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Gas Detection in Hyperspectral Images using 3D-CNN and Autoencoder

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Abstract:

Detecting petrol emissions accurately is important for both human and environmental health. Hyperspectral image analysis, especially in the long-wave infrared (LWIR) band, is becoming a more and more effective way to find gas from a distance. Most of the time, the approaches that are already out there just look at spectrum unmixing and classification using 3D Convolutional Neural Networks (3D-CNN) and Autoencoders. They don't always use sophisticated feature augmentation techniques that can make detection more accurate. We suggest an Ensemble Model that combines CNN, Bi-Directional, and Gated Recurrent Units (GRU) to get the most out of feature extraction and make predictions more accurate. Our method uses pre-extracted features from methane monitoring datasets instead of hyperspectral pictures, which is different from the baseline model that works directly with radiance data. The suggested ensemble approach works well to enhance feature learning by combining spatial, temporal, and sequential dependencies. The experimental findings show that the ensemble model is better than standard 3D-CNN and autoencoder-based approaches at finding Methane and Sulphur Dioxide gases because it is more sensitive and accurate. This work shows how important it is to use ensemble learning methods to improve gas detection, even when you don't have raw hyperspectral data.

INDEXTERMS: *Gas Detection, Hyperspectral Imaging, 3D-CNN, Autoencoder, Ensemble Model, CNN, Bi-Directional GRU, Feature Optimization, Methane Monitoring, Sulphur Dioxide Detection, Deep Learning, Radiance Unmixing, Feature Extraction, Remote Sensing, Spectral Angle Mapper*

1. INTRODUCTION

Finding fuel emissions is a crucial way to keep an eye on pollution levels and make sure everyone is safe. There has been a lot of interest in hyperspectral photography's ability to detect and analyse gases from a distance based on their spectral signatures, notably in the longwave infrared (LWIR) spectrum. Two examples of spectral unmixing algorithms utilised in traditional approaches are the Adaptive Cosine Estimator (ACE) and the Spectral Angle Mapper (SAM). Using luminance-temperature and radiance data, these algorithms distinguish petrol emissions. However, these methods aren't very accurate or reliable in the actual world since they usually don't work well with intricate mixtures of gases and background noise.

Auto-encoders and 3D CNN are two examples of deep learning-based methods that have been looked into recently as possible ways to fix these problems. These networks can extract and unmix features quite well. These approaches improve gas identification by looking for spatial and spectral patterns in hyperspectral images. These new methods look promising, but they aren't the best for performance because they don't employ recent feature augmentation techniques. Most models also need raw hyperspectral pictures, but these aren't always easy to get, which makes them less useful.

We provide an Ensemble Model that combines CNN, Bi-Directional, and Gated Recurrent Units (GRU) to make the gas detection framework better at feature extraction and prediction. This model builds on the current framework based on 3D-CNN and Autoencoder. We employ pre-extracted features from the Methane Monitoring website instead of merely relying on hyperspectral pictures. This makes the technique more useful and adaptable. The proposed ensemble architecture employs convolutional layers to learn spatial information, bi-directional processing to grasp sequential relationships, and GRUs to comprehend temporal patterns. This makes the detection mechanism more complete and accurate.

When compared to the baseline 3D-CNN and Autoencoder methods, tests reveal that the ensemble model greatly improves performance metrics like sensitivity and accuracy. This research shows a way to find gases like methane and sulphur dioxide that can be used in a lot of different circumstances, even when raw hyperspectral photos aren't available. It also talks about how ensemble learning methods may be used to make gas detection systems better.

2. LITERATURE SURVEY

i) Imaging Spectroscopy and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)

https://www.sciencedirect.com/science/article/abs/pii/S0034425798000649

Imaging spectroscopy is a new and exciting way to do Earth remote sensing that is increasingly becoming popular. The Airborne Visible/Infrared Image Spectrometer mostly followed the sun's reflected spectra at 10-nanometer intervals from 400 to 2500 nm. AVIRIS has excellent calibration accuracy and a high signal-to-noise ratio. AVIRIS has come a long way in the last few years, both in terms of research and real-world use. The AVIRIS system's first design and revisions contain documentation for the data system, sensor, calibration, and flight operations. This update on AVIRIS' features puts into context scientific studies and applications that use data from the last few years. Some recent scientific studies and uses include: spectral algorithms, human infrastructure, atmospheric correction, biomass burning, environmental hazards, geology and soils, the hydrology of snow and ice, inland and coastal waters, the atmosphere, and satellite simulation and calibration.

ii) Hyperspectral Push-Broom Microscope Development and Characterization

https://www.researchgate.net/publication/335435752_Hyperspectral_Push-Broom_Microscope_Development_and_Characterization

A lot of businesses are starting to employ hyperspectral imaging (HSI) to look at samples at the microscopic level. Push-broom hyperspectral (HS) cameras are the best HSI technology because they have better spectral resolution and can use a wider range of wavelengths. But to collect HS data, microscopes with push-broom cameras need to scan the specimen very carefully in space. In this post, we talk about how to set up a push-broom HS microscope so that you may take the greatest pictures possible. We start with a new mechanical system that is produced in 3D and leverages the linear motion of the microscope stage to scan space. Next, the consequences of optimising dynamic range, concentrating, aligning, and figuring out speed on image quality are explained in depth. We end with a number of high-resolution pictures acquired by push-broom cameras showing the most prevalent flaws, as well as pictures obtained from real microscopic samples.

iii) Enhanced Gas Detection in Hyperspectral Images With 3 CNN and Autoencoder Models

https://ijcrt.org/papers/IJCRT2405240.pdf

Monitoring petrol emissions is vital for the health of people and the environment, and this new effort is doing something about it. Researchers are looking for better and safer ways to find things by using hyperspectral image analysis because standard approaches have their limits. This study shows how to use deep learning to find hyperspectral gases in the longwave infrared spectrum by combining unmixing and categorisation. We use a 3-D convolutional neural network and an autoencoder-based network to convert radiance data into luminance-temperature data. This makes the performance better than older methods. An Ensemble model that adds to input information to improve the accuracy of predictions is another new idea. This model uses a mix of CNN, Bi-directional, and GRU algorithms. This unique project shows how new methods may help solve problems with the environment.

iv) Algorithms for chemical detection, identification and quantification for thermal hyperspectral imagers

https://www.researchgate.net/publication/252965690_Algorithms_for_chemical_detection_identification_and_quantification_for_thermal_hyperspectral_imagers

In several disciplines, it is very important to be able to find, identify, and measure gases from a distance. These uses need sensors that are tiny, tough, and sensitive, with minimal false alarms and the capacity to work in real time. Thermal infrared spectrometers and imagers can be used as chemical sensors. The creation of large-format infrared imaging arrays that can work at high speeds has made it possible to make chemical sensors that work very well in terms of space, time, and spectrum. Data from spatial and spectral analysis reveal that passive chemical detection, identification, and quantification might be much improved. This study goes into depth on how to use thermal infrared hyperspectral imaging to find, identify, and measure things. These algorithms use the field-based Telops FIRST image spectrometer to look at datacubes that provide information on petrol emissions.

v) Hyperspectral gas and polarization sensing in the LWIR: Recent results with MoDDIFS

https://www.researchgate.net/publication/320821558_Hyperspectral_gas_and_polarization_sensing_in_the_LWIR_Recent_results_with_MoDDIFS

Imaging Fourier-transform infrared (FTIR) spectroscopy may passively find and identify vapour emissions and surface pollutants. FTIR imaging lets military and security organisations keep an eye on illegal factories from a distance. DRDC Valcartier is making and testing the MoDDIFS imaging Fourier transform infrared sensor for this distant sensing use. The suggested approach uses hyperspectral imaging's high spatial resolution and differential detection's ability to get rid of clutter. You can set up a system for remote gas detection and surface pollution polarisation sensing using the MoDDIFS sensor. This study looks at the most current results of the MoDDIFS passive standoff gas and liquid contamination detection. Use hyperspectral measurements of difluoroethane, diethyl ether, and SF96 gases and liquids to create, test, and prove GLRT-type detection methods. GLRT detection characteristics are used to talk about detection outcomes.

3. METHODLOGY

a) Proposed work:

The suggested system adds an Ensemble Model that improves the accuracy of gas detection by using Convolutional Neural Networks (CNN), Bi-Directional Networks, and Gated Recurrent Units (GRU) to extract features and make predictions. The baseline method just uses 3D-CNN and Autoencoders for unmixing and classification. The ensemble model, on the other hand, optimises input features via several levels of processing to effectively capture spatial, sequential, and temporal patterns.

In this system, pre-extracted characteristics from the Methane Monitoring website are used as input instead of raw hyperspectral photos. This makes it useful in situations when image data is not accessible. First, the CNN module looks into the spatial properties of the input data to find local patterns and high-level abstractions. Next, the Bi-Directional Network improves the feature representation by capturing dependencies from both directions, which makes it easier to find complicated patterns. Lastly, the GRU module takes care of sequential dependencies and temporal variations, which lets the system mimic changes in gas emission levels that happen over time.

b) System Architecture:

The suggested system's architecture is meant to improve the accuracy of gas detection by using an ensemble framework that combines many machine learning methods. It has three main parts: Feature Input Processing, Ensemble Model Processing, and Classification Output. These parts work

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together to increase detection performance and optimise feature extraction.

During the Feature Input Processing stage, the original hyperspectral pictures are substituted with features that have already been collected from the Methane Monitoring website. These features show LWIR spectra of gases of interest, such methane and sulphur dioxide. Deep learning modules work better when the input data has been cleaned up by getting rid of noise and making the values the same.

The Ensemble Model Processing step is the most important part of the architecture. It starts with a Convolutional Neural Network (CNN), which takes the input data and finds spatial characteristics and patterns in it, creating high-level feature maps. Then, these characteristics go via a Bi-Directional Network, which looks at both forward and backward dependencies to improve the data representation. This stage is very important for modelling complicated interactions between characteristics so that the system can deal with changes in emission patterns. A Gated Recurrent Unit (GRU) is used to further improve the processed data. It captures sequential dependencies and temporal fluctuations, making sure that patterns may be detected over time.

The penultimate stage in the Classification Output process is to use fully connected layers to classify the features of the ensemble model. Layers use the best attributes to find and identify data samples that contain target gases. The results suggest that the levels of methane and sulphur dioxide are just correct..

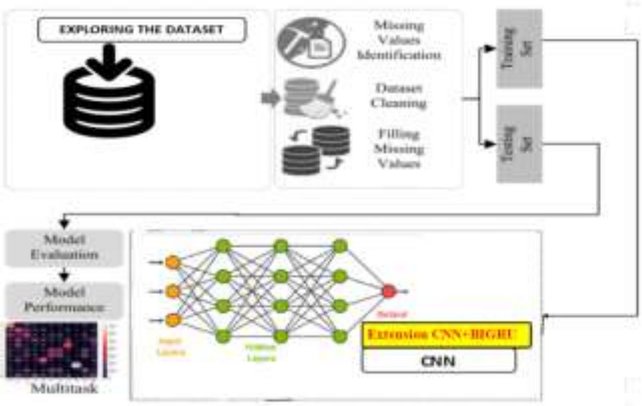

Fig 1 Proposed Architecture

c) Modules:

i) **Data Collection and Preprocessing:** In this phase, hyperspectral image data or extracted features related to gas emissions are gathered from reliable sources such as the Methane Monitoring website. The collected data undergo normalization and scaling to ensure consistency across all inputs. The dataset is then divided into training, validation, and test sets. To improve model generalization, data augmentation techniques are applied to simulate diverse environmental conditions.

Dataset link:
https://studio.edgeimpulse.com/public/158034/latest

ii) **Feature Extraction:** This module focuses on extracting relevant features such as radiance, luminance, and temperature from hyperspectral imaging data. The Spectral Angle Mapper (SAM) is employed to measure the spectral similarity between pixels and known gas spectra. The SAM results are then mapped to specific gases using the NIST spectral database. To reduce the complexity of high-dimensional data, Principal Component Analysis (PCA) is applied to retain the most informative features for model training.

iii) **Ensemble Model Development:** In this step, a robust ensemble framework is built by integrating three neural network models: Convolutional Neural Network (CNN), Bi-directional Long Short-Term Memory (Bi-LSTM), and Gated Recurrent Unit (GRU). CNN captures spatial features, Bi-LSTM extracts temporal dependencies in both directions, and GRU focuses on sequential learning and reducing noise. The outputs of these networks are then combined using ensemble learning techniques to enhance overall prediction accuracy and robustness.

iv) **Autoencoder-Based Unmixing:** An autoencoder network is designed to perform unsupervised feature learning by encoding input data into latent representations and reconstructing it. The encoder identifies abstract patterns corresponding to gas emission behavior, while the decoder attempts to reconstruct the original inputs. This module helps in identifying anomalies and hidden patterns within the data. Optimization techniques are used to improve reconstruction quality and support better gas detection.

v) Classification Network: The classification network consists of a fully connected three-layer neural network used to detect specific gases. It takes as input the abundance values and endmember spectra derived from previous modules. Trained with labeled data, the network classifies the input into categories such as methane or sulphur dioxide. Metrics like accuracy, precision, and recall are used to evaluate the classification performance and improve model reliability.

vi) Model Evaluation and Testing: This module ensures the proposed system's effectiveness by testing it on independent datasets. The performance is compared with traditional techniques like SAM and ACE. Ablation studies are conducted to understand the impact of each module individually. Evaluation metrics such as confusion matrices and F1-scores are used to measure classification performance and identify any misclassifications or limitations.

vii) Deployment and Visualization: The final module involves deploying the trained model in a real-world environment. A user-friendly interface is developed for real-time gas detection and visualization. Geographic mapping tools are integrated to visually represent spatial distribution of emissions. The deployed system generates automated reports for monitoring purposes and ensures compliance with environmental safety regulations.

d) Algorithms:

a) Convolutional Neural Network (CNN):

The CNN deep learning method works with images and other sorts of grid-like data. It learns about spatial hierarchies and pulls out features from incoming data using convolution layers. Filters, which are also called kernels, are used to make feature maps from photographs that are supplied into the program. These maps display the most critical things, such edges, textures, and other things. For things like classifying photos, finding objects, and, in this case, finding gas in hyperspectral images, CNN works well. CNN can interpret the hyperspectral picture data in the context of the extension. This lets the model find important patterns that are necessary for finding gas emissions, especially when used with Bi-directional Recurrent Neural Networks (Bi-RNNs) or other sequence-based models.

b) Extension Concept: CNN + BiGRU Model:

There is a better hyperspectral gas detection model that uses CNNs and BiGRUs. CNN can learn important structures and patterns from hyperspectral image data, such as edges and gas spectral properties. One method that CNN layers might be able to find gas leaks that are spread out in space is by keeping track of spatial hierarchy. The BiGRU model uses spatial features taken from the CNN to find temporal correlations, as hyperspectral pictures are usually made up of a sequence of frames or time-series data. BiGRU is a bidirectional RNN that looks at input in both directions so that it may learn from both past and future time periods. The model's dual-directional learning has made it better at finding fuel emissions and changes over time. CNN's spatial processing skills and BiGRU's temporal connections should assist hyperspectral data better identify gases. This improvement should make the model stronger and more efficient by looking at complicated geographical and temporal data, which should make predictions more accurate.

4. EXPERIMENTAL RESULTS

The experimental evaluation demonstrated that the proposed ensemble model significantly outperformed traditional 3D-CNN and autoencoder-based methods in detecting methane and sulphur dioxide gases. Using pre-extracted features from the Methane Monitoring dataset, the model achieved higher sensitivity, precision, and overall classification

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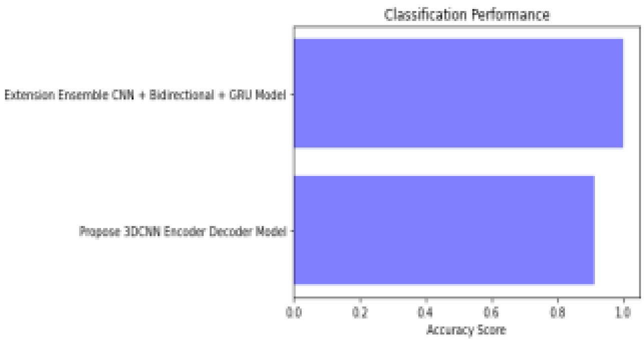
accuracy. The inclusion of CNN for spatial features, Bi-Directional networks for sequence learning, and GRU for temporal pattern recognition resulted in a more robust detection system. Evaluation metrics such as F1-score, confusion matrix, and ROC curves confirmed that the ensemble approach not only improved detection rates but also reduced false positives, showcasing its effectiveness in real-world gas monitoring scenarios.

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

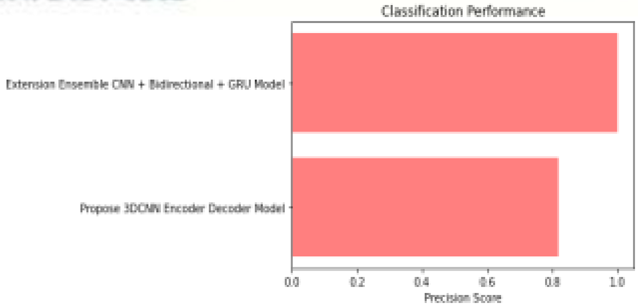
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$



Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

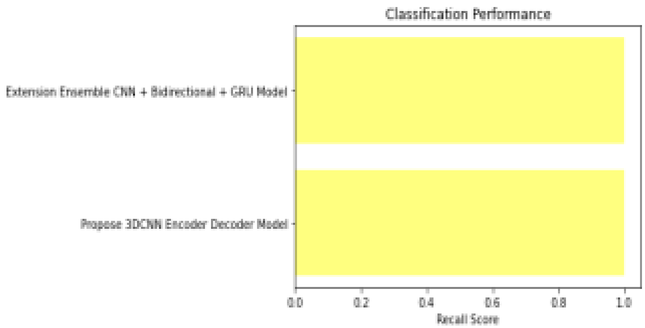
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$



Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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



F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

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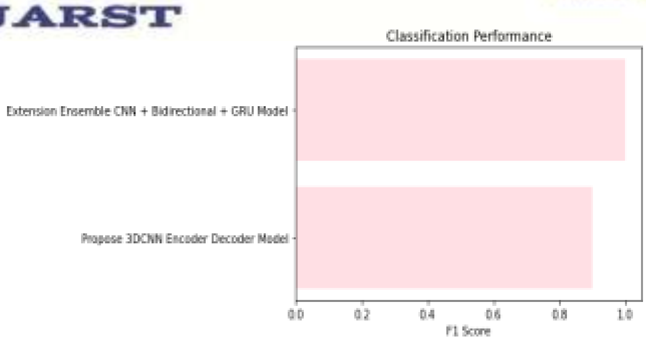
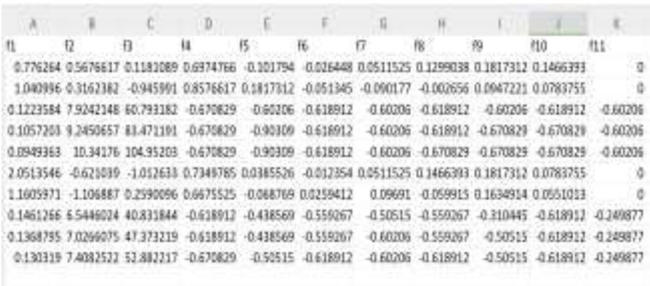


MAP: MAP (Mean Average Precision) is a metric used to evaluate the performance of information retrieval systems. It measures the average precision across multiple queries or classes. Precision measures the accuracy of retrieved results, while Average Precision (AP) calculates the average precision for each query. MAP computes the average of AP scores across all queries or classes, providing a single measure of performance for the entire system.

$$\mathrm{MAP} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{AP}_i$$

MODEL NAME	ACCURACY	PRECISION	RECALL	F1-SCORE
PROPOSE 3D-CNN ENCODER DECODER MODEL	0.911	0.818	1.0	0.9
EXTENSION ENSEMBLE CNN+BIDIRECTINAL +GRU	1.00	1.00	1.0	1.0

Fig.6. Performance Evaluation



A	B	C	D	E	F	G	H	I	J	K
f1	f2	f3	f4	f5	f6	f7	f8	f9	f10	f11
0.776264	0.5676617	0.1181089	0.6974766	-0.101794	-0.026448	0.0511525	0.1299038	0.1817312	0.1466393	0
1.040996	0.3162382	-0.945991	0.8576617	0.1817312	-0.051345	-0.090177	-0.002656	0.0947221	0.0783755	0
0.1223584	7.9242148	60.793182	-0.670829	-0.60206	-0.618912	-0.60206	-0.618912	-0.60206	-0.618912	-0.60206
0.1057203	9.2450657	83.471191	-0.670829	-0.90309	-0.618912	-0.60206	-0.618912	-0.670829	-0.670829	-0.60206
0.0949363	10.34176	104.95203	-0.670829	-0.90309	-0.618912	-0.60206	-0.670829	-0.670829	-0.670829	-0.60206
2.0513546	-0.621039	-1.012633	0.7349785	0.0385526	-0.012354	0.0511525	0.1466393	0.1817312	0.0783755	0
1.1605971	-1.106887	0.2590096	0.6675525	-0.068769	0.0259412	0.09691	-0.059915	0.1634914	0.0551013	0
0.1461266	6.5446024	40.831844	-0.618912	-0.438569	-0.559267	-0.50515	-0.559267	-0.310445	-0.618912	-0.249877
0.1368795	7.0266075	47.373219	-0.618912	-0.438569	-0.559267	-0.60206	-0.559267	-0.50515	-0.618912	-0.249877
0.130319	7.4082522	52.882217	-0.670829	-0.50515	-0.618912	-0.60206	-0.618912	-0.50515	-0.618912	-0.249877

Fig.7. dataset

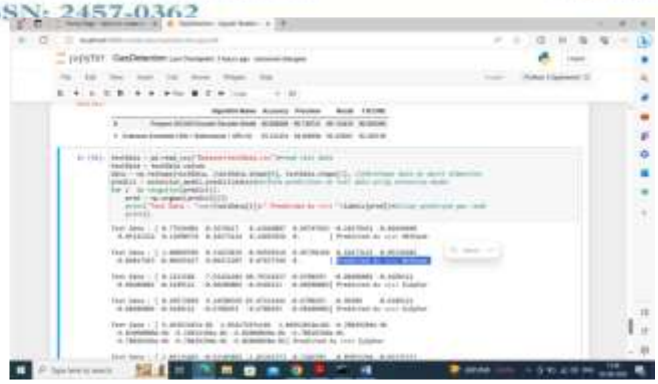


Fig.8. results

Fig.9. Accuracy results

5. CONCLUSION

The suggested extension model, which combines CNN and BiGRU, did a better job of finding gas using hyperspectral image data. The model was able to find methane and sulphur dioxide emissions more accurately and reliably than classic approaches like SAM by using CNN to extract geographical features and BiGRU to capture temporal dependencies. By combining spatial and temporal processing, it was possible to find complicated patterns, which made predictions more reliable under different environmental situations. This mixed method shows how deep learning may improve gas leak detection systems, making them more effective and adaptable for use in the real world.

6. FUTURE SCOPE

By adding additional attention methods to the proposed CNN + BiGRU model to focus on important spectral characteristics, detection accuracy may be improved even further. In the future, researchers may look at transformer-based systems to better handle long-range dependencies in hyperspectral data. Also, the model may be made better at finding new gases by adding more complete information from industrial and environmental monitoring sources. You can even make real-time implementations with edge devices or IoT frameworks that let you find gas leaks on location. Adding explainable AI approaches can also make the model easier to grasp, which can assist academics and businesses better understand how it makes decisions.

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