AN INTEGRATION OF LENET WITH REGULARIZATION TECHNIQUES FOR ELECTRONIC NOSE IN AIR CONTAMINANT CLASSIFICATION

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ABSTRACT: Accurate and rapid air contaminant classification is crucial for electronic nose (e-nose) systems in air quality monitoring applications. Several one-dimensional convolutional neural networks (1D-CNNs) have recently been proposed for the classification of air contaminants using e-nose systems. However, the lack of cross-model evaluation and the limited computational complexity analysis hinder consistent benchmarking among existing 1D-CNN architectures. Additionally, no recent studies have been conducted on integrating regularization techniques into 1D-CNNs in e-nose. Consequently, the effects of different 1D-CNN architectures, including the impact of integrating regularization techniques, have not been investigated. Thus, this study aims to evaluate three existing 1D-CNN architectures (i.e., LeNet, GasNet, and DenseNet) to propose an improved LeNet with regularization techniques (LeNet-R) for e-nose systems in classifying air contaminants. This study adapted the standard LeNet with three regularization techniques (i.e., batch normalization, dropout, and weight decay) to develop the proposed LeNet-R through a series of manual search experiments. Subsequently, LeNet-R was compared with three existing 1D-CNN models in terms of classification performance and computational complexity using a publicly accessible e-nose dataset. The results show that the proposed LeNet-R outperforms the other 1D-CNN models by achieving the highest average accuracy (i.e., 97.60%) and lowest average loss (i.e., 6.50%). Moreover, LeNet-R exhibited the shortest training time (i.e., 86.54 seconds), the shortest inference time (i.e., 1.91 seconds), the fewest total parameters (i.e., 11,644), and the smallest model size (i.e., 45.48 kB) among all the 1D-CNN models. Compared to the standard LeNet, the proposed LeNet-R improved the average accuracy by 1.35%, reduced total parameters and model size by 11%, shortened training time by 36.6%, and decreased inference time by 6.8%. These findings demonstrate that a simpler 1D-CNN integrated with regularization techniques can outperform more complex 1D-CNN models in classifying air contaminants for an e-nose system. This study is the first to show that integrating three regularization techniques into LeNet can improve accuracy and efficiency for e-nose-based air contaminant classification.

ABSTRAK: Pengelasan bahan pencemar udara yang tepat dan pantas adalah penting bagi sistem hidung elektronik (e-nose) pada aplikasi pemantauan kualiti udara. Kebelakangan ini, beberapa rangkaian neural konvolusi satu dimensi (1D-CNNs) telah dibina bagi tujuan klasifikasi bahan pencemar udara menggunakan sistem e-nose. Walau bagaimanapun, ketiadaan penilaian rentas model serta kekurangan kajian terhadap kerumitan pengiraan telah menyukarkan penanda aras konsisten pada model 1D-CNN sedia ada. Tambahan, tiada kajian terkini mengenai integrasi teknik regularisasi ke atas model 1D-CNN dalam bidang e-nose. Akibatnya, pelbagai senibina 1D-CNN, termasuk impak integrasi teknik regularisasi, belum dapat dikaji dengan sewajarnya. Oleh itu, kajian ini bertujuan menilai tiga senibina 1D-CNN sedia ada (iaitu LeNet, GasNet, dan DenseNet) dengan cadangan penambahbaikan model

LeNet berintegrasikan teknik regularisasi (LeNet-R) untuk sistem e-nose dalam pengelasan bahan pencemar udara. Dalam kajian ini, model LeNet sedia ada, diubah suai dengan tiga teknik regularisasi (iaitu normalisasi kelompok, dropout, dan pereputan berat) bagi membangunkan LeNet-R yang dicadangkan melalui siri eksperimen secara carian manual. Seterusnya, LeNet-R dibandingkan dengan tiga model 1D-CNN sedia ada dari segi prestasi pengelasan serta kerumitan pengiraan menggunakan set data e-nose yang boleh diakses secara umum. Dapatan kajian menunjukkan bahawa LeNet-R mengatasi model 1D-CNN lain dengan mencapai ketepatan pengelasan tertinggi (i.e., 97.60%) dan purata ketidaktepatan terendah (i.e., 6.50%). Tambahan, malalui kaedah LeNet-R masa latihan adalah terpantas (i.e., 86.54 saat), masa inferens paling singkat (i.e., 1.91 saat), jumlah parameter paling sedikit (i.e., 11,644), serta saiz model paling kecil (i.e., 45.48 kB) berbanding model 1D-CNN yang lain. Berbanding LeNet biasa, ketepatan klasifikasi bagi LeNet-R meningkat sebanyak 1.35%, mengurangkan jumlah parameter dan saiz model sebanyak 11%, memendekkan masa latihan sebanyak 36.6%, dan menurunkan masa inferens sebanyak 6.8%. Dapatan menunjukkan bahawa model 1D-CNN yang lebih ringkas dengan integrasi bersama teknik regularisasi mampu mengatasi model 1D-CNN yang lebih kompleks dalam pengelasan bahan pencemar udara untuk sistem e-nose. Kajian ini adalah yang pertama menunjukkan bahawa penyepaduan tiga teknik regularisasi ke dalam LeNet dapat meningkatkan ketepatan dan kecekapan bagi pengelasan pencemar udara berasaskan sistem e-nose.

KEYWORDS: *electronic nose, one-dimensional convolutional neural network, LeNet, air contaminants, classification.*

1. INTRODUCTION

The electronic nose (e-nose) is a device that employs a gas sensor array with a classification algorithm to classify gases [1]. Modeled after the human sense of smell, the e-nose overcomes the limitations of human olfaction and provides a reliable method for identifying a variety of gases. It utilizes a cross-sensitive gas sensor array to capture the properties of target gases, which are then analyzed by a classification algorithm for accurate classification [2]. While e-nose technology has been applied in fields such as medical diagnostics [5] and agriculture [6]. It is particularly valuable for air quality monitoring, where rapid and accurate detection of air contaminants is essential for protecting public health [4]. Harmful air contaminants can negatively impact health and quality of life, contributing to respiratory issues, cardiovascular diseases, and allergies.

Effective air quality monitoring systems that classify various air contaminants are increasingly essential. Traditional methods, such as sensory analysis and physicochemical analysis (e.g., gas chromatography-mass spectrometry [9] and fixed monitoring stations), are often limited by high costs, the need for skilled operators, and a lack of portability, making them impractical for real-time or on-site applications. To address these challenges, e-nose systems have emerged as promising alternatives [8], due to their high accuracy, ease of use, low cost, rapid detection, and ability to provide continuous real-time monitoring [7]. By classifying air contaminants using e-nose systems, improvements in air quality for public health and urban environments can be achieved. This effort supports two Sustainable Development Goal (SDG) targets, i.e., SDG 3 (Good Health and Well-being) and SDG 11 (Sustainable Cities and Communities) [10]. Therefore, e-nose systems are crucial for mitigating potential health risks and creating healthier living environments.

In e-nose systems, achieving accurate air contaminant classification depends on the effectiveness of the classification algorithm [3]. Several traditional machine learning (ML) algorithms have been employed for e-nose-based gas classification, including linear discriminant analysis (LDA) [12], principal component analysis (PCA) [13], and support vector

machine (SVM) [14]. However, these algorithms often require extensive feature engineering and may not fully capture the complex, nonlinear relationships in gas sensor data. To overcome these limitations, deep learning methods, especially convolutional neural networks (CNNs), have been introduced to automate feature extraction and improve classification performance. A recent review study concluded that CNNs can extract features from e-nose data better than ML algorithms [15]. In particular, one-dimensional convolutional neural networks (1D-CNNs) have garnered attention and are being utilized as classification algorithms in air contaminant classification for e-nose systems [16]. The architecture of a 1D-CNN is specifically designed to process one-dimensional (1D) data. The architecture consists of convolutional layers that use 1D filters to extract features by sliding across the input sequence, pooling layers that reduce the data dimensions, and fully connected layers that integrate the extracted features for the final prediction [18]. 1D-CNNs are more suitable classification algorithms than conventional 2D-CNNs due to their lower computational complexity, faster training time, and compact configurations [17]. Studies have demonstrated that 1D-CNNs outperform traditional ML algorithms in extracting features from e-nose data and achieving higher classification accuracy in gas classification tasks [12], [13], [14].

Several existing 1D-CNN models have been proposed for air contaminant classification in e-nose systems. For instance, Peng et al. [19] proposed a novel deep convolutional neural network comprising 38 layers, called GasNet, inspired by combinations of the Residual Network (ResNet) and Visual Geometry Group Network (VGGNet) architectures. Furthermore, Li et al. [20] developed an innovative Densely-connected Convolution Network (DenseNet) with multiple dense blocks and transition layers that utilize 1D convolutions, in contrast to the traditional DenseNet architecture, which uses 2D convolutions. Moreover, Wei et al. [21] proposed an improved LeNet architecture model by modifying the hyperparameters in the convolutional and fully connected layers. Despite the advancements in model architecture, there remains a lack of studies systematically comparing these models using the same e-nose dataset. Moreover, while the benefits of integrating regularization techniques into 1D-CNNs are well established in domains, e.g., phonocardiogram (PCG) [23], polysomnography (PSG) [24], electromyography (EMG) [25], electroencephalogram (EEG) [26], and near-infrared spectroscopy (NIRS) [27], no similar investigations have been reported for e-nose data. Consequently, the effect of different 1D-CNN architectures, including the impact of integrating regularization techniques in e-nose-based air contaminant classification applications, has not been thoroughly investigated.

To address these gaps, this study evaluates the three existing 1D-CNN architectures to propose an improved LeNet with regularization techniques (LeNet-R) for electronic nose (e-nose) systems in classifying air contaminants. The model integrates three regularization techniques, i.e., dropout, batch normalization, and weight decay, into the state-of-the-art LeNet model. This design aims to minimize computational complexity without compromising classification performance. The main contributions of this study are as follows. To the best of our knowledge, this is the first study to integrate three regularization techniques into the LeNet model, which is specifically tailored for e-nose systems in classifying air contaminants. This study also provides a comprehensive evaluation of classification performance and computational complexity, which are critical for applying 1D-CNN models in e-nose technology.

The remainder of this paper is structured as follows: Section 2 describes the methodology and model development. In Section 3, the experimental results are reported and discussed. Lastly, Section 4 outlines key takeaways and directions for future research.

2. METHODOLOGY

Figure 1 illustrates the flowchart for evaluating the classification performance and computational complexity of each 1D-CNN model in air contaminant classification. A publicly accessible e-nose dataset (Section 2.1) was preprocessed using two methods (Section 2.2), i.e., data partition and data normalization, before being applied to each 1D-CNN model (Section 2.3). Four 1D-CNN models were used in this study, i.e., GasNet, DenseNet, LeNet, and the proposed LeNet-R. All 1D-CNN models were then trained and evaluated to determine the target classes of air contaminants (Section 2.4). Finally, the models were compared in terms of classification performance and computational complexity based on the evaluation metrics (Section 2.5).
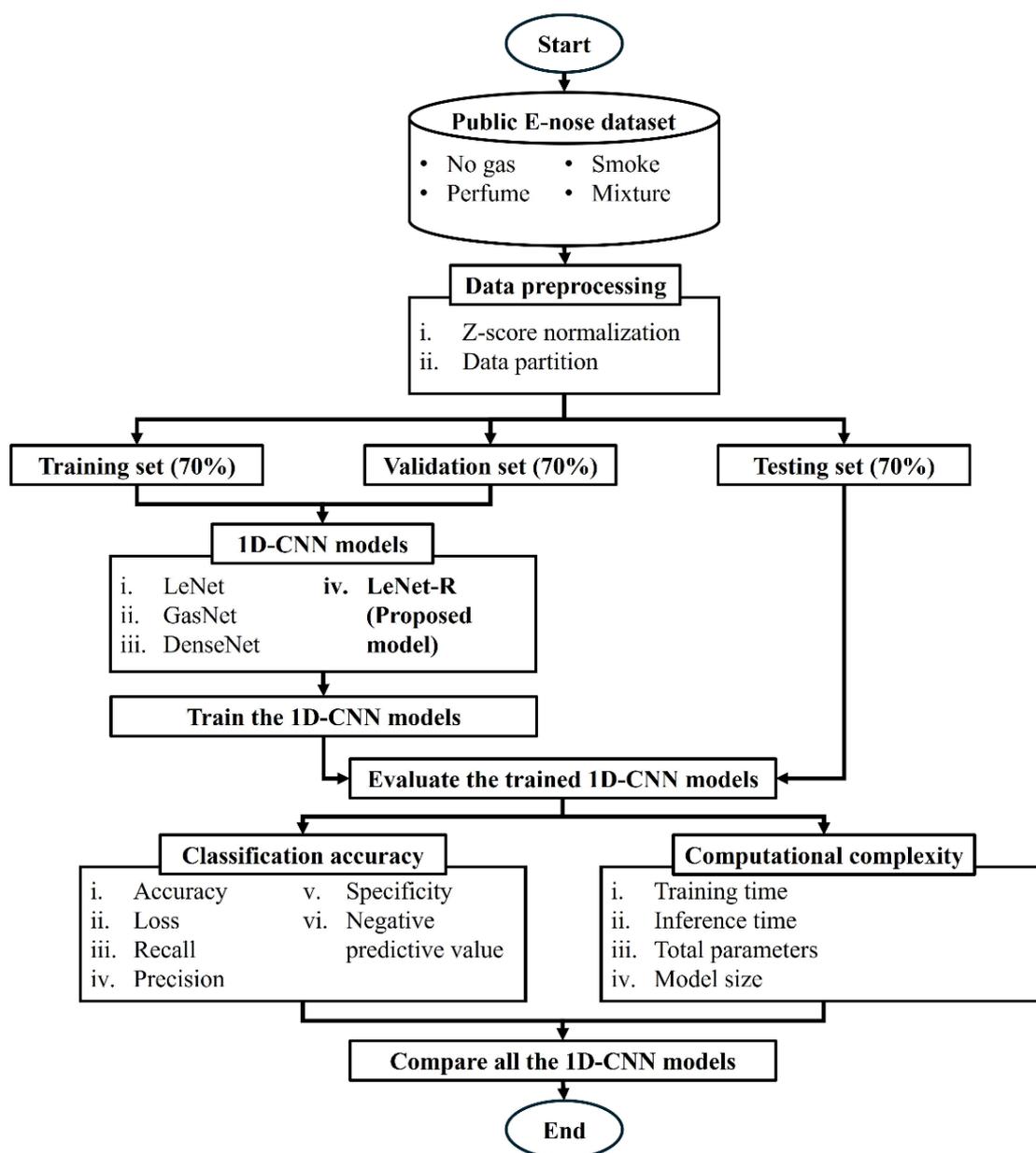

Figure 1. The flowchart for evaluating the classification performance and computational complexity of each 1D-CNN model used in air contaminant classification.

This study was conducted on a laptop computer with an Intel Core i3 CPU running at 2.40 GHz and 8 GB of RAM. The development environment included the frameworks of Keras (version 2.13) and TensorFlow (version 2.14). All 1D-CNN models were trained and evaluated using the R programming language (version 4.3.3) with RStudio software (version 494).

2.1. E-nose dataset

The experimental setup for an e-nose system consists of several key components designed to enable accurate detection and classification of gases, as shown in Figure 2. The system begins with a gas distribution control system that introduces gases into the chamber and is regulated by a mass flow controller, which controls the flow rate of gases to maintain consistent experimental conditions. The core component is the gas sensor array, which detects target gases and outputs signals refined by a signal conditioning circuit. These signals are digitized by a data acquisition system and sent to a computer. Here, a data preprocessing algorithm cleans and prepares the data, while a classification algorithm analyzes the processed signals for accurate gas classification. This setup enables automated gas detection and classification in e-nose applications [28], [29].
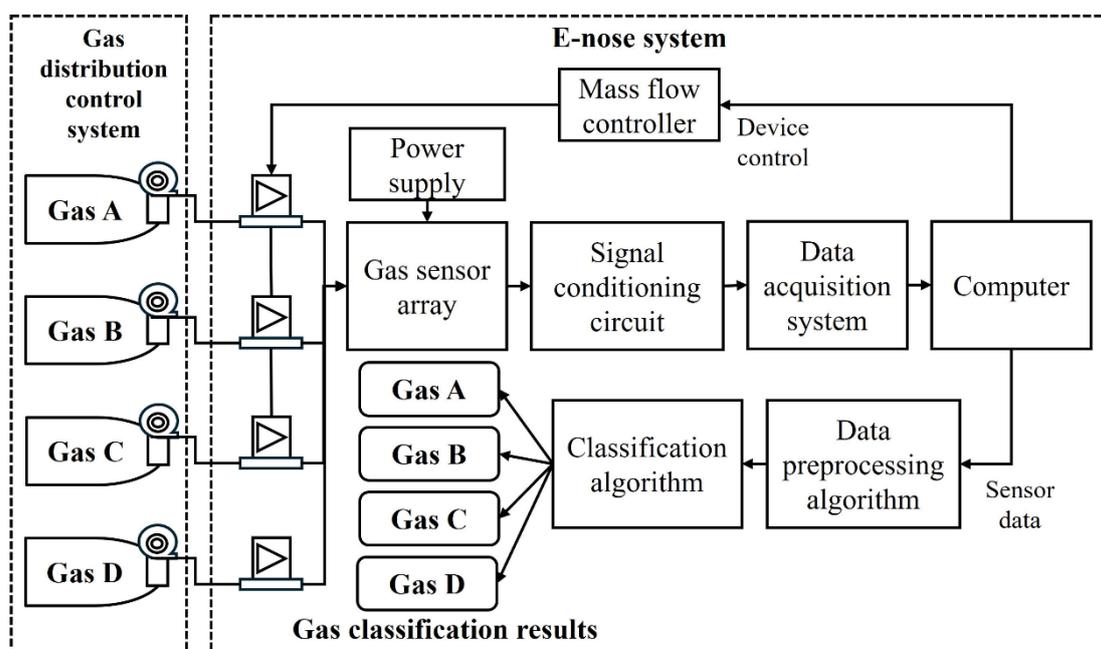

Figure 2. The block diagram of the experimental setup for the e-nose-based gas classification system.

This study used a publicly accessible e-nose dataset that can be obtained from the Mendeley Data repository [28], and the data acquisition methodology is briefly described as follows. This dataset was acquired using seven commercially available gas sensors: MQ2, MQ3, MQ5, MQ6, MQ7, MQ8, and MQ135. Each sensor in this array is sensitive to different gases (e.g., methane, butane, propane, benzine, ethanol, ammonia, liquefied petroleum gas (LPG), alcohol, smoke, natural gas, and carbon monoxide) that enable the detection of a wide variety of gases typically found in industrial and residential environments [30]. Two common gas sources were used: perfume spray and incense stick smoke. These sources were chosen to generate four target classes of air contaminants for the dataset: perfume, smoke, a mixture of perfume and smoke, and no gas (i.e., clean air from the surrounding environment with no

perfume or smoke present). The dataset comprised a total of 6400 samples, with 1600 samples for each class.

This evenly distributed dataset across the four target classes ensures a fair representation of each target class in the dataset. Previous works by Faleh et al. [12] and Narkhede et al. [30], both used 1600 samples per class (with the total of 6400 samples) in their deep learning models and demonstrated robust classification performance. This consistency with prior studies indicates that the dataset size is sufficient for effective training and evaluation of deep learning models, including 1D-CNNs, for air contaminant classification.

2.2. Data preprocessing

Data preprocessing involves two methods: data partition and data normalization. The dataset was divided into a training dataset (70%) and a testing dataset (30%). Then, 20% of the training set was allocated as a validation dataset, which was used to evaluate model performance during the training process continuously. Each target class has a balanced training, validation, and testing dataset. Table 1 shows the sample sizes of the training, validation, and testing datasets for each target class.

All data except for the target variable in the datasets were normalized using the z-score standardization method, where each feature was scaled to achieve a mean of zero and a standard deviation of one [31]. Additionally, the data were reshaped into arrays suitable for model input. The target variable was transformed into a categorical format using one-hot encoding, which is commonly used for multi-class classification problems. Thus, these preprocessing methods ensured the dataset was in a suitable format for an effective 1D-CNN training process.

Table 1. The number of samples for training, validation, and testing datasets of each target class

Target class	Sample Size		
	Training dataset	Validation dataset	Testing dataset
No gas	896	224	480
Perfume	896	224	480
Smoke	896	224	480
Mixture	896	224	480
Total	**3584**	**896**	**1920**

2.3. One-dimensional convolution neural network

In this study, four 1D-CNN models were applied to classify the four target classes of air contaminants. Among these were existing 1D-CNN models (e.g., GasNet, DenseNet, and LeNet), along with the proposed LeNet-R. The existing LeNet, with its simpler architecture, was adapted with three regularization techniques (e.g., batch normalization, weight decay, and dropout) to develop LeNet-R through a series of manual search experiments.

2.3.1. Existing 1D-CNN models

The GasNet consisted of an input layer, six convolutional blocks, two max pooling layers, a global average pooling layer, and a fully connected output layer. The input layer accepted input data with a shape of 7×1. Each convolutional block consisted of two layers, followed by a batch normalization layer and a rectified linear unit (ReLU) activation function layer. The fundamental structure of GasNet is the shortcut connection utilized for convolutional blocks to

enhance learning capabilities and prevent the vanishing gradient issue [19]. The shortcut connection method, forming a residual block, enhances classification accuracy and smooths training without adding extra parameters or computational load, thereby keeping the layer count constant. The model concluded with a fully connected layer with four units and a Softmax activation function to classify one of the four target air contaminant classes. The hyperparameters and structure of the model were the same as those used in the GasNet architecture [19].

Additionally, the DenseNet consisted of an initial convolutional layer, three dense blocks, two transition layers, a global average pooling layer, and a fully connected output layer. The initial convolutional layer processed the incoming gas sensor data with an input shape of 7×1. DenseNet applied three dense blocks, with the first two blocks each followed by a transition layer, which are the fundamental structures of the model. These dense blocks were designed to enhance the network's feature extraction capabilities, tackle the issue of vanishing gradients, and reduce the total parameter count. The convolutional operations within these blocks utilized a growth rate of 12 to determine the extent of new information that each layer adds to the overall model state. Transition layers played a crucial role in distilling the essence of the input data, enabling an efficient classification process [20]. The compression rate was set to 0.5 to control the number of feature maps reserved for the transition layer. The model concluded with a fully connected layer with four units and a Softmax activation function to classify one of the four target air contaminant classes. The hyperparameters and structure of the model, including dense blocks and transition layers, were the same as those used in the DenseNet architecture [20].

Next, the LeNet consisted of two convolutional layers, two average pooling layers, a flatten layer, and three fully connected layers. The model began with a convolutional layer that employed a ReLU activation function to process incoming gas sensor data, with an input shape of 7×1. Following each convolutional layer, an average pooling layer was applied to reduce the data dimensions of the model. Compared to the Tanh activation function used in the LeNet algorithm, the standard LeNet employed the ReLU activation function in the convolutional and fully connected layers, contributing to faster and more efficient model performance. The model concluded with a fully connected layer with four units and a Softmax activation function to classify one of the four target air contaminant classes. The hyperparameters and structure of the model were the same as those used in the LeNet architecture [21].

2.3.2. The proposed LeNet-R model

The proposed LeNet-R consisted of two convolutional layers, two max pooling layers, a flatten layer, two dropout layers, two batch normalization layers, and three fully connected layers. Table 2 shows the architecture summary of LeNet-R. The first convolutional layer, with eight filters, a kernel size of four, a stride of one, same padding, and a ReLU activation function, processed the incoming gas sensor data with an input shape of 7×1. Following this, a max pooling layer with a pooling size and stride of two was applied to reduce the data dimensions of the model. Batch normalization layers were applied between each convolutional layer and its subsequent max pooling layer. The second convolutional layer, batch normalization layer, and max pooling layer mirrored the first set, except that the number of filters in the convolutional layer was increased to 16. Before transitioning to the fully connected layers, a flatten layer converted the 2D array inputs to a 1D array input. Subsequently, two fully connected layers, each equipped with a ReLU activation function and units of 128 and 64, respectively, processed all inputs from the previous layer. Between each dense layer, a batch normalization layer and a dropout layer with a dropout rate of 0.1 were applied. The model

concluded with a fully connected layer with four units and a Softmax activation function to classify one of the four target air contaminant classes.

Table 2. The architecture summary of the proposed LeNet-R obtained from R programming.

Layer (type)	Output Shape	Number of Parameters
conv1d_1 (Conv1D)	(32, 7, 8)	40
max_pooling1d_1 (MaxPooling1D)	(32, 3, 8)	0
conv1d_2 (Conv1D)	(32, 3, 8)	528
max_pooling1d_2 (MaxPooling1D)	(32, 1, 16)	0
flatten (Flatten)	(32, 16)	0
dense_1 (Dense)	(32, 128)	2176
batch_normalization_1 (BatchNormalization)	(32, 128)	512
dropout_1 (Dropout)	(32, 128)	0
dense_2 (Dense)	(32, 64)	8256
batch_normalization_2 (BatchNormalization)	(32, 64)	256
dropout_2 (Dropout)	(32, 64)	0
dense_3 (Dense)	(32, 4)	260

The LeNet-R is a classification algorithm whose architecture is adapted from the LeNet architecture. Figure 3 compares the architecture of the standard LeNet and the LeNet-R. The proposed modifications to develop LeNet-R are as follows: the number of filters and the kernel size in the convolutional layers, and the number of units in the fully connected layers, which are set using numbers within a geometric progression [21]. By implementing this method, LeNet-R was able to optimize the CPU and memory resources, resulting in improved classification accuracy and faster model training [32]. This method is also used in deep learning architectures to systematically adjust the computational complexity and model size of neural networks [33]. Moreover, max pooling layers are used in LeNet-R instead of average pooling layers. They capture the maximum value within a data pool, unlike average pooling layers, which take the average value.

Weight decay (L2 regularization) is applied as a kernel regularizer to all convolutional and dense layers, since these layers have learnable parameters. It adds a penalty equal to the sum of the squared values of the model parameters to the loss function, which helps prevent overfitting by encouraging smaller weights [34]. Furthermore, batch normalization layers were applied between the convolutional and max pooling layers to maintain the same parameter distribution and avoid overfitting [20]. In addition, a dropout layer was applied to randomly remove certain connections between units in the following layers during the training process [35].

This study's optimization of hyperparameters for LeNet-R was conducted through a series of intuitive manual search experiments. This optimization specifically addressed the number of filters and kernel sizes in the convolutional layers, the number of units in the fully connected layers, the constant value of bias initialization for both layers, and the dropout rate. The dropout rate was explored within the range of 0.1 to 0.5 to determine the optimal balance between classification performance and avoidance of overfitting. The weight decay coefficient was examined from 0 to 0.01 in increments of 0.001

For the convolutional layers, the approach was to start with fewer filters in the first layer and increase them for the second layer. Conversely, for the fully connected layers, the approach began with more units and reduced the number for the second layer. The number of filters and units was chosen according to a geometric progression, considering the sequential architecture of the model and its impact on learning capability. Additionally, the kernel size for the convolutional layers was explored within the range of one to seven, considering that the dataset

utilizes up to seven sensors. Finally, optimizing hyperparameters is pivotal in defining the scope of the experiment to develop LeNet-R. It ensures the model achieves high classification accuracy with minimal computational complexity for air contaminant classification.
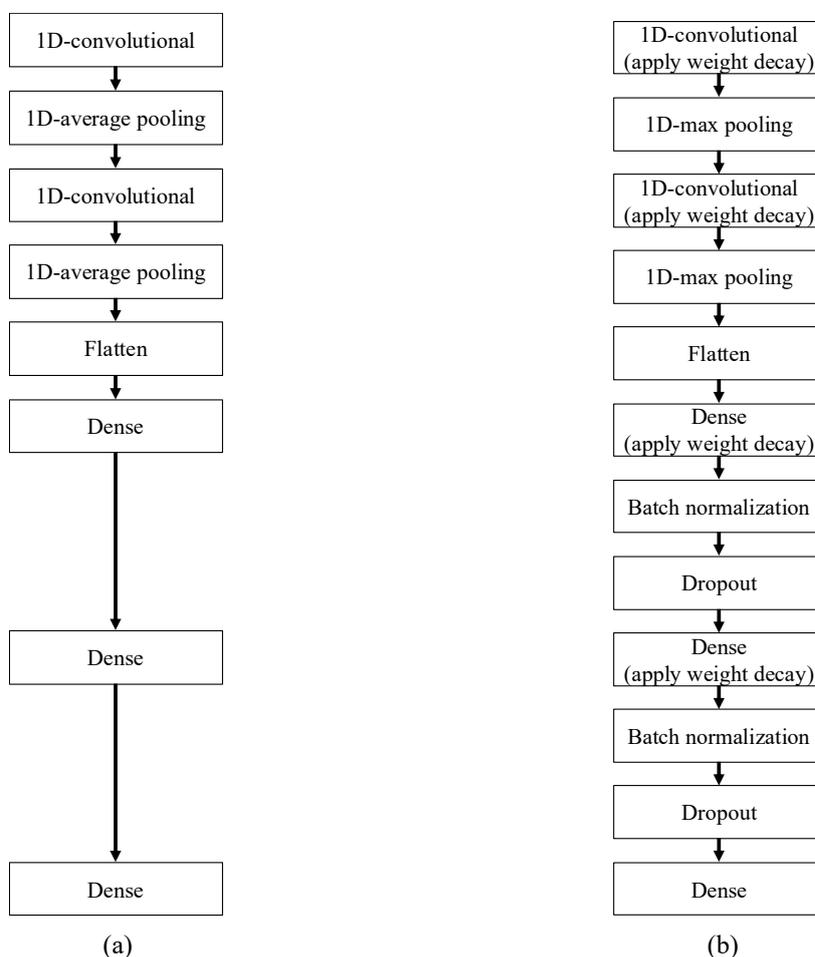

Figure 3. The comparison between the architecture of (a) the standard LeNet and (b) the proposed LeNet-R.

2.4. Model Training

A similar approach was used to train the four 1D-CNN models. This approach ensures that their performance can be compared and evaluated solely based on model architecture differences rather than on training process variations. All the 1D-CNN models were trained in over 100 epochs with a batch size 32. The network updated its weight after processing every 32 samples. Adaptive Moment Estimation (Adam) was used as the optimizer in the network training, with a learning rate set at 0.001. Categorical cross-entropy was applied as the loss function, which is commonly used for multi-class classification problems. To maintain consistency and reproducibility in the results, a random seed number of 42 was set throughout the study [36].

2.5. Evaluation Metrics

The proposed LeNet-R was compared with the three existing 1D-CNN models (i.e. LeNet, DenseNet, and GasNet) in terms of classification performance and computational complexity using a publicly accessible e-nose dataset. The following metrics were obtained to evaluate

classification performance: accuracy, loss, recall, precision, specificity, and negative predictive value. A confusion matrix was used to assess the classification performance of the 1D-CNN models by categorizing predictions into true positive (TP), false negative (FN), false positive (FP), and true negative (TN). It facilitates the calculation of these metrics by comparing predicted with actual class labels.

Accuracy (Eq. 1) measures the proportion of correct predictions out of all predictions, offering a general view of overall performance. Recall (Eq. 2) focuses specifically on how well the model identifies actual positive cases, while precision (Eq. 3) indicates the proportion of predicted positives that are truly positive. Specificity (Eq. 4) complements recall by measuring the accuracy with which negative cases are classified. Finally, the negative predictive value (Eq. 5) reflects the proportion of predicted negatives that are indeed negative. Together, these metrics comprehensively evaluate classification performance from multiple perspectives. The calculation formulas for these metrics are as follows [16]:

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

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Specificity = \frac{TN}{TN+FP} \tag{4}$$

$$Negative\ predictive\ value = \frac{TN}{TN+FN} \tag{5}$$

Loss refers to the average categorical cross-entropy loss across the training dataset [12]. On the other hand, a learning curve is a graphical tool that charts the progression of learning performance over time, helping to identify any overfitting and underfitting issues. Training time, inference time, total parameters, and model size were considered to evaluate the computational complexity of all 1D-CNN models [37]. Therefore, all these metrics were obtained to present a comprehensive evaluation of the classification performance and computational complexity of each 1D-CNN model.

3. RESULTS AND DISCUSSION

The training performance assessment of the four 1D-CNN models (i.e., GasNet, DenseNet, LeNet, and the proposed LeNet-R) is presented using the learning curve in Section 3.1. Additionally, the evaluation of individual air contaminant classification performance is detailed using the confusion matrix in Section 3.2. Furthermore, the review of all models' average classification performance is discussed in Section 3.3. Section 3.4 presents a comparison of total parameters and model size, and Section 3.5 describes the comparison of training time and inference time for all the models.

3.1. Training performance

The training performance for all 1D-CNN models was observed and evaluated using the learning curves of each model, as shown in Figure 4. It is worth highlighting that all the 1D-CNN models were effectively trained for over 100 epochs. The training and validation datasets were used to train all the 1D-CNN models. The learning curves suggest that all the 1D-CNN models achieved an optimal fit, with no evidence of underfitting or overfitting issues during network training.
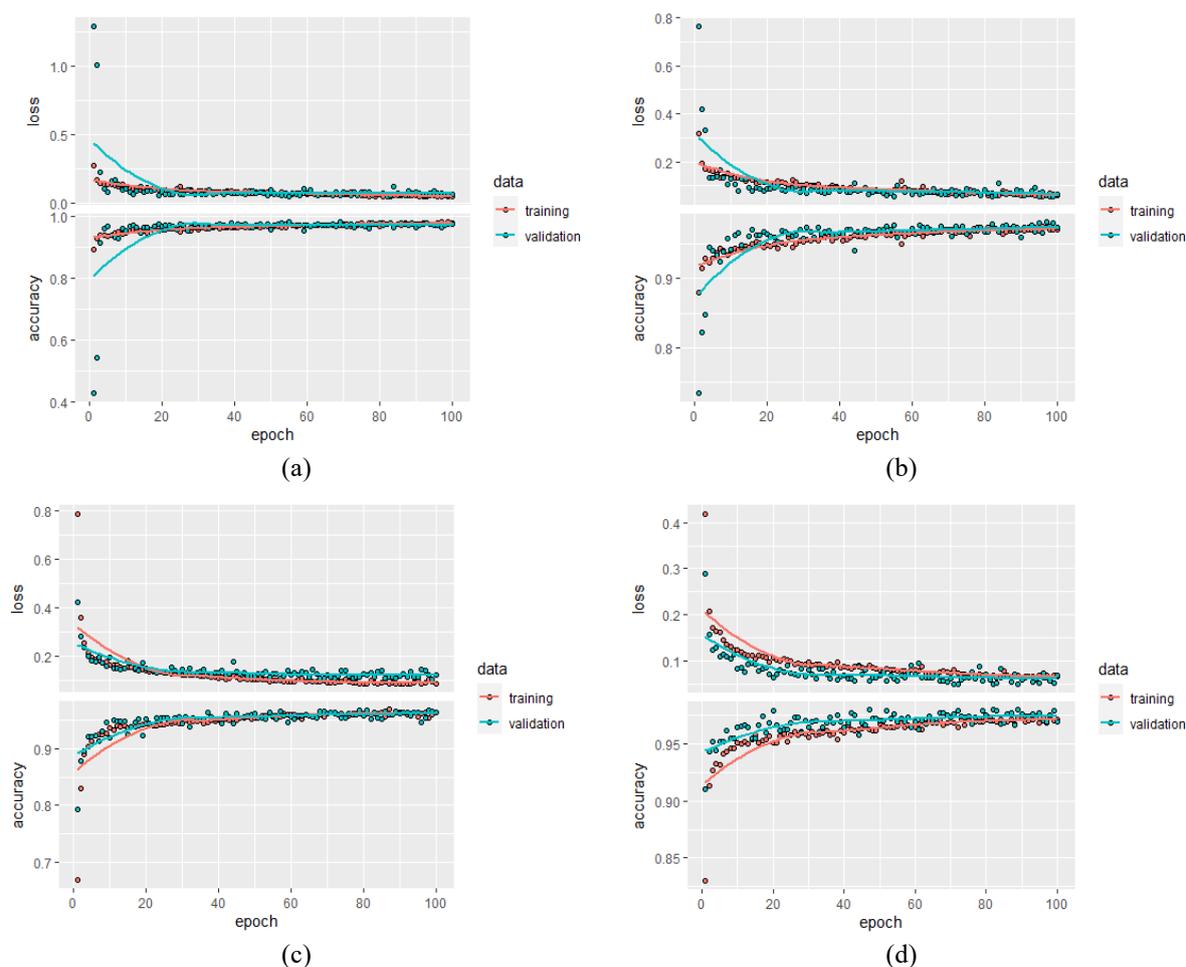
Figure 4. Training and validation learning curves for the four 1D-CNN models: (a) GasNet, (b) DenseNet, (c) LeNet, and (d) the proposed LeNet-R.

3.2. Individual air contaminant classification performance

The classification performance for all the 1D-CNN models was evaluated using the confusion matrix corresponding to each model, as illustrated in Figure 5. The testing dataset was used for the confusion matrix to assess the classification performance of all the models. The confusion matrices demonstrate that all the models are highly effective in accurately classifying two target air contaminants, i.e., smoke and a mixture of smoke and perfume, with no false positives or false negatives detected. However, the two other target classes of air contaminants, i.e., perfume and no gas from the surrounding environment, exhibited a few instances of false positives and false negatives.

Among all models, the proposed LeNet-R exhibited the lowest total number of misclassified samples (i.e., 46), followed by GasNet (i.e., 61), DenseNet (i.e., 66), and LeNet (i.e., 71). This further demonstrates the effectiveness of the proposed LeNet-R model in accurately distinguishing between the different air contaminant classes, particularly in reducing confusion between no gas and perfume. Derived from each confusion matrix, the key metrics (i.e., recall, precision, specificity, and negative predictive value) for each target class were calculated for all the models, as detailed in Table 3.
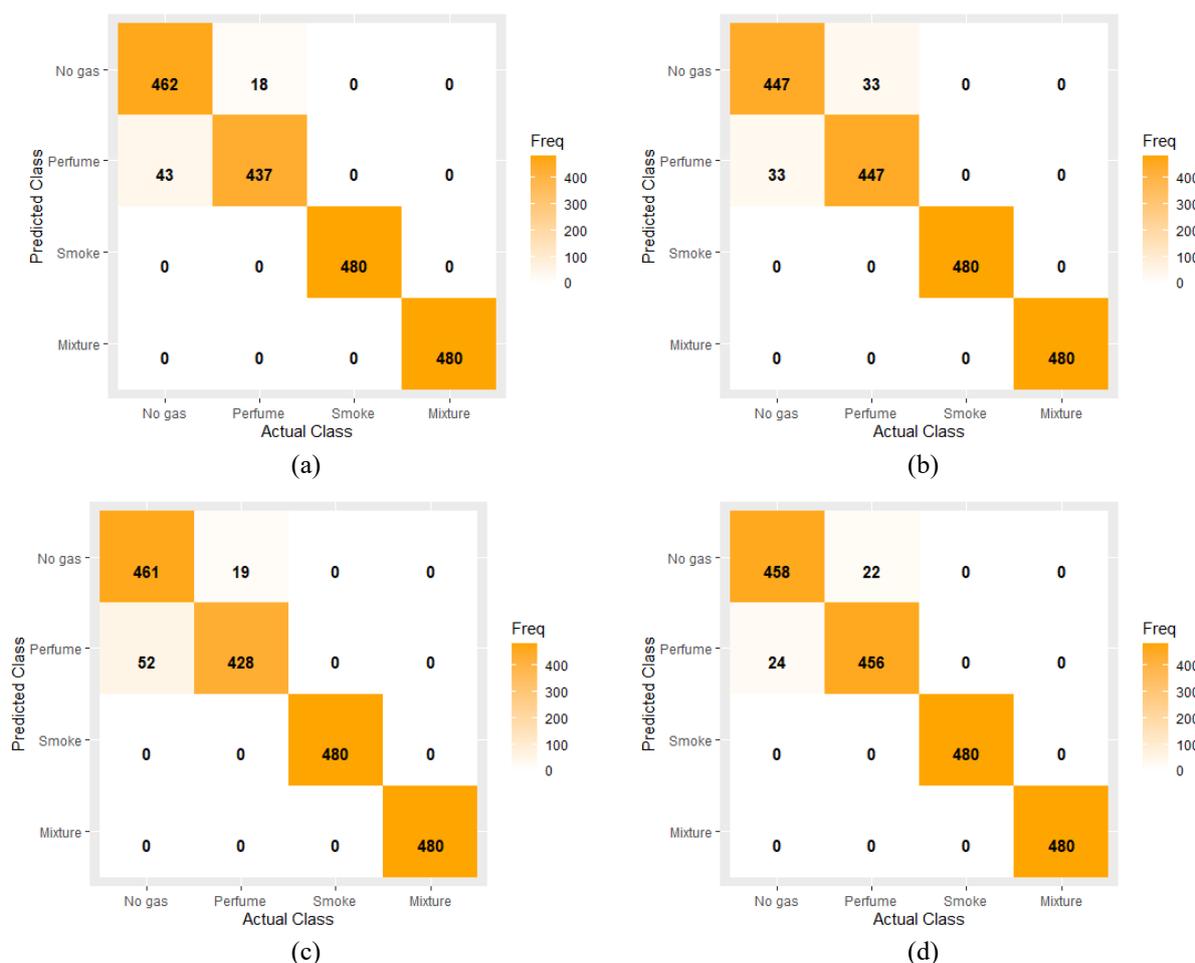
Figure 5. The confusion matrices of (a) GasNet, (b) DenseNet, (c) LeNet, and (d) the proposed LeNet-R.

Table 3. The recall, precision, specificity, and negative predictive value metrics for all four 1D-CNN models across each target class.

Model	Class	Accuracy (%)	Recalling (%)	Precision (%)	Specificity (%)	Negative Predictive Value (%)
LeNet [21]	No gas	89.86	89.86	96.04	**98.65**	96.39
	Perfume	95.75	95.75	89.17	96.47	98.68
	Smoke	100.00	100.00	100.00	100.00	100.00
	Mixture	100.00	100.00	100.00	100.00	100.00
DenseNet [20]	No gas	93.13	93.13	93.13	97.71	97.71
	Perfume	93.13	93.13	93.13	97.71	97.71
	Smoke	100.00	100.00	100.00	100.00	100.00
	Mixture	100.00	100.00	100.00	100.00	100.00
GasNet [19]	No gas	91.49	91.49	**96.25**	98.73	97.01
	Perfume	**96.04**	**96.04**	91.04	97.07	**98.75**
	Smoke	100.00	100.00	100.00	100.00	100.00
	Mixture	100.00	100.00	100.00	100.00	100.00
LeNet-R **(Proposed)**	No gas	**95.02**	**95.02**	95.42	98.47	**98.33**
	Perfume	95.40	95.40	**95.00**	98.34	98.47
	Smoke	100.00	100.00	100.00	100.00	100.00
	Mixture	100.00	100.00	100.00	100.00	100.00

A detailed analysis of the classification metrics in Table 3 shows that the proposed LeNet-R model achieves the highest number of optimum performance metrics (i.e., 5) among all evaluated models. Specifically, LeNet-R demonstrates the highest results in accuracy, recall, and negative predictive value for the no gas class and precision and specificity for the perfume class. GasNet achieves four optimum performance metrics, including the highest precision for the 'no gas' class and the highest accuracy, recall, and negative predictive value for the 'perfume' class. In contrast, the standard LeNet achieves only one optimum performance metric, i.e., the highest specificity for no gas, while DenseNet does not lead in any key metric. These results highlight the effectiveness of the proposed LeNet-R in reducing misclassification for the more challenging 'no gas' and 'perfume' classes.

3.3. Average classification performance evaluation

Figure 6(a) presents the classification performance evaluation of all 1D-CNN models, focusing on the average recall, precision, specificity, and negative predictive value for each target class obtained by each model. The proposed LeNet-R achieved the highest recall, precision, specificity, and negative predictive value of 97.61, 97.60, 99.20, and 99.20%, respectively, followed by GasNet, DenseNet, and LeNet. The high recall of the LeNet-R model significantly reduces the risk of misclassifying the intended target class as another. Similarly, the high precision minimizes the probability of incorrectly predicting the target class of air contaminants. Additionally, the high specificity plays a crucial role in accurately classifying the non-target class of air contaminants. Furthermore, the high negative predictive value provides high confidence in confirming the absence of any target classes of air contaminants. Thus, these metrics show the capabilities of the LeNet-R as the most robust and reliable model for e-nose applications, particularly air quality monitoring, by classifying air contaminants.

Figure 6(b) presents the classification performance evaluation of all 1D-CNN models in terms of averaged accuracy and averaged loss. The proposed LeNet-R outperformed all other models with the highest averaged accuracy of 97.60% and the lowest averaged loss of 6.50%, followed by GasNet, DenseNet, and LeNet. The high accuracy of the proposed LeNet-R underscores its superior reliability in correctly classifying different air contaminants. Additionally, its low loss indicates fewer mistakes during the training process in classifying air contaminants. Thus, the proposed modifications to develop the LeNet-R contribute to its higher classification performance across all key metrics than the other models.
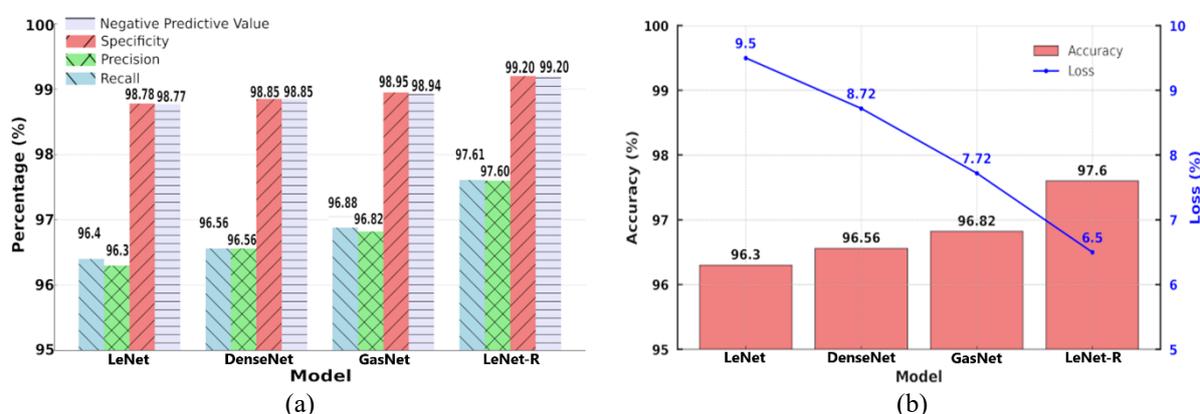

Figure 6. The average classification performance evaluation for all four 1D-CNN models: (a) averaged recall, averaged precision, averaged specificity, and averaged negative predictive value, and (b) averaged accuracy and averaged loss.

Table 4 presents a benchmarking comparison of the averaged accuracy between previous studies and the models evaluated in this study using the same e-nose dataset. Notably, the proposed LeNet-R achieved the highest average accuracy of 97.60%, compared to 96.30% for the standard LeNet model. This corresponds to a relative improvement of 1.35% in average accuracy. It is worth highlighting previous works that used 1D-CNN [12] and CNN [30] with the same dataset and training-to-testing ratio, the testing accuracy of 90% and 93%, respectively. These results demonstrate that the proposed LeNet-R is the most effective model for air contaminant classification using this benchmark e-nose dataset.

Table 4. The average accuracy of the proposed LeNet-R and other models using the same e-nose dataset

Study	Model	Averaged Accuracy
Previous study	1D-CNN [12]	90.00%
	CNN [30]	93.00%
This study	LeNet	96.30%
	DenseNet	96.56%
	GasNet	96.82%
	LeNet-R (Proposed model)	97.60%

3.4. Total parameters and model size

Figure 7(a) compares computational complexity for all 1D-CNN models in terms of total parameters and model size. The proposed LeNet-R exhibited the lowest total parameters of 11,644 and the smallest compact model size of 45.48 kilobytes (kB), followed by LeNet, DenseNet, and GasNet. Specifically, compared to the standard LeNet, LeNet-R reduces total parameters and model size by approximately 10.9% and 11.0%, respectively.
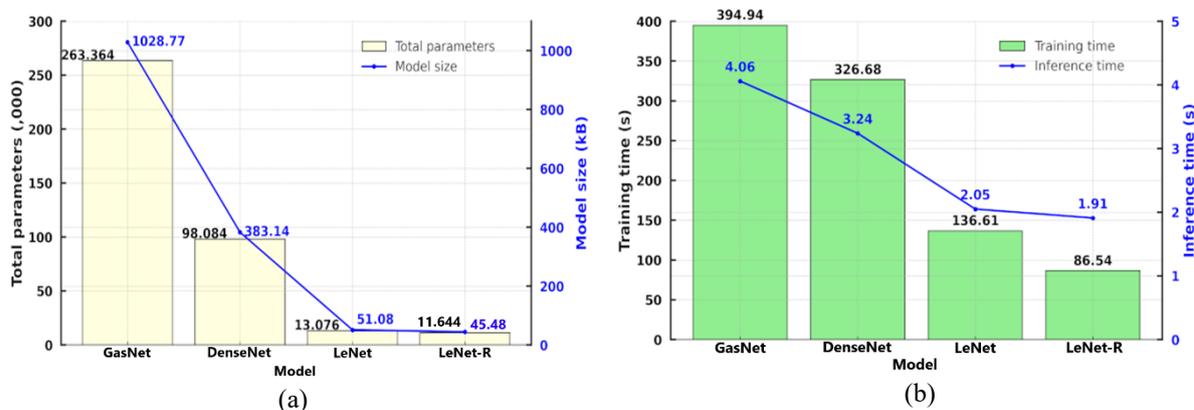

Figure 7. The comparison of computational complexity for all four 1D-CNN models: (a) total parameters and model size, and (b) training time and inference time.

These metrics (i.e., total parameters and model size) help understand each model's practicality for an e-nose system. Models with fewer parameters are advantageous because they require less memory, offer faster training and inference times, and are more suitable for deployment on resource-constrained devices. Smaller models also help conserve battery life and improve overall device performance by minimizing memory usage and computational demand [38]. The proposed adaptations to develop the LeNet-R contribute to a reduction in the total parameters and model size without compromising the classification performance.

Thus, the LeNet-R establishes itself as the most reliable model for air contaminant classification in an e-nose system compared to the other three existing 1D-CNN models.

3.5. Training time and inference time

Figure 7(b) compares computational complexity in terms of training time and inference time. The proposed LeNet-R outperformed all other models with the fastest training time and inference time at 86.54 and 1.91 seconds, respectively, followed by LeNet, DenseNet, and GasNet. Compared to LeNet, LeNet-R reduced training time by 36.6% and inference time by 6.8%, while still achieving superior classification accuracy. The LeNet-R stands out for its ability to provide the fastest classification results without significantly compromising classification performance. Thus, the LeNet-R establishes itself as the most reliable model for the e-nose application, where speed and efficiency are critical. The speed and efficiency of the model are particularly beneficial for e-nose systems requiring immediate data analysis and decision-making.

The results indicate that models with larger total parameters and model size, due to the depth and complexity of the network architecture, i.e., GasNet and DenseNet, require longer training time and inference time than simpler models, i.e., LeNet and LeNet-R. However, the LeNet-R achieved faster training time and inference time, lower total parameters, and a smaller model size than LeNet due to the smaller kernel size in convolutional layers and fewer units in fully connected layers. Rapid identification is as crucial as high accuracy, since delays in detection can increase health risks. This balance of effectiveness and efficiency of a classification algorithm is crucial for real-world e-nose applications. High accuracy ensures reliable detection of hazardous gases, while a smaller and faster model enables rapid, energy-efficient operation on portable e-nose devices [39]. Therefore, the proposed LeNet-R proves to be the simplest 1D-CNN model with the highest classification accuracy for an e-nose system in air contaminant classification compared to the other three existing 1D-CNN models.

4. CONCLUSION

An improved LeNet with regularization techniques (LeNet-R) for air contaminant classification was proposed in this study. The proposed LeNet-R was developed by adapting the LeNet architecture with three regularization techniques (i.e., batch normalization, dropout, and weight decay) through a series of manual search experiments. The proposed LeNet-R was compared with the three existing 1D-CNN models (i.e., LeNet, DenseNet, and GasNet) regarding classification performance and computational complexity using a publicly accessible e-nose dataset. Four target air contaminants were considered: perfume, smoke, a mixture of perfume and smoke, and no gas (i.e., clean air from the surrounding environment with no perfume or smoke present). Each target class had a balanced training, validation, and testing dataset. The findings reveal that the proposed LeNet-R outperforms the three 1D-CNN models by achieving the highest averaged accuracy (i.e., 97.60%) and the lowest averaged loss (i.e., 6.50%). Additionally, the proposed LeNet-R achieved the highest recall, precision, specificity, and negative predictive value of 97.61, 97.60, 99.20, and 99.20%, respectively, followed by GasNet, DenseNet, and LeNet. Furthermore, the LeNet-R produced the shortest training time (i.e., 86.54 seconds), the shortest inference time (i.e., 1.91 seconds), the fewest total parameters (i.e., 11,644), and the smallest model size (i.e., 45.48 kB), followed by LeNet, DenseNet, and GasNet. Thus, the proposed adaptations to develop the LeNet-R contribute to reducing the total parameters and model size without compromising the classification performance. The proposed LeNet-R is the simplest 1D-CNN model with the highest classification accuracy for an e-nose system in air contaminant classification compared to the three existing 1D-CNN

models. Therefore, this study shows that a simpler 1D-CNN integrated with regularization techniques can outperform more complex 1D-CNN models in classifying air contaminants for an e-nose system. In future work, the proposed LeNet-R will be enhanced using hyperparameter tuning algorithms to increase classification accuracy further.

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