

Article

PropNet-R: A Custom CNN Architecture for Quantitative Estimation of Propane Gas Concentration Based on Thermal Images for Sustainable Safety Monitoring

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Abstract

Liquefied petroleum gas (LPG), composed mainly of propane and butane, is widely used as an energy source in residential, commercial, and industrial sectors; however, its high flammability poses a critical risk in the event of accidental leaks. In Peru, where LPG constitutes the main domestic energy source, leakage emergencies affect thousands of households each year. This pattern is replicated in developing countries with limited energy infrastructure. Early quantitative detection of propane, the predominant component of Peruvian LPG (~60%), is essential to prevent explosions, poisoning, and greenhouse gas emissions that hinder climate change mitigation strategies. This study presents PropNet-R, a convolutional neural network (CNN) designed to estimate propane concentrations (ppm) from thermal images. A dataset of 3574 thermal images synchronized with concentration measurements was collected under controlled conditions. PropNet-R, composed of four progressive convolutional blocks, was compared with SqueezeNet, VGG19, and ResNet50, all fine-tuned for regression tasks. On the test set, PropNet-R achieved MSE = 0.240, R^2 = 0.614, MAE = 0.333, and Pearson's r = 0.786, outperforming SqueezeNet (MSE = 0.374, R^2 = 0.397), VGG19 (MSE = 0.447, R^2 = 0.280), and ResNet50 (MSE = 0.474, R^2 = 0.236). These findings provide empirical evidence that task-specific CNN architectures outperform generic transfer learning models in thermal image-based regression. By enabling continuous and quantitative monitoring of gas leaks, PropNet-R enhances safety in industrial and urban environments, complementing conventional chemical sensors. The proposed model contributes to the development of sustainable infrastructure by reducing gas-related risks, promoting energy security, and strengthening resilient, safe, and environmentally responsible urban systems.

Keywords: propane detection; thermal imaging; convolutional neural networks; regression models; gas concentration estimation; industrial safety; sustainable safety; environmental monitoring



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1. Introduction

Liquefied petroleum gas (LPG), composed primarily of propane and butane, is a byproduct of petroleum refining and natural gas processing, stored under pressure in liquid state to facilitate its transportation and use [1]. Due to its efficiency and low cost, it is widely employed as a clean energy source in households, hotels, urban businesses, and as an alternative to conventional fossil fuels in transportation, contributing to the reduction of pollutant emissions [2–10]. However, its highly flammable nature renders accidental leaks a threat to safety and sustainability, as they can lead to fires, explosions, and asphyxiation [7,11–15], while also intensifying atmospheric pollution and affecting air quality [16–18].

These risks are exacerbated by technical factors, such as failures in regulators, cylinders, and hoses [19,20]; operational factors, such as insufficient maintenance and exposure to ignition sources [21–23]; and environmental factors, such as high temperatures, poorly ventilated spaces, or the proximity of plants to residential areas [24,25]. The magnitude of the problem is reflected in the statistics: in 2022, 640,093 residential fires were recorded in 25 countries, resulting in 17,666 injuries and 12,815 deaths, while 4853 incidents were specifically linked to gas equipment in 10 countries [26,27]. These figures underscore the urgency of innovative solutions for early detection and continuous monitoring of LPG concentrations, the implementation of which not only strengthens the safety of communities and industries but also contributes to sustainability objectives by preventing human losses, reducing environmental impacts, and ensuring safer and more responsible energy use.

In the Peruvian context, LPG is the primary residential fuel, used by approximately 80% of households for food cooking, with an average monthly consumption of one 10 kg cylinder per family [28]. This dependence translates into high risk indices: in 2023 alone, 5916 emergencies due to gas leaks were recorded, and in 2024 the figure remained high with 5787 reported incidents, with Lima being the city with the highest concentration of fires and explosions in homes, restaurants, factories, and buildings [29]. The standard mixture used in Peru corresponds to 60% propane (C_3H_8) and 40% butane (C_4H_{10}), the official proportion adopted in parity price calculations [30]. Within this framework, the present research focuses on propane detection, as it is the predominant component with the greatest impact on domestic and industrial safety, thereby reinforcing the need for innovative monitoring systems that promote safer, more resilient energy management aligned with sustainability principles.

In response to this growing problem, various detection technologies have been developed, ranging from traditional systems to advanced approaches based on artificial intelligence. Conventional systems employ electrochemical or catalytic sensors integrated into IoT platforms with microcontrollers such as Arduino (Arduino LLC, Somerville, MA, USA) or NodeMCU (Espressif Systems, Shanghai, China), enabling basic real-time monitoring and automatic alert transmission.

Although direct gas sensors provide punctual and accurate measurements of propane concentration, thermal imaging offers complementary capabilities that enhance gas detection systems. Thermal sensing enables quantitative estimation of gas concentration through visual analysis, providing an alternative measurement approach that can operate when direct sensors are unavailable or compromised [31]. Furthermore, this visual modality allows continuous remote monitoring from safe locations, eliminating the need to expose personnel and equipment to potentially hazardous environments during inspection and maintenance operations [32]. Additionally, thermal images enable detection of concentration changes across wider fields of view compared to point sensors, allowing detection of gas releases that might occur beyond the immediate proximity of the sensor [33]. More importantly, it provides critical redundancy in industrial safety systems where chemical

sensor failure could compromise early detection of gas leaks. The integration of automated thermal analysis through neural networks could offer continuous supervision without human intervention, improving operational efficiency and reducing maintenance costs in industrial facilities.

Various studies have demonstrated the potential of thermal and infrared imaging in safety and monitoring applications, proving their effectiveness in tasks such as detecting faults in electrical equipment through thermography [34,35], identifying gases in mid-infrared spectral images [36], and early recognition of fires from infrared images [37].

In the case of gas leaks, the use of thermal imaging enables remote detection of associated heat patterns, which enhances safety and reduces the need for physical sensors in the risk area [38–40]. Meanwhile, deep learning techniques have demonstrated their efficacy in the detection, classification, and, in some cases, regression of gas leaks using thermal images. Models such as convolutional neural networks (CNNs) and hybrid architectures have achieved accuracies exceeding 95% in the identification and classification of gas leaks [41–43]. These advances reflect the versatility of thermal vision assisted by artificial intelligence as a non-invasive, wide-reaching detection tool for application in more complex scenarios such as gas leaks.

Furthermore, multimodal approaches have been developed that combine data from sensors and thermal cameras to enhance the robustness and precision of systems [44–47]. These are employed in deep learning models not only for classifying the type of gas or leak size but also for precise localization and segmentation of affected areas, and even estimation of leak magnitude through regression in some cases [48–51]. Various applications have been experimentally validated, both in simulated environments and real-world settings, where they have shown high accuracy, real-time processing capability, and potential for implementation in industrial surveillance systems [52,53]. These results confirm that deep learning-based techniques overcome several limitations of conventional sensors.

Efforts in visual detection of leaks through thermal imaging and deep learning techniques have predominantly focused on gases such as hydrogen, natural gas, methane (CH_4), carbon dioxide (CO_2), and hydrocarbon combinations associated with natural gas, demonstrating the feasibility of estimating concentrations in gaseous flows [54,55]. Models combining sensors and thermal vision to identify different gases in complex mixtures have also been tested, achieving improvements in robustness and precision [56]. Nevertheless, despite these advances, focus on propane (C_3H_8), or on representative LPG mixtures, has received scarce attention; consequently, a thermal vision model based on deep learning specialized in quantitative estimation of propane concentrations in real operational contexts has not been consolidated thus far. This gap is significant, as propane is the major component in LPG widely used in residential and industrial applications; therefore, there exists an unmet demand for methodologies capable of detecting, quantifying, and monitoring propane leaks with the robustness, coverage, and automation offered by advanced thermal vision methods.

Given this methodological and contextual gap, we pose the following research questions: Is it possible to train deep learning models that not only detect the presence of LPG but also estimate its concentration from thermal patterns? Which architectures prove most efficient in scenarios with limited data and thermal noise? And finally, how can these models be optimized considering the specific composition of Peruvian LPG (60% propane, 40% butane)?

To address these research questions, this work presents PropNet-R, a specialized convolutional neural network architecture designed specifically for quantitative estimation of propane concentrations from thermal images. Unlike generic architectures such as SqueezeNet, VGG19, or ResNet50, originally conceived for classification tasks on natural

images, PropNet-R incorporates architectural components optimized for regression of thermal patterns associated with different propane gas concentrations. The model was trained and validated using an experimental dataset obtained under controlled laboratory conditions, where thermal images were captured synchronized with precise concentration measurements expressed in ppm. The effectiveness of PropNet-R is evaluated comparatively against three reference architectures (SqueezeNet, VGG19, and ResNet50), all adapted through fine-tuning for the regression problem, demonstrating superior performance in key metrics such as R^2 , mean absolute error (MAE), and Pearson correlation.

The remainder of this document is organized as follows: Section 2 describes the materials and methods employed; Section 3 presents the results obtained; Section 4 provides analysis and discussion of the findings; and finally, Section 5 presents the study conclusions.

2. Materials and Methods

2.1. Hardware for Multi-Sensor Data Collection for Gas Leak Detection

We developed a monitoring system based on IoT technology [57–59] to measure propane gas concentration. The system comprises an electronic board that integrates a gas sensor and a thermal camera, connected to a Raspberry Pi 4 Model B (Raspberry Pi Foundation, Cambridge, UK) running Raspberry Pi OS 13 (Trixie, 64-bit) development board that acts as a database server in an edge computing environment [60,61], as shown in Figure 1. Python 3.12.7 was employed as the programming language for data acquisition and structured storage.

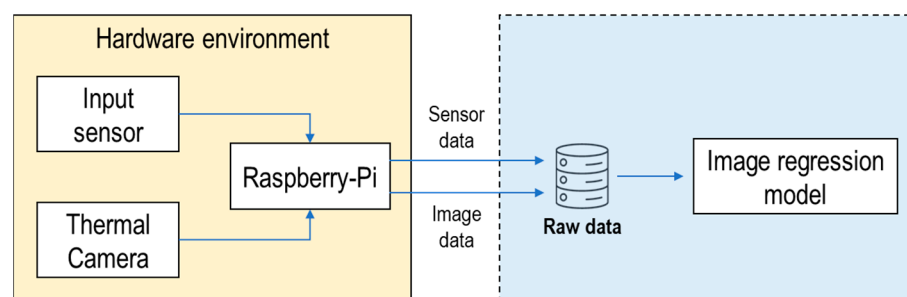


Figure 1. High-level architecture of the data acquisition system using sensors and thermal camera.

Figure 2a illustrates the design of a custom shield-type printed circuit board (PCB), while Figure 2b depicts its integration with the Raspberry Pi module and the direct connection of its pins without requiring additional external components. This PCB enables the parallel acquisition of numerical data from the gas sensor and thermal images from the camera, which are subsequently transmitted to the Raspberry Pi module for processing and storage. Full hardware specifications are listed in Appendix A, Table A1.

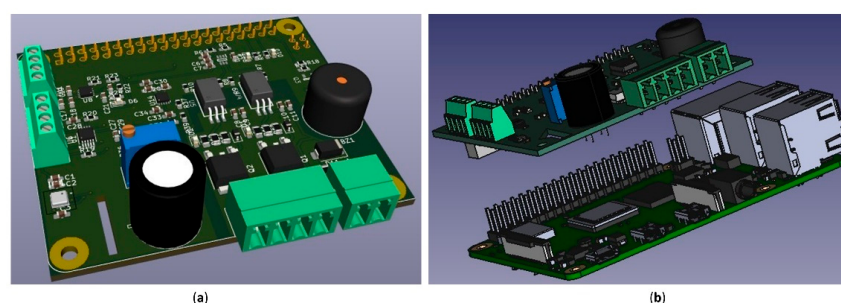


Figure 2. Electronic module design and integration: (a) custom shield-type PCB and (b) coupling onto the Raspberry Pi module.

The experimental procedure began with the injection of gas from an LPG cylinder over a period of one minute, followed by a ten-minute dispersion interval inside the controlled glass chamber. This injection–dispersion cycle was repeated several times throughout the experiment. During each session, thermal images and gas sensor readings were continuously recorded at a sampling frequency of 5 s, over a total duration of approximately 120 min distributed across three different days. As a result, a dataset comprising 4860 samples was obtained, simultaneously integrating both visual and sensor information for subsequent analysis. The complete experimental setup within the controlled glass chamber environment is illustrated in Figure 3.

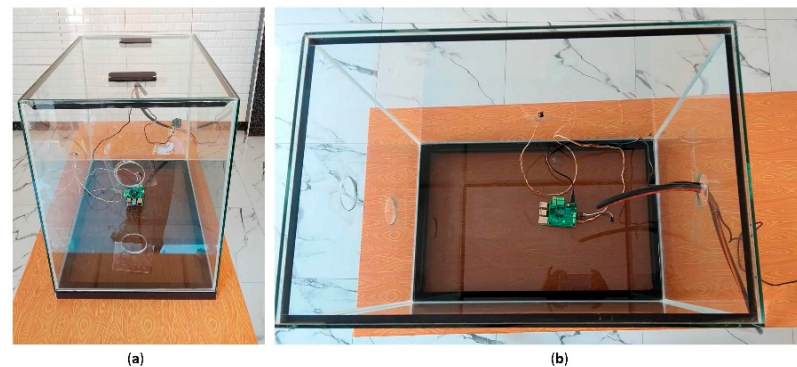


Figure 3. Experimental setup in glass chamber: (a) front view of the electronic circuit and (b) top view of the internal arrangement.

We conducted continuous monitoring of environmental conditions within the controlled glass chamber during the propane dispersion sessions. The recorded parameters were ambient temperature of 46.9 ± 2.3 °C, relative humidity of $22 \pm 3.6\%$, and atmospheric pressure of 989 ± 1.2 hPa. These values remained within stable ranges throughout the experiment, ensuring the consistency and reliability of thermal image measurements and gas sensors. The distribution of these environmental parameters is presented in Figure A1.

2.2. Framework for Quantitative Estimation of Propane Gas Concentration

Figure 4 presents the proposed framework for quantitative estimation of propane concentration from thermal images. This framework is structured into four main stages: (1) Data Loading, (2) Data Preprocessing, (3) Model Training, and (4) Model Evaluation.

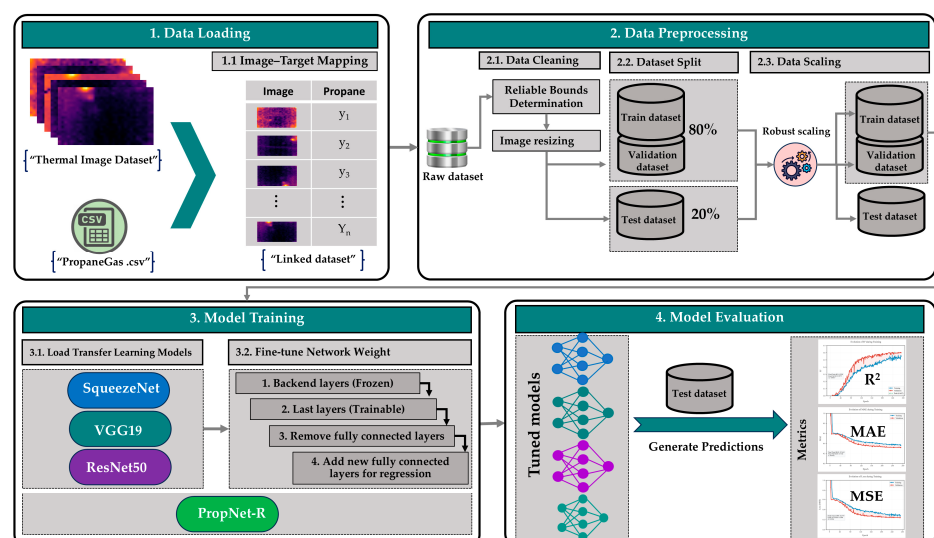


Figure 4. Proposed framework for quantitative estimation of propane concentration.

2.2.1. Data Loading

At this stage, the dataset was structured from the information collected during the experimental procedure. A total of 4860 color thermal images were available, each with a resolution of 960×720 pixels, synchronously captured with propane concentration measurements expressed in parts per million (ppm). These measurements were stored in a CSV file. The correspondence between each image and its associated concentration value was established through timestamp matching, resulting in a regression-oriented dataset in which each instance contains the image file path and the corresponding quantitative propane concentration value.

2.2.2. Data Preprocessing

Data preprocessing plays an important role given its influence on deep learning model performance [34,62], particularly in regression problems with thermal images [34]. It has been demonstrated that even minor variations in preprocessing procedures can generate greater variability than that introduced by modifications in network architecture, evidencing their critical impact on results [63]. The following subsections describe the specific activities carried out during this phase.

Data Cleaning

Within the preprocessing stage, data cleaning constitutes an essential aspect. In this case, the employed sensors could be exposed to external interference that manifests as noise in the measurements. Such sensor-induced noise can significantly affect machine learning model performance; therefore, its proper treatment is essential to minimize prediction error [64].

To ensure the reliability of the observations and to discard measurements dominated by instrumental noise or extreme outliers, the $k\sigma$ rule was applied. In this approach, two data subsets are considered: $\mathcal{L}_{\min}$, comprising the 15% lowest observations of propane concentration, and $\mathcal{L}_{\max}$, corresponding to the 15% highest. For each subset, the mean μ and the standard deviation σ were calculated. Finally, κ represents the confidence factor, acting as a weighting parameter that determines the degree of tolerance to the natural variability of the data: larger κ values lead to wider thresholds, whereas smaller values yield stricter thresholds. Based on these values, the reliable minimum and maximum thresholds were defined, as shown in Equations (1) and (2).

$$T_{\min} = \mu\mathcal{L}_{\min} + \kappa\sigma\mathcal{L}_{\min}, \quad (1)$$

$$T_{\max} = \mu\mathcal{L}_{\max} + \kappa\sigma\mathcal{L}_{\max}, \quad (2)$$

In this work, $\kappa = 3$ was used, in accordance with the three-sigma rule commonly applied in statistical process control, anomaly detection, and sensor noise filtering [65].

Figure 5 displays the distribution of propane gas concentration measurements recorded before (blue) and after the data filtering process (light coral), through which observations significantly affected by sensor noise were systematically removed.

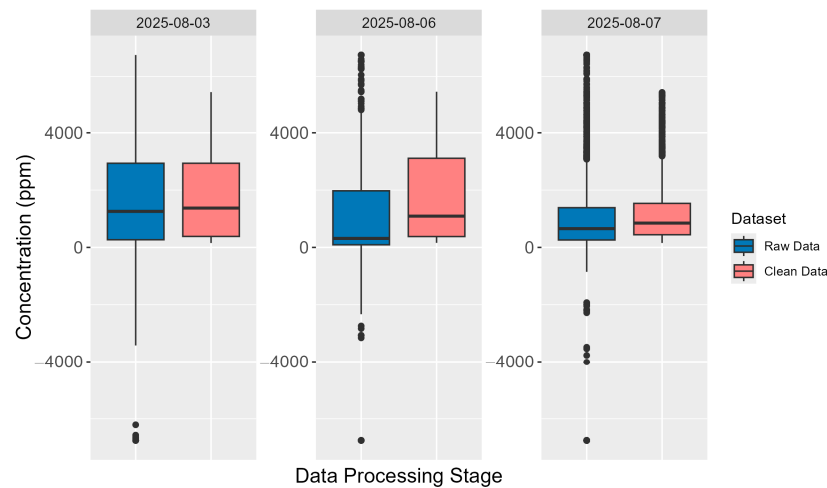


Figure 5. Distribution of propane gas concentration measurements before and after data filtering.

To conclude this phase, thermal images were resized to 256×256 pixels using bilinear interpolation, standardizing their dimensions to ensure compatibility with the regression model. Figure 6 shows three randomly selected examples after applying this procedure.

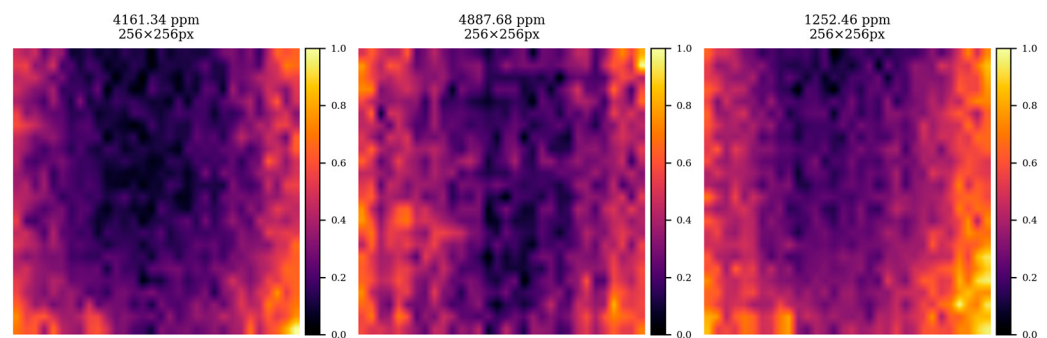


Figure 6. Thermal images representing propane gas concentration after spatial resizing.

As a result of this task, a clean dataset was obtained comprising 3574 propane gas concentration records, measured in parts per million, along with their corresponding associated thermal images.

Data Splitting

A fundamental step in constructing convolutional neural network models is the partitioning of the dataset into training, validation, and test subsets [66–68]. While the training set is employed to adjust the model parameters, the validation set enables monitoring of its performance during the fitting process and prevents overfitting. Finally, the test set remains isolated and is used exclusively to evaluate the model's generalization capability once training is completed.

The dataset was divided using an initial proportion of 80% for training and 20% for testing. From the training subset, an additional 20% was further allocated for validation, resulting in 2287 images for training, 572 for validation, and 715 for testing. The partitioning was performed randomly using a fixed random seed to ensure reproducibility and to prevent data leakage between subsets. Each image was assigned exclusively to one subset (training, validation, or testing), thereby eliminating any overlap or similarity and ensuring the statistical independence of the data partitions.

Data Scaling

Data scaling constitutes an essential step in preprocessing, as it ensures that all input features are within a comparable range [69,70]. In regression tasks with convolutional neural networks, scaling the target variable is particularly important, as it reduces the magnitude of values to a more uniform range. This not only facilitates the network's ability to learn more stable relationships between the representations extracted from images and the desired output, but also improves numerical precision during training and accelerates model convergence [70,71].

In this study, robust scaling using RobustScaler from scikit-learn was employed to mitigate outlier effects in propane concentration measurements. The scaler was fitted exclusively on the training set and applied to all datasets using consistent parameters. This technique utilizes median and interquartile range, making it suitable for non-Gaussian distributions with outliers. The mathematical formulation is detailed in Appendix A.2.

2.2.3. Model Training

Model training was conducted using the PyTorch deep learning framework (version 2.6.0 + cu118), which offers native support for CUDA 11.8 and enabled GPU acceleration throughout the experiments. This phase involved two key tasks: loading pre-trained models via transfer learning and fine-tuning their weights for regression. Both are detailed below.

Load Transfer Learning Models

Transfer learning constitutes a machine learning approach where a pre-trained model is adapted to solve a new specific problem [72]. Through this technique, models can be initialized with weights previously optimized on extensive datasets such as ImageNet [34]. This approach is particularly valuable in contexts where data are scarce or difficult to obtain, as in our case: thermal images representing propane gas concentrations in parts per million.

Although most transfer learning applications in thermal imaging have focused on classification, their principles of low-level feature extraction are equally useful for regression tasks. The initial layers of CNNs learn edge, texture, and gradient detectors that are invariant to the spectral domain, which facilitates their transfer to thermal images. A direct precedent in regression is provided by Zhang et al. [36], who employed ResNet50 with mid-infrared spectral images to predict CO₂ concentrations in exhaust gases, demonstrating the feasibility of pretrained CNNs for continuous estimations in the infrared domain.

In our case, we selected SqueezeNet [73], VGG19 [74], and ResNet50 [75] for three reasons. First, they have shown positive results in thermal and infrared imaging: SqueezeNet, VGG19, and ResNet50 have been applied to fault detection in electrical equipment through thermography [34,35], gas detection in mid-infrared spectral images [36], and fire recognition with infrared images [37]. Second, they represent contrasting architectural paradigms: SqueezeNet (~1.2 M parameters) as a lightweight and efficient network, VGG19 (~144 M) as a deep sequential architecture, and ResNet50 (~25 M) as a residual network that enables greater trainable depth, which allowed us to analyze the effect of complexity in the thermal domain. Third, all of them provide pretrained weights on ImageNet, whose low-level feature extractors have been shown to be transferable to thermal images under fine-tuning schemes.

Fine-Tune Network Weight

The fine-tuning technique consists of selectively adapting a previously trained model to improve its performance on a specific task through strategic modifications to its architecture and configuration [76]. This approach typically focuses on the final layers of the

model, as they are most directly responsible for decision-making in tasks such as classification or regression. However, fine-tuning is not limited to structural adjustments: it also involves optimizing key hyperparameters, such as learning rate and batch size, which directly influence convergence speed and the model's ability to effectively adapt to new datasets [72,77].

The following presents the application of fine-tuning on the SqueezeNet, VGG19 and ResNet50 models for predicting propane gas concentration in ppm from thermal images.

- The implementation of SqueezeNet v1.1 retained the frozen initial convolutional layer to preserve low-level feature extraction, while fine-tuning all subsequent layers. After adapting it to the regression task, the final model contained 723,009 parameters, of which 721,217 were trainable and 1792 remained frozen. Fine-tuning focused on the last ten layers, corresponding to Fire modules 2 through 9 and the final convolutional layer.

The original classifier was redesigned for regression by incorporating a channel reduction layer, a dropout-based regularization layer, and an adaptive average pooling mechanism, ultimately producing a scalar value representing propane gas concentration. Figure 7 presents a conceptual diagram of the architecture and the training configuration.

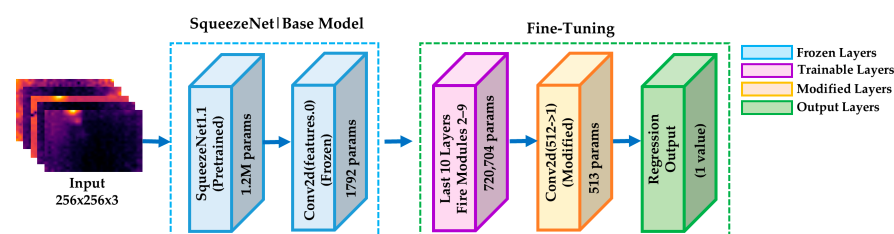


Figure 7. Fine-tuned SqueezeNet architecture for propane concentration estimation.

In Table 1, we present the specific details of the unfrozen layers for training in this model.

Table 1. Fine-tuned layers of the SqueezeNet architecture.

Layer Block	Type	Trainable	Input Dimension *	Output Dimension *	Activation	# Parameters
Features.3 (Fire)	Fire	Yes	[−1, 64, 63, 63]	[−1, 128, 63, 63]	ReLU	11,408
Features.4 (Fire)	Fire	Yes	[−1, 128, 63, 63]	[−1, 128, 63, 63]	ReLU	12,432
Features.6 (Fire)	Fire	Yes	[−1, 128, 31, 31]	[−1, 256, 31, 31]	ReLU	45,344
Features.7 (Fire)	Fire	Yes	[−1, 256, 31, 31]	[−1, 256, 31, 31]	ReLU	49,440
Features.9 (Fire)	Fire	Yes	[−1, 256, 15, 15]	[−1, 384, 15, 15]	ReLU	104,880
Features.10 (Fire)	Fire	Yes	[−1, 384, 15, 15]	[−1, 384, 15, 15]	ReLU	111,024
Features.11 (Fire)	Fire	Yes	[−1, 384, 15, 15]	[−1, 512, 15, 15]	ReLU	188,992
Features.12 (Fire)	Fire	Yes	[−1, 512, 15, 15]	[−1, 512, 15, 15]	ReLU	197,184
Regression Head	Conv2d + GAP + Flatten	Yes	[−1, 512, 15, 15]	[−1, 1]	Linear	513
Total						721,217

* Dimensions are reported in PyTorch 2.6.0+cu118 format: (Batch size, Channels, Height, Width). # = number.

- In the case of VGG19, a conservative fine-tuning strategy was adopted to mitigate early overfitting identified in preliminary experiments. The original architecture comprises approximately 143.7 million parameters. Following adaptation to the regression problem, the final model was reduced to approximately 23.2 million parameters, of which approximately 5.6 million remained trainable and 17.7 million were kept frozen.

Training was concentrated solely on the last convolutional layer of the feature extractor and on the new fully connected head designed for the regression task.

The fine-tuning consisted of replacing the original classifier with an output head specifically designed for regression tasks. This configuration includes a dimensionality reduction layer, a nonlinear activation function, and regularization through dropout. Figure 8 illustrates the adapted architecture, highlighting the unfrozen components, the modified regression head, and the applied regularization strategy.

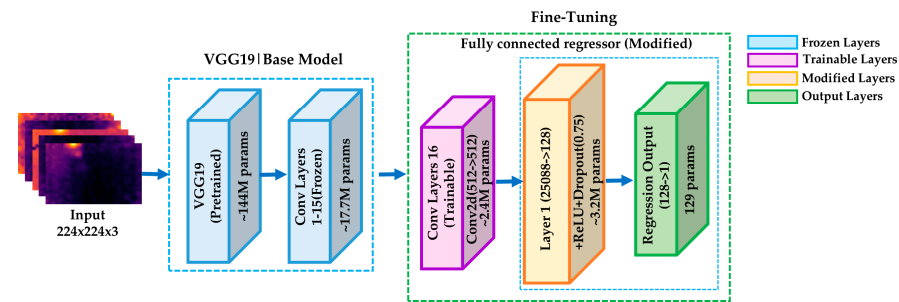


Figure 8. Fine-tuned VGG19 architecture for propane concentration estimation.

We present the specific details of the unfrozen layers for training of this model in Table 2.

Table 2. Fine-tuned layers of the VGG19 architecture.

Layer Block	Type	Trainable	Input Dimension *	Output Dimension *	Activation	# Parameters
Features.35	Conv2d	Yes	$[-1, 512, 14, 14]^*$	$[-1, 512, 14, 14]^*$	ReLU	2,359,808
FC Layer 1	Fully Connected	Yes	$[-1, 25,088]$	$[-1, 128]$	ReLU	3,211,392
Regression Head	Fully Connected	Yes	$[-1, 128]$	$[-1, 1]$	Linear	129
Total						5,571,329

* Dimensions are reported in PyTorch 2.6.0+cu118 format. Batch dimension (−1) indicates variable batch size. # = number.

- The base architecture of ResNet50, composed of approximately 23.6 million parameters, was initially frozen in its entirety. Subsequently, the residual blocks were organized into a unified list grouping the four main sets of the network, layer1 (3 blocks), layer2 (4 blocks), layer3 (6 blocks), and layer4 (3 blocks), constituting a total of 16 architectural components. From this structure, only the upper portion of the model was enabled for training, corresponding to the last block of layer4 (layer4.2) and the regression head. Thus, the model was reduced to approximately 4.5 million trainable parameters, while 19.1 million remained frozen.

As with the two previous baseline models, the final layer was replaced with a new output head designed for regression. This incorporates dropout regularization, an intermediate dimensional reduction layer, nonlinear activations, and additional dropout before the final regression output. Figure 9 graphically presents this architecture, highlighting the unfrozen components, the modified classifier, and the applied regularization strategy.

of the hyperparameter space. We present the hyperparameters, search space, and optimal values for each model in Appendix A.3, Table A2.

- The custom convolutional neural network architecture (PropNet-R) was designed to quantitatively estimate propane gas concentration from thermal images, predicting a single scalar value in ppm corresponding to the entire image, as recorded by the sensor at the time of capture. The network is organized into four progressive convolutional blocks that follow a systematic channel expansion pattern: $3 \rightarrow 32 \rightarrow 64 \rightarrow 128 \rightarrow 256$.

The expansion pattern in PropNet-R was adopted based on empirical design principles widely used in convolutional architectures, where progressive enlargement of feature maps enables hierarchical feature extraction. This geometric progression allows hierarchical extraction of features: from low-level features (edges, textures) in initial layers to complex semantic representations in deep layers [74,75,80]. Similar patterns have been successfully employed in recent studies on thermal image analysis and gas detection [81–83], where the increase in channel depth contributed to better representation and regression accuracy.

Each block comprises two sequential convolutional layers with 3×3 kernels, followed by batch normalization, non-linear activation, and spatial downsampling through max-pooling operations. This hierarchical configuration enables the extraction of features ranging from low-level patterns to complex domain-specific representations.

To enhance generalization and prevent overfitting in feature maps, spatial regularization was applied after each convolutional block using a probabilistic masking strategy. The feature extraction process concludes with a global aggregation mechanism that compresses the spatial dimensions into a one-dimensional vector of 256 elements, ensuring invariance to input resolution.

The final regression head adopts a minimalist design with three fully connected layers: $256 \rightarrow 128 \rightarrow 64 \rightarrow 1$. It integrates normalization in the initial dense layer and applies dropout-based regularization in the intermediate layers to improve robustness.

The complete architecture comprises approximately 1.22 million trainable parameters, primarily distributed between the convolutional blocks (1,174,176 parameters, 96.6%) and a compact regression head (41,409 parameters, 3.4%). Weight initialization was performed using the Kaiming (He initialization) scheme, which promotes stable gradient propagation during training. Figure 10 illustrates the detailed structure of PropNet-R, highlighting the active components and regularization strategies employed.

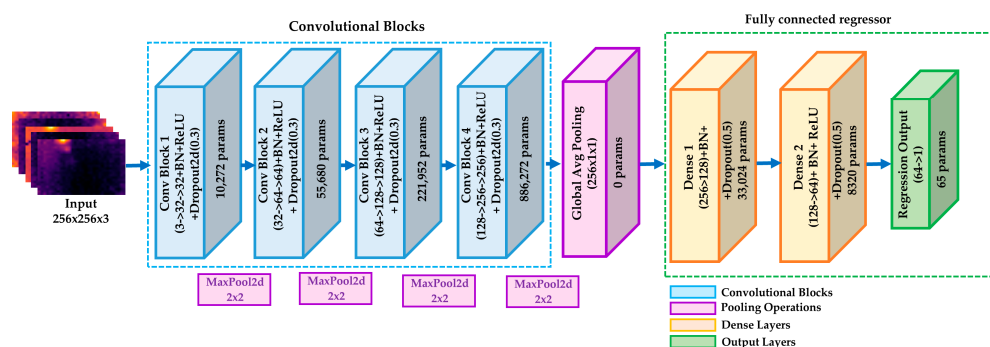


Figure 10. PropNet-R architecture for propane concentration estimation.

2.2.4. Model Evaluation

Model performance was assessed using the test dataset. The validation set was employed during the training process to monitor model fitting and support hyperparameter selection, whereas the test set remained completely isolated and was used exclusively for the final performance evaluation. Since the target variable is continuous, standard regression metrics were used: coefficient of determination (R^2), mean absolute error (MAE),

and mean squared error (MSE). These metrics allow quantifying prediction accuracy and characterizing the goodness of fit of the model in regression scenarios.

Let y_i be the observed value, $\hat{y}_i$ the predicted value, $\bar{y}$ the mean of the observed values, and n the number of observations in the test set. Based on these variables, the metrics are mathematically formalized in Equations (3)–(5).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (3)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|, \quad (4)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2, \quad (5)$$

3. Results

In this section, we present the results obtained with our PropNet-R architecture for estimating propane gas concentration from thermal images. To evaluate its effectiveness, we compared PropNet-R's performance with three widely recognized models in the computer vision field: SqueezeNet, VGG19, and ResNet50, all adapted through fine-tuning to address our regression problem.

Figure 11 illustrates the evolution of the coefficient of determination (R^2) during the training of the four evaluated models. Although 300 training epochs were initially defined, all models stopped earlier due to the early stopping mechanism with a patience of 20. Figure 11a shows that PropNet-R, despite requiring approximately 280 epochs to converge, exhibits a stable and consistent upward trend, achieving the best validation performance with an R^2 of 0.607. SqueezeNet (Figure 11b) achieved the second-highest performance with an R^2 of 0.464, converging after approximately 80 epochs. The VGG19 and ResNet50 models (Figure 11c,d, respectively) obtained R^2 values of 0.352 and 0.305, indicating a lower predictive capacity on the validation set and suggesting greater difficulty in learning meaningful patterns from thermal images.

The loss function plots shown in Figure 12a–d allow for an analysis of model convergence and provide insights into the training dynamics. In particular, Figure 12a shows that PropNet-R exhibits a constant and sustained reduction of the mean squared error (MSE), reaching a final value of 0.241. Among the baseline models, SqueezeNet (Figure 12b) converges with an MSE of 0.331, VGG19 (Figure 12c) reaches 0.395, while ResNet50 (Figure 12d) exhibits the highest MSE at 0.414. Although PropNet-R requires more training epochs, it achieves a more stable convergence compared to the baseline models.

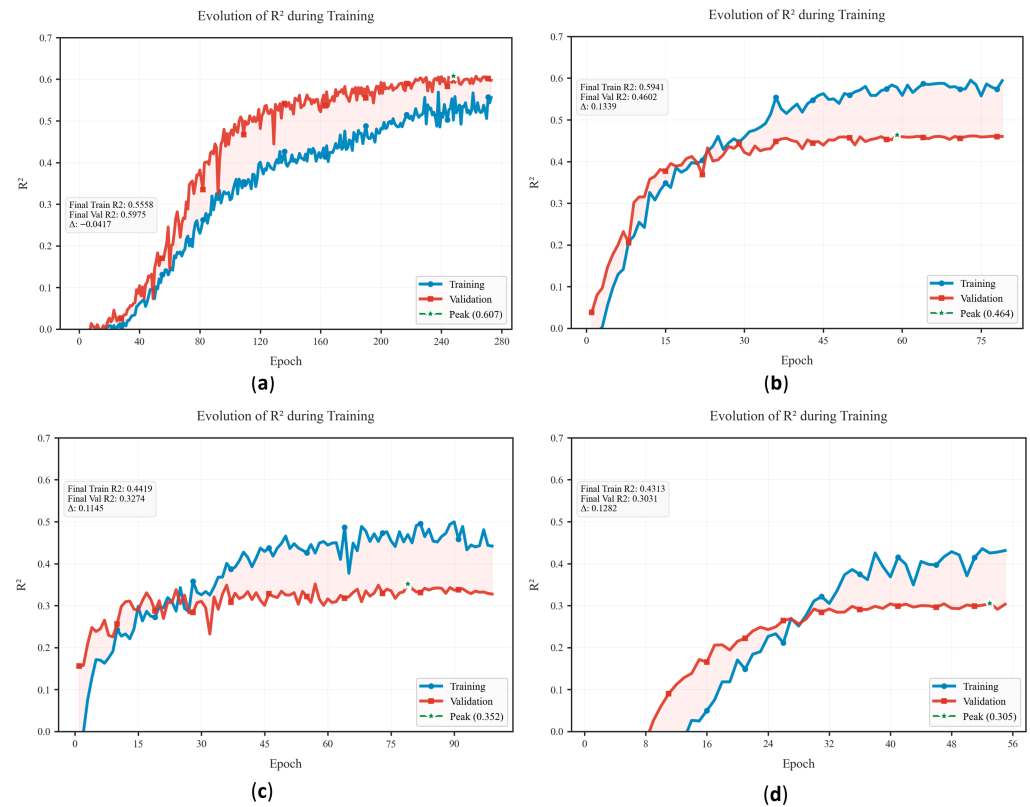


Figure 11. Evolution of the coefficient of determination (R^2) during training for (a) PropNet-R; (b) SqueezeNet; (c) VGG19 and (d) ResNet50.

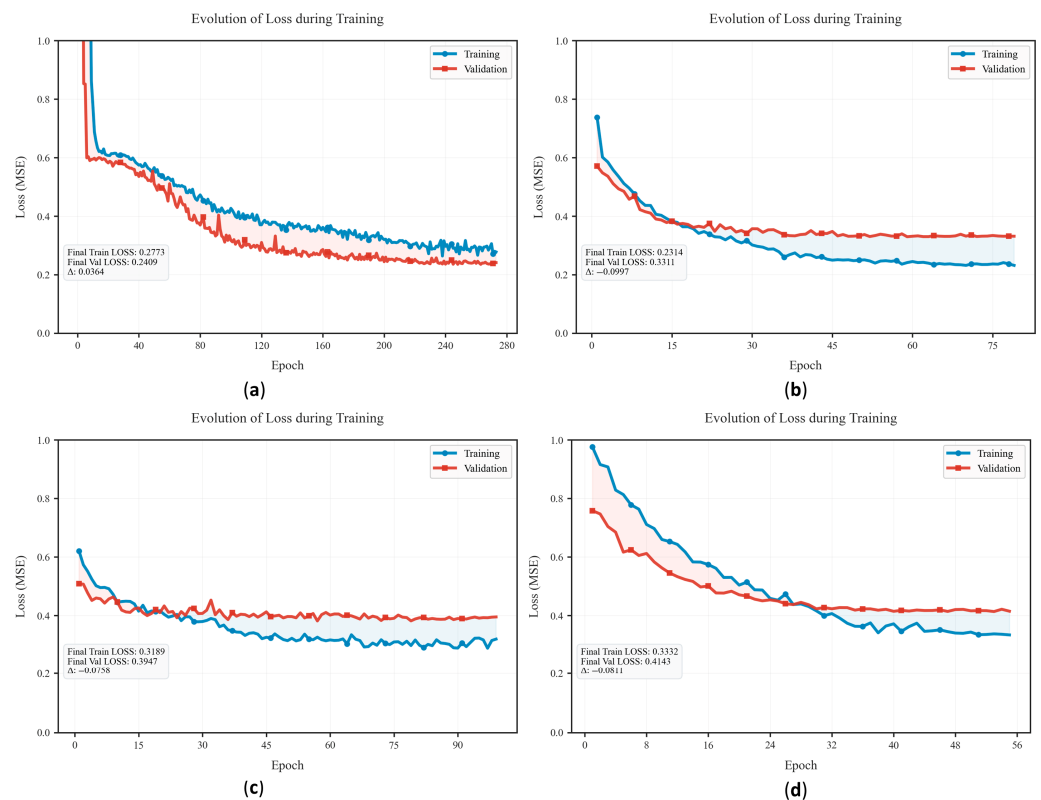


Figure 12. Evolution of Loss (MSE) during training for (a) PropNet-R; (b) SqueezeNet; (c) VGG19 and (d) ResNet50.

The evolution of mean absolute error (MAE), shown in Figure 13, confirms the patterns observed in previous metrics. PropNet-R (Figure 13a) maintains its characteristic stability during convergence, achieving a final MAE of 0.314, the lowest among the evaluated models. SqueezeNet (Figure 13b) records the second-lowest final MAE at 0.391, while VGG19 (Figure 13c) and ResNet50 (Figure 13d) reach values of 0.425 and 0.449, respectively. This progression aligns with the performance ranking observed in the test metrics reported in Table 5.

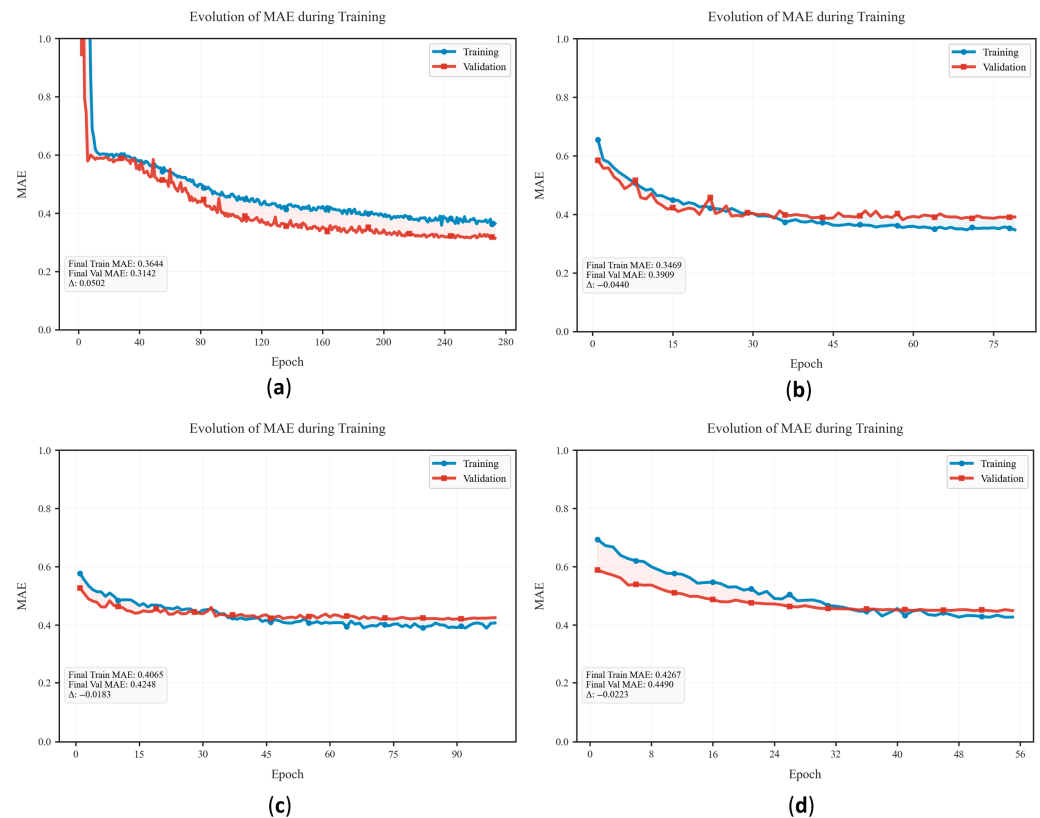


Figure 13. Evolution of mean absolute error (MAE) during training for (a) PropNet-R; (b) SqueezeNet; (c) VGG19; and (d) ResNet50.

Table 5. Comparative performance of the models evaluated on training and test sets *.

Models	R ²		MAE		MSE		RMSE		Pearson's r	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
PropNet-R	0.607	0.614	0.328	0.333	0.236	0.240	0.485	0.489	0.781	0.786
SqueezeNet	0.451	0.397	0.390	0.418	0.329	0.374	0.574	0.612	0.673	0.637
VGG19	0.364	0.280	0.420	0.465	0.381	0.447	0.617	0.668	0.655	0.564
ResNet50	0.311	0.236	0.447	0.496	0.413	0.474	0.643	0.689	0.583	0.514

* All metrics were computed on the normalized scale used during training. MAE and RMSE values represent fractions of the interquartile range (IQR) of the original ppm distribution, as derived from the RobustScaler transformation.

Table 5 shows that PropNet-R achieves superior performance on the test set, with MSE = 0.240 and RMSE = 0.489, demonstrating improved generalization with nearly identical metrics between training and test sets (Δ MSE = 0.004). This stability indicates effective regularization that prevents overfitting while maintaining predictive accuracy. The MSE values confirm that PropNet-R minimizes prediction variance more effectively than the baseline models.

In contrast, ResNet50 and VGG19 exhibit overfitting, with MSE increases of 0.061 and 0.066 between training and test sets, reaching test values of 0.474 and 0.447, respectively. Despite reasonable training performance, these pre-trained models struggle to generalize, likely due to their large parameter counts (approximately 23.6 and 26.4 million in the adapted versions), which favor memorization of thermal noise over meaningful feature extraction. SqueezeNet shows intermediate behavior (test MSE = 0.374, Δ MSE = 0.045), consistent with its more compact architecture of 723,000 parameters in the domain-adapted version.

Regarding the coefficient of determination, PropNet-R maintains virtually identical R^2 values between training (0.607) and testing (0.614), evidencing generalization capability for quantitative estimation of propane concentrations. Additionally, the Pearson correlation coefficient ($r = 0.786$) validates the strong linear relationship between predictions and actual values. These results indicate that, under conditions of limited data and presence of thermal noise, PropNet-R, with its feature extraction architecture ($3 \rightarrow 32 \rightarrow 64 \rightarrow 128 \rightarrow 256$) and regression head ($256 \rightarrow 128 \rightarrow 64 \rightarrow 1$), represents the most efficient option, combining predictive capacity with cross-set stability.

Table 6 summarizes the computational efficiency of the evaluated models. PropNet-R stands out for achieving the lowest inference time (4.897 ± 0.005 ms per image) and the lowest GPU memory usage (408.53 MB), outperforming the reference models in both aspects. In terms of trainable parameters, PropNet-R comprises approximately 1.2 million—more than SqueezeNet (721,217)—yet remains suitable for scenarios involving limited data and thermal noise, where efficiency is prioritized without compromising representational capacity.

Table 6. Computational efficiency of CNN models in thermal regression.

Model	Inference Time	GPU Used (MB)	Trainable/Total Params
SqueezeNet	8.081 ± 0.008	514.51	721,217/723,009
VGG19	7.997 ± 0.009	426.36	3,211,521/23,235,905
ResNet50	17.001 ± 0.008	662.20	4,528,257/23,573,697
PropaNet-R	4.897 ± 0.005	408.53	1,231,969/1,231,969

4. Discussion

This study addressed the challenge of quantitatively estimating propane concentrations from thermal images using deep learning. The results reveal clear differences in both predictive performance and generalization capability across the evaluated models. PropNet-R achieved a coefficient of determination $R^2 = 0.614$, explaining approximately 61% of the variability in propane concentrations. This value represents an improvement of 21.7 percentage points over the second-best model, SqueezeNet ($R^2 = 0.397$). The difference is both technically significant and operationally relevant in gas monitoring applications, where predictive accuracy directly impacts system reliability.

The transfer learning baselines displayed different levels of adaptation to thermal imaging despite fine-tuning. ResNet50 and VGG19 showed larger training–validation gaps than SqueezeNet, likely reflecting an architectural mismatch between natural-image priors and thermal representations. Their larger parameter counts (23.6 M and 23.2 M) also demanded stronger regularization to prevent memorization of training-specific noise instead of learning generalizable concentration–temperature relationships. Among these baselines, SqueezeNet achieved the best performance, outperforming both deeper architectures. Its compact structure contributed to this outcome, as fine-tuning all layers except the first

convolution enabled the network to adapt effectively to thermal-specific features without severe overfitting.

For VGG19, unfreezing additional convolutional blocks beyond conv5 caused rapid overfitting even with dropout, so training was limited to the last block and the regression head, yielding more stable results. In ResNet50, extending fine-tuning beyond layer4.2 also reduced generalization. To address this, a Batch Normalization layer was added, dropout rates were adjusted to [0.4, 0.3], and the early stopping patience was reduced from 20 to 15 epochs to halt training once validation loss plateaued. SqueezeNet, due to its compact design, allowed broader fine-tuning—all layers except the initial convolution were retrained—achieving adaptation to thermal features without severe overfitting. The final settings were determined through systematic optimization of learning rate and weight decay (Table A2) combined with selective layer freezing to ensure stable convergence. Additional experiments tested dropout values of [0.5, 0.7, 0.75] across all models, as well as wide search spaces for learning rate and regularization parameters (Table A2). Although other setups, such as partial unfreezing of earlier blocks or layer-wise adaptive learning rates, were explored, the chosen configuration offered the best balance between stability and generalization for this dataset.

Our findings are related to those of Elgohary et al. [35], who evaluated four transfer learning models (AlexNet, SqueezeNet, VGG19, and GoogLeNet) applied to thermal images of electrical transformer rooms for fault classification. In their study, SqueezeNet achieved a validation accuracy of 87.83% and a loss of 0.293. Similarly, Mahmoud et al. [34] evaluated eleven pre-trained architectures for binary fault detection in switchgear using thermal images, where SqueezeNet achieved a test accuracy of 96.77%. In our case, although the objective was different—quantitative estimation of propane concentrations through regression—SqueezeNet behaved in a relatively more stable manner than the other reference architectures, achieving $MSE = 0.374$ and $R^2 = 0.397$ on the test set. While this level of variance explanation cannot be considered high, it does suggest that, among the generic models considered, SqueezeNet offers a more consistent foundation for addressing regression tasks with thermal data.

Regarding ResNet50, our findings suggest a tendency toward overfitting, as indicated by a performance gap between training and testing phases (MSE increasing from 0.413 to 0.474; $\Delta MSE = 0.061$). This behavior contrasts with that reported by Zhang et al. [36], who developed a CO_2 concentration prediction model in ship emissions from mid-infrared spectral images using ResNet50. In their study, the model demonstrated high predictive accuracy and low discrepancy with respect to actual values with $MAE < 0.15$, validating the capability of this architecture to capture the relationship between radiometric signals and gas concentrations under controlled laboratory conditions. The divergence from our results could be explained by the more complex and noisy nature of thermal data in the propane monitoring context, where spatial resolution and environmental conditions introduce additional variability.

The results suggest that PropNet-R presents promising characteristics for integration into continuous gas monitoring systems, acting as a complement to conventional chemical sensors. Unlike CNN-based approaches relying solely on binary detection, the proposed model offers quantitative estimates that enable implementation of gradual response protocols adjusted to specific concentration levels. This functionality contributes to improved responsiveness in industrial environments, while reinforcing critical redundancy in safety systems: when direct sensors fail or are compromised, automated thermal analysis ensures continuity of monitoring and reduces personnel exposure to hazardous conditions [32]. Additionally, this approach enables detection of concentrations across wider fields of view

compared to point sensors [33]. Collectively, the complementarity between both modalities constitutes a safer, more resilient, and sustainable strategy for gas leak management.

Furthermore, PropNet-R's computational efficiency reinforces its practical viability. With inference times below 5 ms per image and moderate memory requirements, the model processes continuous thermal image streams in near real-time on standard hardware. This performance, combined with its fully trainable architecture, enables effective integration into continuous monitoring systems with rapid leak response. Note that this study evaluated only prediction performance; total system response time, including image acquisition and preprocessing, remains for future assessment.

Despite these computational advantages, the results must be interpreted within the constraints of the experimental design. Measurements were conducted in controlled laboratory conditions using a glass chamber, which enabled precise variable control but does not fully represent real operational complexity. The dataset, while carefully synchronized, covers a specific concentration range and environmental profile. Factors such as ambient temperature variations, humidity fluctuations, air currents, and external thermal interference—common in industrial settings—were not systematically evaluated and may affect model performance. Additionally, the LPG composition used (60% C₃H₈, 40% C₄H₁₀, specific to Peru) may limit applicability to regions with different propane–butane ratios.

Practical deployment introduces additional considerations. While the model runs efficiently on standard computing hardware, thermal imaging cameras remain necessary for data acquisition. System calibration across diverse operational environments and long-term performance validation require further investigation. Although performance is reported in normalized units for consistency, future work must verify that prediction errors remain within acceptable margins relative to propane's lower explosive limit (LEL) and occupational exposure standards to ensure safe real-world deployment.

These results establish a foundation for methodological extensions. Validation in uncontrolled industrial environments represents the immediate priority, followed by assessment under variable environmental conditions and extension to other combustible gases common in industrial applications.

5. Conclusions

This study demonstrates that architectures designed for thermal image regression outperform generic transfer learning approaches in quantitative gas concentration estimation. PropNet-R achieved MSE = 0.240 and R² = 0.614. The model surpassed SqueezeNet (MSE = 0.374, R² = 0.397) in both metrics. Deep generic architectures (ResNet50, VGG19) failed to adapt effectively even after fine-tuning, exhibiting considerable overfitting with test MSE values exceeding 0.44 and R² below 0.30, while the proposed specialized architecture outperformed all baseline models.

PropNet-R's inference time below 5 ms and standard hardware requirements enable real-time deployment without specialized computing infrastructure, reducing implementation costs and energy consumption. This computational efficiency aligns with sustainable technology principles while providing quantitative concentration estimates that complement traditional point sensors.

The sustainability implications are direct. PropNet-R strengthens the redundancy of safety systems in facilities handling combustible gases, particularly when direct sensors fail or become compromised. This reduces accident risk and facilitates real-time decision-making. In high-vulnerability scenarios such as processing plants, LPG warehouses, or urban areas with aging infrastructure, its implementation can directly protect human lives, prevent material losses, and ensure regulatory compliance. Likewise, automated thermal

analysis covers broader fields of view than point sensors, establishing a safer, more resilient, and sustainable strategy for gas leak management.

Field validation in industrial environments remains the immediate priority. Testing under variable conditions will establish operational boundaries before deployment. Extension to other combustible gases and edge device optimization represent secondary objectives.

This work establishes thermal image regression as a viable approach for continuous gas monitoring that balances technical performance with sustainability: reduced hardware requirements, lower energy consumption, decreased sensor waste, and improved worker safety. The methodology contributes to SDG 9 (Industry, Innovation and Infrastructure) and SDG 11 (Sustainable Cities and Communities) through safer, more resource-efficient industrial operations.

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Appendix A

Appendix A.1

Table A1 shows the hardware specifications used for multisensor data collection for gas leak detection.

Table A1. System hardware components and specifications.

Component	Model	Key Specifications	References
Processing Unit	Raspberry Pi 4 Model B	ARM Cortex-A72, 40 GPIO pins, Bluetooth 5.0, WiFi	[84]
Gas Sensor	TGS6810	Propane/methane detection, linear response, low power	[85–87]
Thermal Camera	Adafruit MLX90640	32 × 24 IR array, −40 °C to 300 °C, 32 Hz max	[88]
Temperature, humidity, air pressure and air quality sensor	BME690	Operating range Pressure: 300 to 1100 hPa Humidity: 0 to 100% Temperature: −40 to 85 °C	[89]

Appendix A.2

For a given concentration value x , where Q_{75} and Q_{25} represent the 75th and 25th percentiles of the training data, respectively, and Q_{50} represents the median, the robust scaling transformation is defined by Equation (A1).

$$y = \frac{(x - Q_{50})}{(Q_{75} - Q_{25})} \quad (\text{A1})$$

Appendix A.3

Table A2. Search spaces and optimal hyperparameter values for each architecture.

Model	Hyperparameter	Search Space	Optimal Value
SqueezeNet	lr	[0.0000: 0.002] step 0.0001	1.00×10^{-4}
	weight_decay	[0.00: 0.100] step 0.01	6.00×10^{-2}
VGG19	lr	[0.0000: 0.002] step 0.0001	3.00×10^{-4}
	weight_decay	[0.000: 0.050] step 0.005	2.50×10^{-2}
ResNet50	lr	[0.00000: 0.0002] step 0.00001	5.00×10^{-5}
	weight_decay	[0.000: 0.010] step 0.001	7.00×10^{-3}
PropNet-R	lr	[0.000: 0.020] step 0.001	1.00×10^{-3}
	weight_decay	[0.000: 0.010] step 0.001	1.00×10^{-3}

Appendix A.4

Figure A1 presents the daily statistical distributions of temperature, relative humidity, and atmospheric pressure recorded during the propane dispersion experiments.

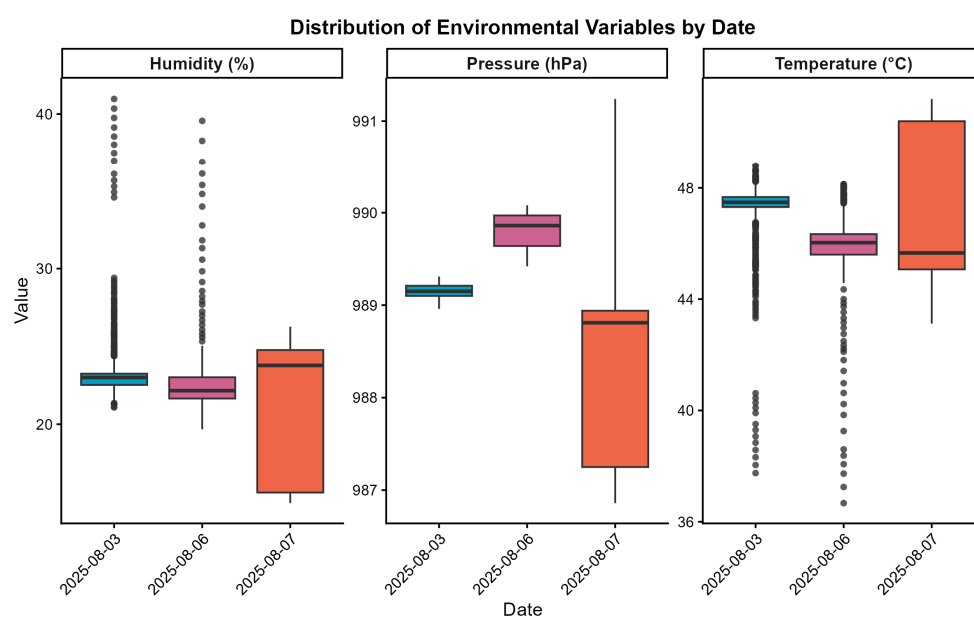


Figure A1. Distribution of Environmental Variables by Date.

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