Enhancing Gas Leak Detection: Using Multimodal Sensors For Gas Identification via CNN & LSTM Neural Network Fusion

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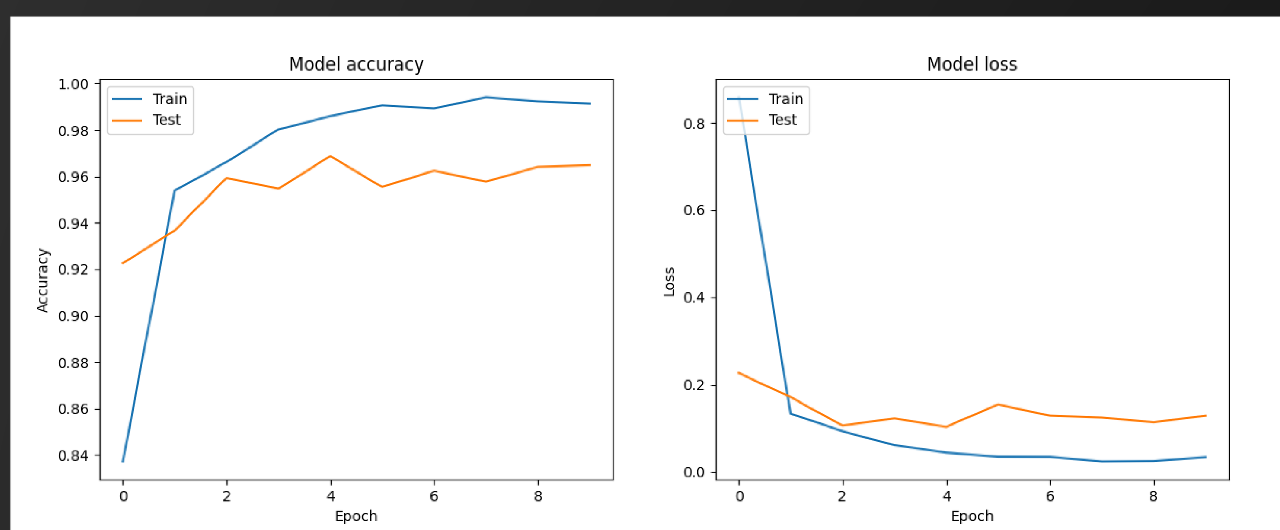
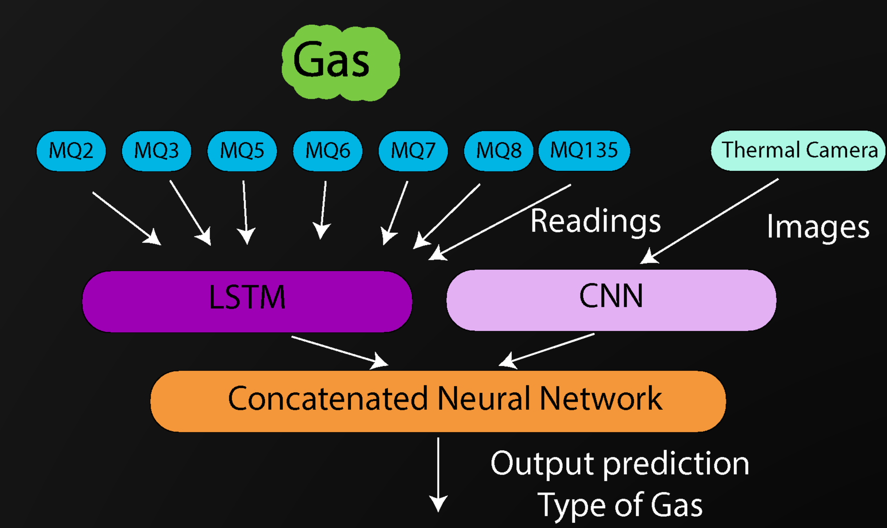
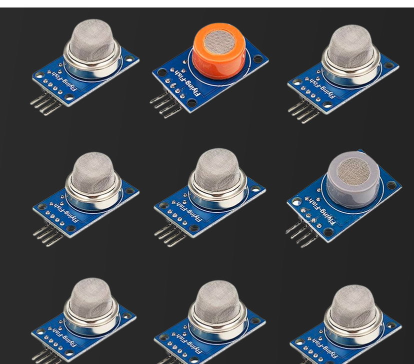
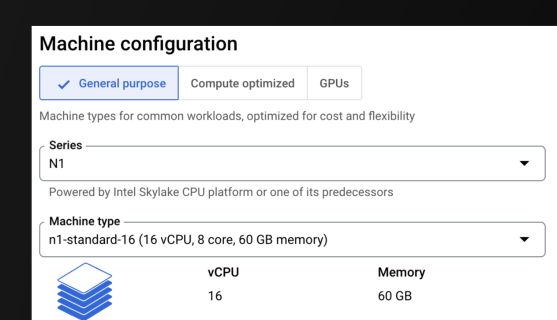
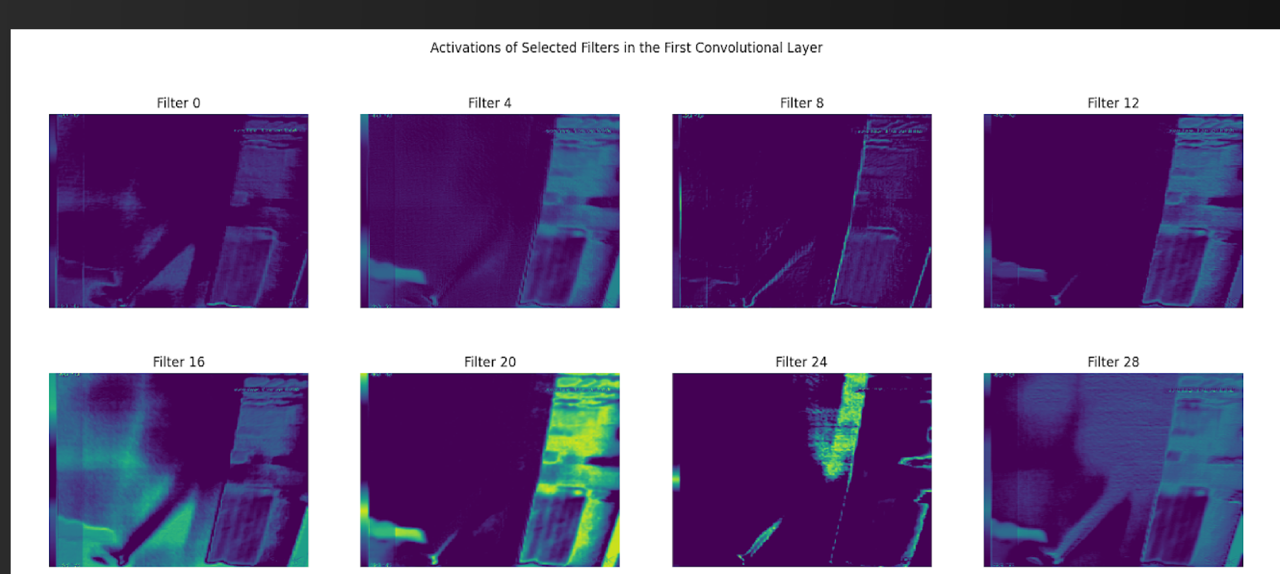
Materials and Methods







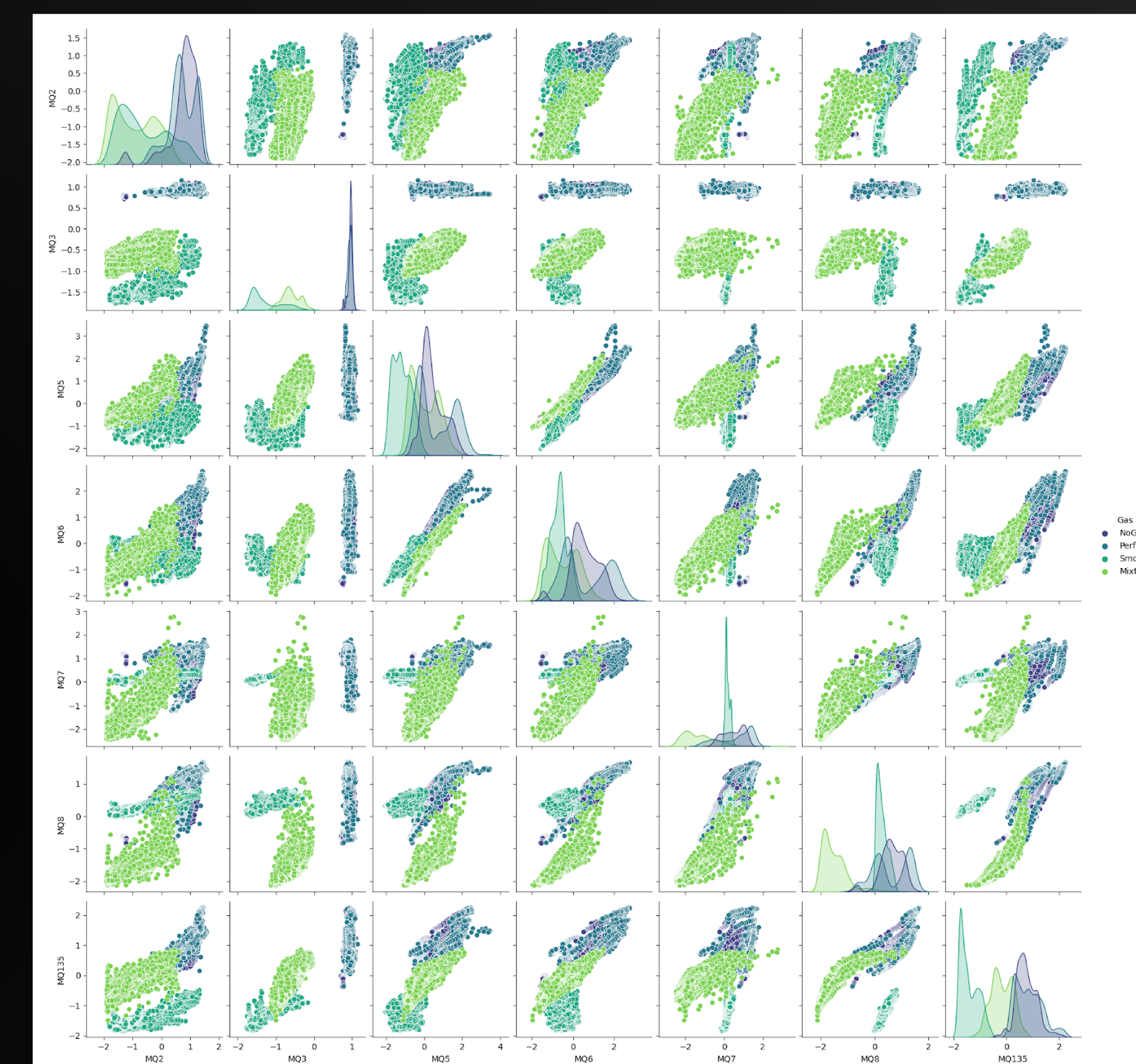




The activation maps of the neural network's first convolutional layer offer a condensed visual representation of the model's feature recognition.

- Filters like 0 and 4 highlight edge detection, capturing the image's structure.
- Filter 8 focuses on textural details
- Filter 12 responds to broader light and shadow contrasts.
- Filters 16 and 20 show varied sensitivity to image details
- Filter 24's selectivity hints at object recognition.
- Filter 28's widespread response implies a general feature awareness.

Together, these maps illustrate the network's layered interpretation, guiding model refinement and revealing its visual analytic depth.



The pair plot is a sophisticated matrix of scatter plots and histograms, offering a condensed overview of the dataset's dimensionality and the distinct characteristics of various gas types:

- Diagonal plots illustrate the data distribution for each sensor, reflecting unique trends that aid in gas differentiation.
- Off-diagonal plots detail sensor interrelations, highlighting correlations critical for the model's classification accuracy.
- Color hues demarcate gas categories, providing visual cues about their distribution across sensor readings and indicating potential classification challenges.

In essence, this pair plot is a visual encapsulation of the data's complexity and the model's classification landscape, emphasizing the nuanced sensor interactions that inform the model's decision-making process.

Abstract

In the quest to enhance industrial safety protocols, the development of sophisticated gas detection systems is paramount, particularly to mitigate the risks associated with invisible and odorless hazardous gases. This research proposes an innovative multimodal artificial intelligence framework that capitalizes on the strengths of both semiconductor gas sensor arrays and thermal imaging to detect and categorize various gas emissions. Our methodology harnesses a robust dataset of 6400 gas samples, distributed among four distinct classes. We constructed a convolutional neural network that integrates early fusion techniques for a comprehensive synthesis of sensor data, followed by a concatenated layer that coalesces the sensory features, culminating in a dense neural network layer tasked with the precise classification of gases. This approach not only demonstrates superior accuracy in gas identification but also underscores the potential for implementing such AI-driven systems in critical scenarios.

Background

Problem: Industrial hazards, particularly gas leaks, pose serious risks to the environment and human health, resulting in explosions, fires, and harmful emissions. Identifying and containing gas leaks swiftly is crucial to prevent disasters. Current methods of gas detection, including chemical-based approaches and various AI-based techniques, often face limitations in accuracy, efficiency, and sensor sensitivity. The conventional gas sensor-based methods might produce false readings due to low gas concentrations, leading to inaccuracies. Additionally, thermal imaging cameras have been explored for gas leak detection by analyzing temperature changes in the environment. However, individual sensor systems have limitations in identifying gas types and achieving necessary accuracy.

Solution: To overcome these limitations, a multimodal data fusion approach is proposed, combining information from various sensors and thermal imaging. This fusion enables a more accurate and robust gas detection system by integrating deep learning techniques like CNN and LSTM for early fusion of sensor data. The main contributions of this proposed methodology include the development of an innovative multimodal AI-based framework for robust gas detection and the demonstration of early fusion techniques using CNN and LSTM architectures. These contributions aim to create a more reliable and faster gas detection system capable of identifying specific gases within mixed environments.

Conclusion

The visual analyses presented here paint a promising picture of a model that is both adept at learning from the present data and robust enough to apply these learnings to new, unseen data. The balanced nature of the dataset bodes well for the model's equitable performance across various gas types, a factor of critical importance in the practical detection and classification of gases in safety-critical applications. While the current model's performance is laudable, the pursuit of perfection in such applications dictates a continuous quest for improvement. Therefore, additional visualizations and diagnostics would be prudent to fine-tune the model's performance further, ensuring reliability and trustworthiness in its real-world deployment.

Acknowledgments

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Future Direction

For future experimentation, we will further refine and optimize our deep learning models used in the fusion process, explore the integration of additional sensors or advanced sensor technologies to augment the fusion system, work on possibly developing a real-time implementation for the system, and creating public awareness campaigns to promote understanding and awareness regarding gas leakages, their risks, and the importance of early detection systems.

Results

Our fusion model classifies the images with an accuracy of 96.48%, which matches very similarly to the original experiment of 96% signifying success