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Optimized Deep Learning for Gas Sensor

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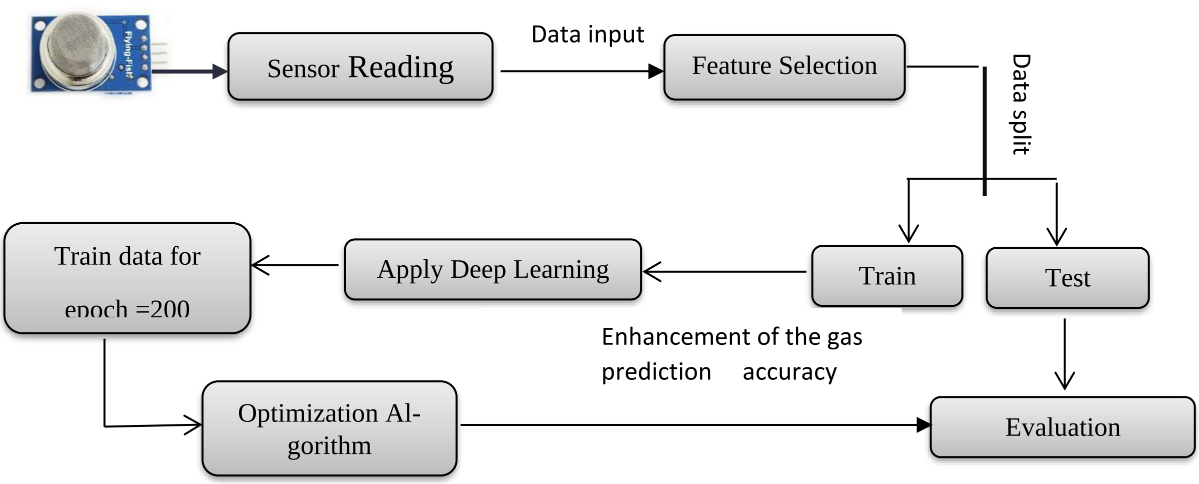
ABSTRACT

Gas sensors are widely used to detect the presence of hazardous gases in our daily lives, and their accuracy is crucial for ensuring the safety of individuals and environments. Gas sensors are essential in a variety of applications, such as environmental monitoring, industrial safety, and healthcare. These sensors are intended to detect and measure the presence of certain gases in their surroundings. Significant progress has been achieved in the development of gas sensor technology in recent years, resulting in better sensitivity, selectivity, and miniaturization. In this paper, we propose an optimized deep-learning approach for gas sensor data analysis that improves gas prediction accuracy. The proposed approach includes advanced data preprocessing techniques, feature selection, and model optimization to increase gas prediction performance. The contribution of this research is the development of a novel deep learning-based approach that optimizes the accuracy of gas prediction, making it more trustworthy and practical for real-world applications. The proposed method has significant implications for gas detection and can potentially save lives by providing early warning of dangerous gas levels.

Graphical abstract



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1. Introduction

Gas detection is an essential aspect of ensuring safety in various industrial and domestic environments. Gas sensors play a crucial role in detecting and identifying the presence of hazardous gases that pose a significant risk to human health and the surrounding environment. The detection of a specific gas or a group of gases in a mixture of gases is a tough task that requires extensive technological understanding. Various methodologies have been proposed to detect gas leakage, including chemical methods and advancements in interdisciplinary technologies [1]. In situations involving gas leakage, human intervention may not always be feasible due to the inherent hazards associated with these gases. Smoke emissions resulting from leaks can impair vision, and Individuals with mobility restrictions must be evacuated immediately in the event of a fire or smoke. Inhaling these hazardous gases can cause dizziness, unconsciousness, and even mass disasters if not addressed immediately. Moreover, gas leaks in chemical plants offer a considerable risk of explosion. Therefore, the timely detection of gas leaks and explosions is of utmost importance. To achieve this, there is a crucial need for advanced assistive technology solutions that offer accurate and reliable early detection capabilities. Detecting gas leaks promptly and with precision necessitates the employment of state-of-the-art procedures. It is also a challenge to detect specific gases or different gas mixtures, requiring focused technological advancements. Existing methods for detecting mixed gases include the utilization of colorimetric tape, which provides a viable solution in certain cases. However, there is room for improvement in terms of accuracy and reliability [2]. Machine learning and deep learning algorithms are examples of artificial intelligence-based techniques that have shown promise in detecting gases and classifying them in recent years. In addition to chemical gas detection methods and advances in multidisciplinary technologies, the literature mentions the application of a variety of artificial intelligence (AI)-based approaches. In past studies, several machine learning techniques, including support vector machine (SVM) algorithms, were proposed for gas identification [3]. Khalaf [4] examines the development of an electronic nose (ENose) designed to fulfill two primary objectives: gas type identification and determination of purity, along with the estimation of component concentrations in a mixture of LPG gases (methane, hexane, or hydrogen) and sulfuric acid, which are frequently encountered within refineries.The ENose system comprises a total of 8 sensors. The proposed hardware-software system leverages the principles of least squares for both classification and regression tasks. Initially, a training model utilizing the least squares approach is employed to instruct the system on discriminating between different gases and determining whether a gas sample is pure or a mixture. Subsequently, another training model is developed using least squares regression to estimate the concentrations of the identified gases. Abdul Majeed [5] proposed the RF-based top-k highly weighted feature selection technique, which is based on random forest estimation (RF). This algorithm's major goal is to reduce the time overheads of various machine learning algorithms (MLAs) while maintaining a sufficient degree of accuracy. To efficiently reduce the calculation time of MLAs, the suggested approach focuses on picking the top k most essential characteristics from a collection of N available features. This approach is particularly beneficial when dealing with datasets that have a substantial number of features. The method quantifies the weights of each feature in the dataset using a random forest and employs the classification error rate as the criteria for feature selection. Optimal RF parameters are adapted, taking into account the data distribution and the number of features, to identify influential features with high predictive power. Parag Narkhede [6] proposed a unique multimodal AI-based fusion framework for reliable gas identification and detection has been developed. This paradigm considers several modalities to satisfy the demand for accurate gas detection. Data was collected from four unique classes in study of two distinct gases: alcohol vapor obtained from perfume, smoke from incense sticks, a blend of these gases, and a class indicating the lack of gas. A thermal camera was used to capture the thermal signature of the gases, while an array of seven gas sensors was used to detect each specific gas. This study's dataset is unique, with 5200 samples that include both thermal pictures and gas sensor sequences expressed as vectors of size 1 * 7. This paper focuses on exploring the potential of assistive technology solutions for gas detection using gas sensors and deep learning algorithms to achieve higher accuracy and reliability in gas classification. The proposed approach aims to contribute to the development of more effective and efficient gas detection systems that can improve safety in various environments. In this work, we employed feature selection and deep learning algorithms for the classification of gas sensor data. Focused on selecting the most relevant features from the gas sensor measurements, which were then used as input for the deep learning algorithm. This approach allows for a more interpretable model and can reduce the risk of overfitting.

This paper's key contribution is:

- The application of an optimized deep learning approach to address the problem at hand. Specifically, we leverage the Adam optimizer, a popular and effective optimization algorithm, to enhance the performance of our deep learning model.
- Additionally, we incorporate feature selection techniques to preprocess the data before feeding it into the deep learning model. By selecting relevant features, we aim to reduce the dimensionality of the input and improve the efficiency and effectiveness of the model.
- By combining the power of optimized deep learning with feature selection, our approach

demonstrates enhanced accuracy and efficiency in solving the problem. The optimized deep learning model, driven by the Adam optimizer drives the optimized deep learning model, enabling more effective training and learning from the data. Additionally, feature selection ensures the utilization of only the most informative features, reducing noise and enhancing overall performance.

The subsequent portions of this paper are organized as follows: Section 2 goes over the content and method. Section 3 focuses on the dataset that was used in our research. Section 4 presents the experimental results, which compare the classification accuracy of several machine learning and deep learning algorithms. Finally, Section 5 gives concluding remarks that summarize the research's significant findings and contributions.

2. Material and Method

This segment outlines the approaches we intend to utilize in this paper as a preliminary measure for our system framework and experimentation setup.

2.1. Deep Learning and Adam Optimization

Deep learning (DL), a subset of machine learning (ML), uses neural networks with multiple layers to model intricate data interactions. DL has gained attention for its outstanding results in image and audio recognition, natural language processing, and robotics. The neural network architecture in DL comprises layers collaborating to learn from input data, process it, and provide an output. Each layer consists of artificial neurons executing computations and sending data to the next layer, fully connected, with each connection assigned a weight determining its strength. Artificial Neural Networks (ANNs), fundamental to most DL structures, are prominent and typically include an input layer, an output layer, and one or more hidden layers [7]. The input layer introduces data, while the output layers [8] and [9] produce the outcome. Hidden layers, representing the network's depth, learn the mapping between input and output using nonlinear activation functions such as Rectified Linear Unit (RELU) [10], soft plus, and soft sign. Traditional neural networks use stochastic gradient descent (SGD) for weight optimization, with various loss functions, including cross-entropy [11], for estimating errors in classification tasks. DL requires a vast amount of data for proper training, posing a significant barrier in many applications. However, DL can learn data representations without explicit feature engineering, making it valuable for analyzing massive amounts of unstructured data. Adam (Adaptive Moment Estimation) [12] is an optimization algorithm combining AdaGrad and RMSProp advantages. It dynamically adjusts the learning rate during training, functioning as an adaptive learning rate optimization algorithm. Adam maintains a decaying average of past gradients and squared gradients to compute adaptive learning rates [13] for each parameter, including bias correction for biased initial estimates. The algorithm calculates the first and second moments of gradients to adjust hyperparameters like the learning rate for each weight in the network. The learning rate, generally predetermined before training and ranging from 0.0 to 1.0, makes Adam suitable for deep neural networks with large parameter spaces. In various deep learning challenges, Adam has demonstrated faster convergence and greater performance than classical SGD. Hyperparameters in DL designs, including batch size, dropout rate, and the total number of neurons in hidden levels, significantly influence network performance and are typically randomly assigned. Evaluation of these hyperparameter values occurs through a validation set, with the dataset divided into three sections: training optimizes the network's parameters, the validation set adjusts hyperparameters and measures performance during training, and the test set evaluates performance after training.

2.2. Feature Selection

The process of discovering and selecting a subset of relevant features from a larger set of features to be utilized in model training is known as feature selection. This process can be performed before splitting data into training and testing sets to prevent any data leakage from the test set into the training set. Performing feature selection [14] before splitting the data helps to ensure that the selected features are independent of the outcome variable and unbiased. This is because if feature selection is performed after splitting the data, the selection process may be influenced by the test set, which could lead to overfitting on the test set. Filter methods, wrapper methods, and embedding methods are examples of feature selection strategies. Filter methods assess and rank characteristics based on their connection with the outcome variable using statistical measurements. Wrapper approaches choose features by assessing the performance of a model trained on a subset of them. Embedded techniques pick features as part of the model training process, in which the model decides which characteristics to employ. In summary, performing feature selection before splitting the data can help ensure unbiased and independent feature selection and prevent any data leakage from the test set into the training set.

2.3. Machine Learning and Supervised Techniques

Machine Learning (ML), a subset of Artificial Intelligence (AI), enables computer systems to learn and improve without explicit programming. ML algorithms automatically learn patterns and relationships in data, making predictions or decisions based on that learning. The ML process involves three stages: data preparation, model training, and evaluation. In the data preparation stage, data is cleaned, preprocessed, and transformed into a suitable format, involving feature selection or engineering for relevant input variables. In the model training stage, the ML algorithm applies to prepared data, learning patterns, and relationships, adjusting parameters to minimize the gap between predictions and actual output. Various ML algorithms, including supervised learning like Support Vector Machine (SVM) [15], unsupervised learning, and reinforcement learning, are applied. SVM is a well-known supervised ML technique utilized for classification or regression applications. It locates a hyperplane in the feature space to effectively divide various classes. Decision Tree [16], a popular technique for predicting and categorizing tasks, has a flowchart-like structure. Internal nodes represent tests on attributes or features, branches represent test outcomes, and leaf nodes represent class labels or choices. Decision trees are widely employed due to their simplicity, interpretability, and ability to handle both categorical and numerical data. However, they may suffer from bias towards features with many values, biased trees due to class imbalance, and instability from small changes in data. Combining decision trees with other algorithms, such as random forests or gradient boosting, improves performance.

3. Dataset Description

Gas detection is an important area of study with numerous uses in industry, safety, and health. There has been a rise in interest in multimodal gas detection in recent years, which incorporates data from several sources such as sensors, pictures, and sounds. However, there is a scarcity of high-quality multimodal gas detection datasets. This study included the MultimodalGasData dataset [7], a new dataset for gas detection and classification that combines sensor data and photos. Certain gases are detected by gas sensors by turning them into electrical impulses. Metal oxide semiconductor (MQ) technology-based sensors are frequently chosen among the different types of gas sensors available due to their small size, quick response time, and extended lifespan. Each sensor is made up of a heating element that generates an output voltage proportional to the goal gas concentration. Table 1 provides an overview of various sensors as well as the gases to which they are sensitive, which is useful information for gas detection applications. The dataset has two sections: training and testing. There are 4480 samples in the training set, 960 samples in the testing set, and 960 samples in the validation set. MultimodalGasData [2] gives simultaneous data from seven distinct gas sensors as well as photos from a thermal camera. Two different gases are considered, and four groups are created: no gas, perfume, smoke, and a blend of perfume and smoke. The dataset is gathered using seven distinct metal oxide gas sensors (MQ5, MQ135, MQ8, MQ6, MQ7, MQ3, and MQ2) and a thermal imaging camera (as stated in Table 1). The collection is made up of numerical values from gas sensors and photos captured with a thermal camera.

Table 1. Shows a list of gas sensors and sensitive gases.

Sensors	Gas of Sensitivity
MQ5	Natural Gas, LPG
MQ135	Air Quality (Benzene, Smoke)
MQ8	Hydrogen Gas
MQ6	Butane Gas, LPG
MQ7	Carbon Monoxide
MQ3	Alcohol, Ethanol, Smoke
MQ2	Butane, Smoke, **propane**, LPG, Methane

4. Proposed Model

Figure 1 displays the gas sensor system, which contains several gas sensors. This diagram depicts the network's structure as well as the training procedures that were followed. The mechanisms depicted in the diagram will be described in depth in subsequent sections.

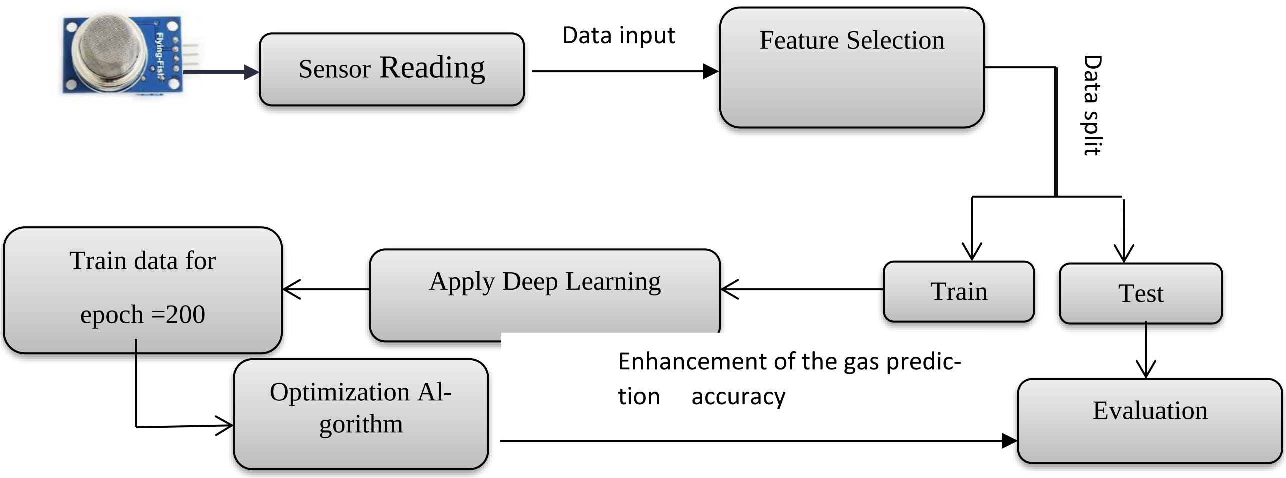

Figure 1. Structure and the training steps that were followed for developing the network

4.1. Gas Sensor Reading

Gas sensors [21] are devices that detect and measure the concentration of different gases in the air. Various types of gas sensors, including MQ5, MQ135, MQ8, MQ6, MQ7, MQ3, and MQ2, were used in this study.. These sensors are highly sensitive to different types of gases such as methane, smoke, LPG, alcohol, butane, natural gas, carbon monoxide, and air quality, as outlined in Table 1. Each sensor has a unique sensitivity range and response time, and it can detect a specific gas or a range of gases. MQ2 and MQ5 sensors are commonly used for detecting LPG and natural gas, respectively, while MQ3 and MQ7 sensors are commonly used for detecting alcohol and carbon monoxide, respectively. The MQ6 sensor is used for detecting liquefied petroleum gas (LPG), while the MQ8 sensor is commonly used for detecting hydrogen gas. Lastly, the MQ135 sensor is used for detecting air quality and hazardous gases such as nitrogen dioxide, benzene, and carbon dioxide. The readings from these gas sensors are crucial for monitoring the air quality [22] and detecting the presence of harmful gases in various settings such as homes, industries, and public places. The sensors provide real-time data on gas concentration levels, which can be used for further analysis and decision-making.

4.2. Feature Selection from Gas Sensor Measurements

In this dataset, feature selection [23] was performed to identify the most relevant features that contribute to the classification of gas readings.

Before splitting the dataset into train and test sets, feature selection is carried out using the k-best method with a value of k set to 6. Feature selection is a technique used to choose a subset of relevant features from a larger set in order to enhance model performance and reduce complexity.

The k-best feature selection method identifies the k most informative features based on a scoring metric. This metric assesses the predictive power of each feature individually and ranks them accordingly. Features with higher scores are deemed more important for the model.

By setting k to 6, the model specifically selects the top six features with the highest scores. This approach allows for a balance between model complexity and performance, as it focuses on capturing the most relevant information while reducing the dimensionality of the feature set.

4.3. Gas Sensor Measurements Using Deep Learning

Gas sensor measurements were used as inputs to an artificial neural network to accurately classify different gas types and concentrations. The artificial neural network was designed using 5 input layers and optimal values for the hyperparameters used by deep learning, as shown in Table 2. Deep learning was utilized to compare and comparison several optimizers with a constant learning rate of 0.001 and a decay rate of 1 * 10^-3. After conducting a thorough experimentation process, it was determined that the Adam optimizer demonstrated the strongest model fit and the fastest convergence rate. Therefore, the Adam optimizer was chosen for further analysis and experimentation.

5. Results

This section contains two important experiments. The first experiment is concerned with selecting features.The second experiment will assess the effectiveness and comparison of deep learning and other classifiers in machine learning across four distinct classes.: no gas, perfume, smoke, and mixed. The suggested model is implemented on the TensorFlow platform using Python 3 and the Keras framework. The suggested model is trained and tested using open-source Google Colab CPUs. It is powered by an Intel Core i7 processor and comes with 12 GB of RAM.

5.1. Evaluation Stage

During the evaluation phase, the proposed approach is assessed using four measures, including accuracy, precision, recall, and the F1 score.

Table 2. shows the optimal values for the hyperparameters determined by ANN.

Algorithm	Hyper-parameters	Optimal Values
ANN	Dropout rate	0.2
	Number of epoch	200
	Batch Size	8

Accuracy: Accuracy [17] is a measure of the overall performance of a binary classification model. It calculates the ratio of the number of correct predictions to the total number of predictions made by the model, this term refers to the data points that the model incorrectly classifies, and it can be computed using Eq. (1) .

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

Where True positives (TP) are the number of positive cases that were accurately predicted; True negatives (TN) are the number of correctly anticipated negative cases; false positives (FP) are the number of incorrectly predicted positive instances; and false negatives (FN) are the number of incorrectly estimated negative instances.

Precision: Precision is a measure of the number of true positives divided by the total number of positive predictions made by the model [18], as shown in Eq. (2).

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

Recall: Recall, as shown in Eq. (3), is a measure of the number of true positives divided by the total number of actual positive instances in the data set[19].

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

F1 Score: The F1 score is a mean of harmonics of precision and recall. Eq. (4) calculates it as a measure of the overall performance of a binary classification model [20].

$$\text{F1 Score} = 2 * ((\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})) \quad (4)$$

5.2. Feature Selection Phase Results

The experimental results in this phase demonstrate that the MultimodalGasData dataset is a difficult and relevant dataset for gas detection and classification. To train and assess the model on the dataset, we employed deep learning with the Adam optimizer. On testing, the deep learning model attained an accuracy of 94%. We performed feature selection and retrained the model to boost the model's performance even further. The retrained model achieved 95% accuracy on the testing set, and optimal values for the deep learning-determined hyperparameters are reported in Table 3.

For each of the four gas classes, the classification model's performance was tested using several metrics such as accuracy, loss, precision, recall, and F1 score. Table 4 shows the individual training and testing metrics for all classes.

Table 3. Optimal hyperparameter values

Hyperparameters	Optimal values
Batch size	8
Learning rate	1e-4
Number of neurons of the first dense layer	1500
Dropout rate	0.1

Figure 2 represents the accuracy of an ANN model at every epoch before optimization (a). The training accuracy increases rapidly at first but then plateaus. The validation accuracy also increases, but more slowly than the training accuracy. This suggests that the model is learning the training data well. From the loss of an ANN model at every epoch before optimization (b). The training loss decreases rapidly at first but then plateaus. The validation loss also decreases, but more slowly than the training loss. This suggests that the model is learning the training data well, but it may not be able to generalize to new data as well. The accuracy of an ANN model at every epoch after optimization(C). The training accuracy increases rapidly at first but then plateaus. The validation accuracy also increases, but more slowly than the training accuracy. This suggests that the model is learning the training data well.[redacted]the training loss decreases rapidly over the first few epochs but then plateaus at around 0.2. The validation loss also decreases, but more slowly than the training loss. This suggests that the model may be learning the training data too well after optimization (d).

Table 4. Results Report

ANN Model	Accuracy of Training	Accuracy of Testing	Class	Precision	recall	F-measure
Before Optimization	0.95	0.94	No Gas	1.00	1.00	1.00
			Perfume	0.90	0.86	0.88
			Smoke	0.87	0.91	0.89
			Mixture	1.00	1.00	1.00
After Optimization	0.96	0.95	No Gas	1.00	1.00	1.00
			Perfume	0.92	0.88	0.90
			Smoke	0.89	0.93	0.91
			Mixture	1.00	1.00	1.00

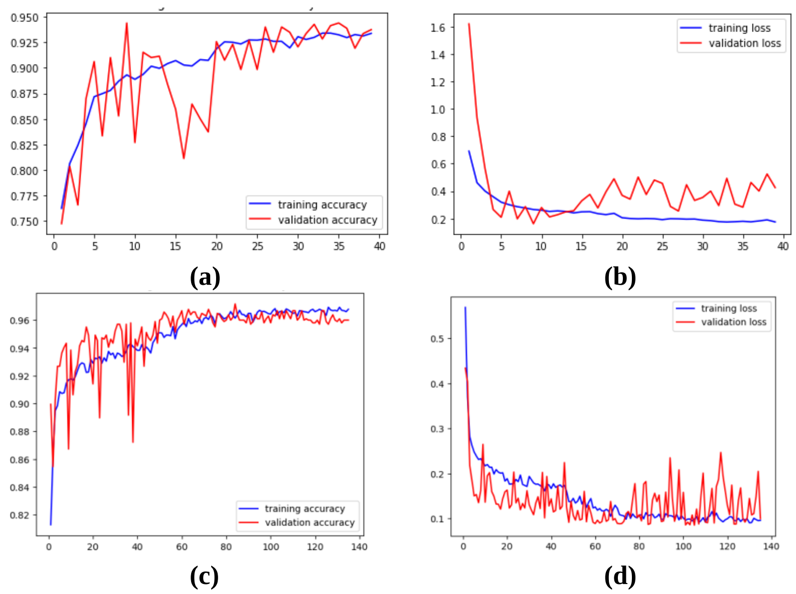

Figure 2. The accuracy and loss of the proposed model at every epoch: a) Accuracy of ANN model before optimization, b) Loss of ANN model before optimization, c) Accuracy of ANN model after optimization, d) Loss of ANN model after optimization.

5.3. Comparison Deep Learning and Machine Learning Results

During this Section, several experiments were conducted on the dataset to determine the most suitable classifier with optimal parameter settings for classifying NO-Gas, perfume, smoke, and mixtures. The performance of deep learning was compared to that of different machine learning classifiers, such as SVM with parameters kernel='rbf', C=100000.0, gamma='' auto,'', and DecisionTree with parameter criterion='gini', in Table 5. The results clearly indicate that deep learning achieved the highest accuracy and is therefore considered the optimal choice.

Table 5. Comparison Deep Learning and Machine Learning Results

Machine Learning Model	Accuracy
SVM	0.81

Decision Tree	0.83
Deep Learning Model	0.94

6. Conclusion

In this paper, the problem addressed was the detection of gas leaks, which pose significant safety and environmental hazards, and detecting them accurately and efficiently is crucial for ensuring public safety and minimizing potential damage. The study's goal was to investigate the efficacy of optimized deep-learning approaches following feature selection in the context of gas sensors. The objective was to contrast the performance of classic machine learning like support vector machines (SVM) and decision trees (DT) with that of a deep learning model. Through the application of feature selection, the dimensionality of the input data was reduced, enhancing the efficiency and accuracy of the subsequent models. Additionally, an optimized deep learning approach was adopted, leveraging advanced algorithms such as the Adam optimizer to improve the deep learning model's performance. The experimental results showcased the superiority of the optimized deep learning model over classic machine learning algorithms. The deep learning model demonstrated higher accuracy and reliability in gas detection, outperforming SVM and DT. This highlights the potential of deep learning for effectively analyzing and interpreting complex patterns in gas sensor data. Overall, this study emphasizes the need for optimized deep-learning approaches following feature selection in gas sensor data interpretation. The findings suggest that deep learning models have the potential to enhance the performance and reliability of gas detection systems compared to traditional machine learning algorithms. Future research can further explore and refine these techniques to achieve even more robust and accurate gas detection systems.

References

1. Narkhede, P.; Walambe, R.; Mandaokar, S.; Chandel, P.; Kotecha, K.; Ghinea, G. Gas Detection and Identification Using Multimodal Artificial Intelligence Based Sensor Fusion. Appl. Syst. Innov. 2021, 4, 3. https://doi.org/10.3390/asi4010003.
2. MDC Systems Inc. Detection Methods. Online Resource. Available online: https://mdcsystemsinc.com/detection-methods/ (accessed on 17 July 2020).
3. Peng, Pai, Xiaojin Zhao, Xiaofang Pan, and Wenbin Ye. 2018. "Gas Classification Using Deep Convolutional Neural Networks" *Sensors* 18, no. 1: 157. https://doi.org/10.3390/s18010157.
4. Khalaf, W.M.H. Electronic Nose System for Safety Monitoring at Refineries. J. Eng. Sustain. Dev. 2012, 16, 220–228.
5. Majeed, A. Improving Time Complexity and Accuracy of the Machine Learning Algorithms Through Selection of Highly Weighted Top k Features from Complex Datasets. Ann. Data. Sci. 6, 599–621 (2019). https://doi.org/10.1007/s40745-019-00217-4.
6. Narkhede, P.; Walambe, R.; Mandaokar, S.; Chandel, P.; Kotecha, K.; Ghinea, G. Gas Detection and Identification Using Multimodal Artificial Intelligence Based Sensor Fusion. Appl. Syst. Innov. 2021, 4, 3. https://doi.org/10.3390/asi4010003.
7. Narkhede, Parag; Walambe, Rahee; Chandel, Pulkit; Mandaokar, Shruti; Kotecha, Ketan (2022), "MultimodalGasData: Multimodal Dataset for Gas Detection and Classification", Mendeley Data, V2, doi: 10.17632/zkwgkjkjn9.2, MultimodalGasData: Multimodal Dataset for Gas Detection and Classification - Mendeley Data.
8. Ardabili Sina, Abdolalizadeh Leila, Mako Csaba, Torok Bernat, Mosavi Amir," Systematic Review of Deep Learning and Machine Learning for Building Energy" , 10.3389/fenrg.2022.786027.
9. Weizheng Shen, Ding Tu, Yanling Yin, Jun Bao, A new fusion feature based on convolutional neural network for pig cough recognition in field situations, https://doi.org/10.1016/j.inpa.2020.11.003.
10. Yang, D., Ngoc, K.M., Shin, I. et al. DPReLU: Dynamic Parametric Rectified Linear Unit and Its Proper Weight Initialization Method. Int J Comput Intell Syst 16, 11 (2023). https://doi.org/10.1007/s44196-023-00186-w.
11. Kevin P. Murphy," Probabilistic Machine Learning: An Introduction", https://books.google.com/books?hl=ar&lr=&id=wrZNE-AAAQBAJ&oi=fnd&pg=PR27&dq=Deep+Learning.+MIT+Press.&ots=L9tfLBbqQg&sig=LSRsSoa1UQgkAc4FG1EmkWX_eT0 .
12. Ioannou, G., Tagaris, T. & Stafylopatis, A. AdaLip: An Adaptive Learning Rate Method per Layer for Stochastic Optimization. Neural Process Lett (2023). https://doi.org/10.1007/s11063-022-11140-w.
13. Tilottama Goswami, G.R. Sinha,"Fundamental optimization methods for machine learning, Statistical Modeling in Machine Learning", https://doi.org/10.1016/B978-0-323-91776-6.00005-
14. J. Park, D. Yi and S. Ji, "A novel learning rate schedule in optimization for neural networks and it's convergence", *Symmetry*, vol. 12, no. 4, pp. 660, Apr. 2020.
15. Anwar Ul Haq, Adnan Zeb , Zhenfeng Lei and Defu Zhang," Forecasting daily stock trend using multi-filter feature selection and deep learning, 5 December 2020 https://www.sciencedirect.com/science/article/abs/pii/S095741742031099X.
16. E. Osuna; R. Freund; F. Girosi, An improved training algorithm for support vector machines

17. Martijn Gösgens, Anton Zhiyanov, Aleksey Tikhonov, Liudmila Prokhorenkova," Good Classification Measures and How to Find Them", https://proceedings.neurips.cc/paper_files/paper/2021/file/8e489b4966fe8f703b5be647f1cbae63-Paper.pdf.
18. M. Valavan and S. Rita," Predictive-Analysis-based Machine Learning Model for Fraud Detection with Boosting Classifiers", DOI: 10.32604/csse.2023.026508.
19. Goutte C. and Gaussier E.Proceedings of European Conference on Information Retrieval, Springer, Berlin, Heidelberg (2005), pp. 345-359"A probabilistic interpretation of precision, recall and f-score, with implication for evaluation".
20. Miao, J., Zhu, W. Precision–recall curve (PRC) classification trees. Evol. Intel. 15, 1545–1569 (2022). https://doi.org/10.1007/s12065-021-00565-2.
21. Muhammad Izzudin Ahmad Asri, Md. Nazibul Hasan, Mariatul Rawdhah Ahmad Fuaad, YusriMd Yunos, and Mohamed Sultan Mohamed Ali, Senior Member, IEEE 'MEMS Gas Sensors: A Review' June 21 DOI: 10.1109/JSEN.2021.3091854.
22. Maria Vesna Nikolic, Vladimir Milovanovic, Zorka Z. Vasiljevic,and Zoran Stamenkovic, 2020 Nov 'Semiconductor Gas Sensors: Materials, Technology, Design, and Application' , DOI: 10.3390/s20226694.
23. Thakkar, A., Lohiya, R. A survey on intrusion detection system: feature selection, model, performance measures, application perspective, challenges, and future research directions. Artif Intell Rev 55, 453–563 (2022). https://doi.org/10.1007/s10462-021-10037-9.