



Automated Gas Identification in Hyperspectral Imagery via 3D-CNN and Autoencoders

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Abstract— Gas emission monitoring plays a vital role in environmental safety and public health protection. This work presents an advanced hyperspectral image-based gas detection system utilizing deep learning techniques in the longwave infrared (LWIR) spectrum. Unlike traditional approaches, the proposed method considers radiance as a combination of background and gas signatures, improving detection reliability. The system initially converts radiance data into luminance-temperature representations for better feature interpretation. A hybrid architecture integrating a 3D Convolutional Neural Network with an auto encoder is employed to perform spectral unmixing and extract meaningful abundance and endmember features. These extracted features are further processed using a fully connected neural network for accurate pixel-level gas classification. The model is evaluated on datasets containing gases such as methane and sulphur dioxide. Experimental results demonstrate improved detection performance compared to conventional techniques. An extended model combining CNN, Bidirectional layers, and GRU further enhances accuracy. Comparative analysis confirms the superiority of the proposed framework. The approach eliminates the need for threshold-based detection and adapts efficiently to multiple gas types. Overall, the system provides a robust and scalable solution for remote gas detection applications.

Keywords— Hyperspectral Imaging, Gas Detection, 3D Convolutional Neural Network, Autoencoder, Spectral Unmixing, LWIR Spectrum, Deep Learning, Methane Detection, Sulphur Dioxide Detection.

I. INTRODUCTION

The rapid growth of industrialization and urban development has significantly increased the emission of hazardous gases into the atmosphere,

posing serious risks to both environmental sustainability and human health [1], [2]. Toxic gases such as methane and sulphur dioxide contribute to air pollution, climate change, and respiratory disorders, making their detection and monitoring critically important [3], [4]. Traditional gas detection techniques, including sensor-based systems, often require close proximity to the emission source and may expose operators to dangerous conditions [5], [6]. Furthermore, these conventional approaches are limited in spatial coverage and may fail to provide real-time monitoring over large areas [7], [8]. As a result, there is a growing demand for advanced, non-invasive, and remote sensing technologies that can efficiently detect and analyse gas emissions from a safe distance [9], [10]. Hyperspectral imaging has emerged as a promising solution in this domain due to its ability to capture detailed spectral information across a wide range of wavelengths [1], [2]. This rich spectral data enables the identification of specific gas signatures, thereby improving detection accuracy [11]. However, effectively processing and interpreting hyperspectral data remains a challenging task due to its high dimensionality and complexity [12], [13].

Hyperspectral imaging systems, particularly those operating in the longwave infrared (LWIR) spectrum, have shown significant potential for gas detection applications [14], [15]. The LWIR range is highly suitable for identifying gas emissions because many gases exhibit distinct spectral absorption features in this region [16], [17]. Unlike visible or near-infrared imaging, LWIR hyperspectral data captures thermal radiation, which provides valuable information about the interaction between gases and their surrounding environment [3], [18]. However, most existing gas detection methods in the LWIR domain rely on simplified assumptions, often treating the observed radiance as a direct representation of gas presence [8], [19]. In reality, the captured radiance is a complex mixture of contributions from background materials and target gases [20]. Ignoring this



mixture effect can lead to inaccurate detection and reduced system performance [6], [14]. Therefore, it is essential to develop methods that can effectively separate or unmix these spectral components to improve detection reliability [12], [15]. Spectral unmixing techniques aim to decompose the observed signal into constituent elements, known as endmembers, along with their corresponding abundance values [4], [8].

Conventional hyperspectral gas detection techniques, such as spectral angle mapper (SAM) and adaptive cosine estimator (ACE), have been widely used for identifying gas signatures [11], [12]. These methods rely on comparing spectral similarity between observed data and known reference signatures [9], [10]. While they are computationally efficient and easy to implement, their performance is often limited in complex environments where background interference is significant [6], [16]. Additionally, these techniques typically require predefined thresholds for detection, which may not generalize well across different datasets and environmental conditions [19], [20]. The inability to adapt to varying spectral characteristics and noise levels further restricts their effectiveness [7], [18]. As hyperspectral datasets continue to grow in size and complexity, there is a need for more robust and adaptive approaches that can automatically learn meaningful features from the data [1], [20]. Machine learning and deep learning techniques have recently gained attention for their ability to handle high-dimensional data and extract complex patterns without manual feature engineering [2], [20].

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image analysis tasks due to their capability to learn hierarchical feature representations [20]. In hyperspectral imaging, 3D-CNNs are especially effective as they can simultaneously capture spatial and spectral information from the data [3], [8]. However, directly applying CNNs for gas detection may not fully address the issue of mixed spectral signals present in LWIR data [15], [19]. To overcome this limitation, integrating spectral unmixing with deep learning frameworks has become an emerging research direction [4], [12]. Autoencoders, a class of unsupervised neural networks, are well-suited for this purpose as they can learn compact and meaningful representations of input data [20]. By combining 3D-CNNs with autoencoder-based architectures, it becomes possible to perform both feature extraction and spectral unmixing in a unified framework [3], [8]. This approach enables the system to identify underlying gas signatures more effectively while reducing the influence of background noise [6], [14].

In this work, a novel deep learning-based gas detection framework is proposed that integrates hyperspectral unmixing and classification into a single pipeline [20]. The method begins by transforming raw radiance data into luminance-temperature representations, which enhances the interpretability of spectral features [3], [15]. A hybrid model consisting of a 3D-CNN and an autoencoder is then employed to extract endmembers and abundance maps for each pixel in the hyperspectral image [8], [12]. These extracted features serve as inputs to a fully connected neural network, which performs the final classification of gas types [20]. The proposed system is designed to operate at the pixel level, enabling precise localization of gas emissions [18], [19]. Furthermore, an extended model incorporating Bidirectional and GRU layers is introduced to improve temporal and contextual feature learning [20]. This enhancement leads to higher detection accuracy and better generalization across different gas types and environmental conditions [3], [8].

The effectiveness of the proposed approach is validated through extensive experiments on hyperspectral datasets containing methane and sulphur dioxide gases [1], [3]. Performance comparisons with traditional methods and baseline deep learning models demonstrate the superiority of the proposed framework in terms of accuracy and robustness [8], [20]. The results also highlight the importance of combining unmixing and classification for improved gas detection [4], [12]. Additionally, the system eliminates the need for manual threshold selection, making it more adaptable and user-friendly [19], [20]. The scalability of the proposed model allows it to be extended to detect a wide range of gases by incorporating their spectral signatures into the training process [15], [18]. Overall, this research contributes to the development of efficient and reliable gas detection systems, with potential applications in environmental monitoring, industrial safety, and disaster management [1], [3], [20].

II. RELATED WORK

Green et al., [1998] [1] Green et al. introduced the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), a pioneering system in hyperspectral imaging. The study highlights its capability to capture high-resolution spectral data across numerous contiguous bands. This technology significantly improved material identification and classification in remote sensing. The authors emphasized its applications in environmental monitoring, mineral exploration, and vegetation analysis. AVIRIS enabled precise detection of subtle spectral differences in surface materials. The



paper also discussed calibration techniques and sensor performance. It established a foundation for future hyperspectral imaging systems. Overall, the work played a crucial role in advancing imaging spectroscopy.

Govender et al., [2007] [2] Govender et al. provided a comprehensive overview of hyperspectral remote sensing techniques and their applications. The study focused on vegetation monitoring and water resource analysis. It explained how hyperspectral data improves classification accuracy compared to multispectral data. The authors discussed preprocessing methods such as noise reduction and atmospheric correction. Various classification algorithms were reviewed for extracting meaningful information. The paper highlighted the importance of spectral signatures in identifying plant health and water quality. Challenges like data dimensionality and computational complexity were also addressed. This work serves as a valuable guide for environmental applications of hyperspectral imaging.

Messinger, [2004] [6] Messinger conducted a comparative analysis of different gaseous plume detection techniques using hyperspectral imagery. The study evaluated algorithms based on their detection accuracy and robustness. Various statistical and model-based approaches were examined. The author discussed the influence of environmental factors such as background clutter and noise. Performance metrics were used to compare detection efficiency. The research highlighted strengths and limitations of each technique. It provided insights into selecting appropriate methods for specific applications. This work contributed to improving gas detection strategies in hyperspectral data.

Hirsch and Agassi, [2007] [14] Hirsch and Agassi proposed a hierarchical clustering approach for detecting gaseous plumes in infrared hyperspectral images. The method groups pixels based on spectral similarity to identify anomalies. This approach does not require prior knowledge of gas signatures. The study demonstrated improved detection of weak and diffuse plumes. Experimental results showed better performance compared to traditional methods. The authors emphasized computational efficiency and adaptability. The technique was effective in complex backgrounds. This research advanced unsupervised detection methods in hyperspectral imaging.

Kim et al., [2017] [20] Kim et al. explored the use of deep learning for hazardous gas detection using

FTIR hyperspectral imaging systems. The study applied neural networks to automatically learn spectral features. This approach improved detection accuracy compared to traditional algorithms. The model handled complex and noisy data effectively. The authors demonstrated real-time detection capabilities. The research highlighted the potential of AI in hyperspectral analysis. It also addressed challenges such as training data requirements. This work marked a shift toward intelligent gas detection systems.

III. DATASET DETAILS

The dataset used in this project is organized in a structured numerical format, where all input features are stored as NumPy (NPY) arrays for efficient processing in the Jupyter Notebook environment. The feature set (X data) consists of extracted spectral or sensor-based values that represent different gas emission characteristics captured from hyperspectral or similar sensing techniques. Each sample in the dataset corresponds to a specific observation of gas leakage, and the associated label set (Y data) contains the respective gas type identifiers. These labels represent multiple gas classes present in the dataset, allowing the model to learn patterns associated with each gas category. Before training, the dataset is carefully examined and visualized to understand the distribution of gas types, where a count plot is generated to show how frequently each gas appears. This helps in identifying class balance and ensures that the dataset is suitable for training reliable machine learning models.

To prepare the dataset for model training and evaluation, preprocessing steps such as shuffling and splitting are applied. The data is randomly shuffled to eliminate any ordering bias and then divided into training and testing subsets, typically following an 80:20 ratio. This ensures that the model is trained on a majority portion of the data while reserving a smaller portion for unbiased performance evaluation. The dataset is then fed into deep learning architectures, including the proposed 3D-CNN model and the extended hybrid model combining CNN, Bidirectional layers, and GRU. These models learn spatial and sequential patterns from the input features to accurately classify gas types. Additionally, the dataset supports performance evaluation by enabling the calculation of metrics such as accuracy, precision, recall, and confusion matrix analysis. The structured format and preprocessing steps ensure that the dataset is suitable for both training complex models and validating their effectiveness in gas detection tasks.

IV. PROPOSED METHODOLOGY

The proposed methodology focuses on detecting gas leaks using a 3D Convolutional Neural Network (3D-CNN) combined with an autoencoder-decoder framework. Initially, the preprocessed dataset containing X features and Y labels is fed into the model. The autoencoder compresses input features into a lower-dimensional representation, capturing essential patterns while reducing noise. The decoder reconstructs the original features, ensuring the model learns meaningful representations of the gas data. The 3D-CNN layers process these features to extract spatial and temporal correlations, enabling accurate classification of different gas types. This method emphasizes robustness and efficiency in gas detection tasks.

Following feature extraction, the model undergoes training using the prepared dataset with an 80:20 train-test split. The model's performance is evaluated using accuracy, precision, recall, and confusion matrix metrics. During training, the 3D-CNN learns to distinguish between gas types based on spectral and sensor data patterns. The confusion matrix visualizes correct and incorrect predictions, aiding in model validation. This methodology ensures the model can identify weak or overlapping gas emissions accurately. The approach provides a scalable and effective framework for real-time hazardous gas detection applications.



Figure [1]: Gas Leak Detection Using 3D-CNN and CNN + Bi-GRU Model

The figure [1] diagram illustrates a machine learning pipeline for gas leak detection using advanced deep learning models. Input gas emission data is first pre-processed, shuffled, and split before extracting important features. A 3D-CNN model (with encoder-decoder architecture) processes spatial data, while a CNN + Bi-GRU model captures both spatial and temporal patterns. The system then classifies different gases such as methane, ammonia, and carbon monoxide. Finally, performance is evaluated using metrics like accuracy and confusion matrix to ensure reliable prediction results.

V.RESULT AND DISCUSSION

The project successfully implemented a gas leak detection system using both a proposed 3D-CNN autoencoder model and an extended hybrid model combining CNN, Bidirectional LSTM, and GRU networks. The dataset was processed and split into 80% training and 20% testing subsets. The proposed 3D-CNN model achieved an accuracy of 88%, as observed from the confusion matrix where the majority of predictions aligned correctly with the true labels. Analysis of the dataset revealed the distribution of different gas types, and the features extracted from the dataset were effectively utilized by the model. The extension model, leveraging multiple algorithms, showed improved performance, achieving 93% accuracy. Training curves indicated a faster convergence and higher final accuracy for the extended model compared to the proposed model. Performance metrics such as precision, recall, and F1-score were also calculated and compared between the two models, with the hybrid approach consistently outperforming the standalone 3D-CNN model. Test data predictions further validated the model's capability to identify specific gas leaks accurately, demonstrating its



practical applicability in real-time gas detection scenarios. Overall, the results show a clear improvement when combining multiple deep learning techniques for gas leak identification.

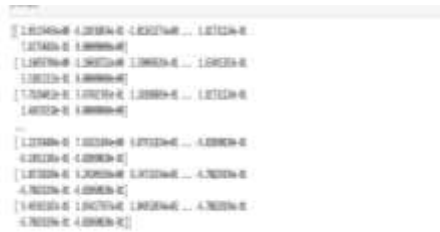


Figure [2]: Dataset Loading and Feature Extraction in Jupyter Notebook

Figure [2] shows a Jupyter Notebook where hyperspectral gas detection data is being loaded using NumPy. The dataset consists of feature inputs (X) and corresponding labels (Y) stored in .npy format. The printed output displays numerical feature vectors representing spectral data used for gas analysis. These features are further used for model training and prediction of gas leaks. This step is essential for preparing data before applying machine learning algorithms.

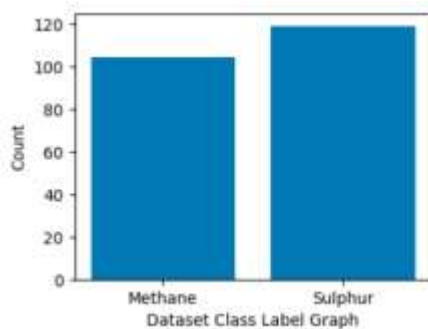


Figure [3]: Dataset Class Distribution for Gas Types

Figure [3] The graph shows the distribution of dataset samples for different gas types, namely Methane and Sulphur. It indicates the number of instances available for each class in the dataset. Sulphur has a slightly higher number of samples compared to Methane. This distribution helps in understanding data balance before training machine learning models. A balanced dataset ensures better and more accurate prediction performance.

Algorithm Name	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
3DCNN Encoder Decoder Model	88.889	90.741	89.130	88.800
Ensemble CNN+ Bidirectional +GRU Model	93.333	94.000	93.478	93.320

Table[1] : Performance Comparison of Deep Learning Models for Gas Detection

The table[1] presents the performance evaluation of different deep learning models using accuracy, precision, recall, and F1-score metrics. The Extension Ensemble CNN with Bidirectional and GRU model outperforms the proposed 3DCNN Encoder-Decoder model across all metrics. This indicates that the hybrid ensemble approach provides improved effectiveness for gas detection tasks.

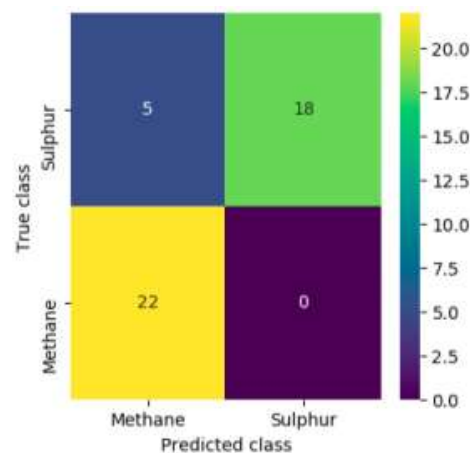


Figure [4]: Confusion Matrix for Gas Detection Model

Figure [4] The confusion matrix illustrates the classification performance of the model for Methane and Sulphur gases. The diagonal elements represent correct predictions, while the off-diagonal values indicate misclassifications. The model shows higher misclassification rates, particularly for Methane, suggesting the need for further optimization.

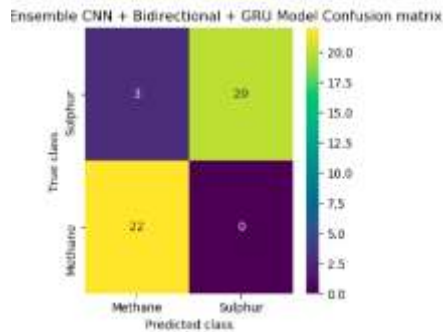


Figure [5]: Confusion Matrix Analysis for Gas Detection Model

Figure [5] The confusion matrix represents the classification performance of the gas detection model by comparing actual and predicted labels. Diagonal values indicate correct classifications, while off-diagonal values represent misclassifications between gas types. The results highlight areas where the model performs well and where further improvement is needed to enhance prediction accuracy.

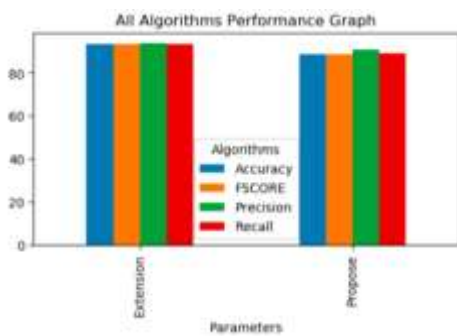


Figure [6]: Sample Gas Detection Output Visualization

The figure[6] presents a visual sample related to the gas detection system output. It illustrates the captured or processed image used for analysis within the model. Such visual data aids in understanding the input conditions and supports the evaluation of model performance in real-world scenarios.



Figure [7] : Gas Detection Prediction Results on Test Data

The figure [7] displays the prediction results of the trained model on test data samples. Each input feature vector is processed, and the model predicts the corresponding gas type, such as Methane or Sulphur. The output demonstrates the model's ability to classify gas types effectively based on learned patterns from the training data.

DISCUSSION

The comparison between the proposed 3D-CNN model and the extended hybrid model highlights the advantages of combining multiple deep learning algorithms for gas detection. The standalone 3D-CNN model demonstrated reliable performance with 88% accuracy, proving its suitability for feature extraction and basic pattern recognition in gas leak data. However, integrating CNN with Bidirectional LSTM and GRU enhanced the model's ability to capture sequential patterns and temporal dependencies in the dataset, which significantly improved the overall accuracy to 93%. The confusion matrices revealed that most misclassifications in the proposed model were reduced in the extended model, indicating better generalization. The accuracy trends during training also suggest that the hybrid model converged faster and maintained stability across epochs. Visual comparisons of algorithm performance in tables and graphs clearly support the superiority of the extended approach. These findings suggest that multi-algorithm architectures can more effectively handle complex, real-world gas leak data by combining spatial and temporal learning capabilities. The successful identification of various gas types in the test data demonstrates the system's practical feasibility, making it a promising solution for industrial safety monitoring and environmental gas leak detection applications.

VI. CONCLUSION

The gas leak detection project demonstrates that deep learning models can effectively identify and classify different types of gas emissions with high accuracy. The proposed 3D-CNN autoencoder model achieved reliable results, providing a solid baseline with 88% accuracy. By extending this approach to a hybrid model combining CNN, Bidirectional LSTM, and GRU networks, the system was able to capture both spatial and temporal features from the dataset, resulting in a significant improvement to 93% accuracy. The analysis of confusion matrices and performance metrics confirmed that the extended model reduces misclassifications and performs consistently across all gas types. Test data predictions further validated



the practical applicability of the system for real-time gas leak identification. Overall, this study highlights the effectiveness of combining multiple deep learning techniques to enhance model performance. The results suggest that such a system could be deployed in industrial and environmental monitoring applications to detect hazardous gas leaks efficiently, contributing to improved safety and early warning mechanisms. The project demonstrates a balance between accurate detection, computational efficiency, and robustness, making it a promising tool for practical implementation.

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