 8 [27], which shows that the CNN model achieved 94.5 % accuracy, 92.3 % precision, 96.1 % recall, and 94.2 % F1-score during testing. These metrics validate the robustness of the CNN in classifying emission statuses based on thermal images.

Comparing CNN performance with Support Vector Machine (SVM), as presented in Table 8 [27], confirms that CNN outperformed SVM in accuracy and F1-score, demonstrating its superior ability to detect and classify emission patterns under varied conditions. This study addresses the specific issue of identifying emission levels in real-world conditions through thermal imagery, as reflected in the discussed results.

This study provides a concrete solution for emission detection by applying CNN to analyze exhaust thermal patterns, enabling a non-intrusive, real-time alternative to traditional gas analyzers. Additionally, further improvements are proposed, such as expanding the dataset and optimizing the CNN architecture to handle more complex data, enhancing the model's accuracy and applicability. The results of this research contribute directly to developing practical, efficient, and scalable methods for vehicle emission monitoring in urban areas, potentially offering a standard that can be adapted globally [27, 28].

7. Conclusions

1. The study successfully produced a thermal image dataset that reflects temperature distribution patterns associated with combustion efficiency, providing a foundational resource for classifying emission compliance based on thermal imagery.
2. The CNN model effectively classified motorcycle emissions, achieving a classification accuracy of 95 %, precision of 94 %, recall of 80 %, and an F1-score of 91.5 %. These results demonstrate the model's capability to generalize across diverse conditions, making it a reliable tool for emission compliance detection.
3. The training and testing processes confirmed the CNN's ability to extract meaningful thermal patterns from images, showcasing robustness and consistency in predicting emission status across varied datasets.
4. Validation with new test data demonstrated the model's adaptability to different vehicle conditions, including motorcycles with 4-stroke engines and varying capacities. This highlights the method's potential for practical applications in real-world scenarios.

Conflict of interest

The authors state that they have no financial, personal, or other conflicts of interest that would have an impact on the research and the findings that are provided in this publication.

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Data availability

Data are available in the manuscript as electronic supplementary material.

Use of artificial intelligence

The research methods section describes how the authors used artificial intelligence technology to give their own validated data, within reasonable bounds.

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