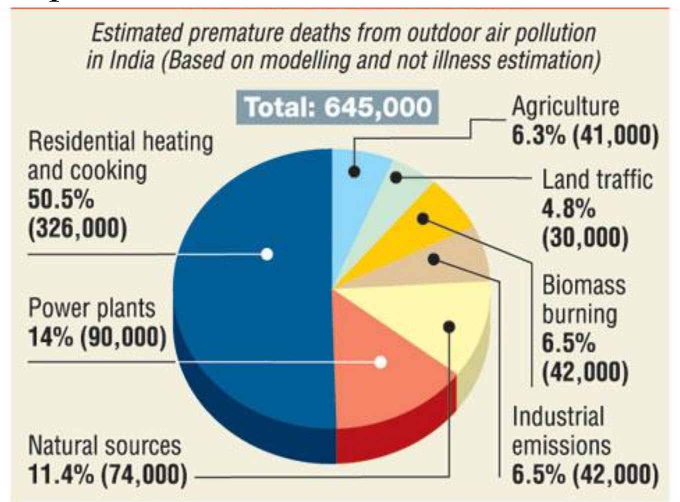
Gas Detection and Identification using Multimodal AI based Sensor Fusion

Rahee Walambe[1], Parag Narkhede[1] , Shruti Mandaokar[1] , Pulkit Chandel[1] , Ketan Kotecha[1], George Ghinea[2]
[1]Symbiosis Center of Applied Artificial Intelligence, Symbiosis International (Deemed University), Pune, India 412115
[3]Brunel University, London, United Kingdom UB8 3PH

INTRODUCTION

With the rapid developments in the industrialization and automated chemical plants, **gas leakage** is a common issue. Explosions, fires, spills, leaks, and waste emissions are some of the consequences of industrial accidents.



-

Need of Research?

- Flammable Gases are dangerous.
- Hydrocarbons are toxic.
- Some gases are odorless and colorless.
- Need of the hour to detect toxic fumes

Problems -

Single Gas Sensor fails to classify gas in a mixed gas environment. A Thermal Imaging System detects the presence of gas but fails to detect its type.

Primary Research Question?

In a mixed gas environment, how to detect a particular gas and achieve better gas classification accuracy?

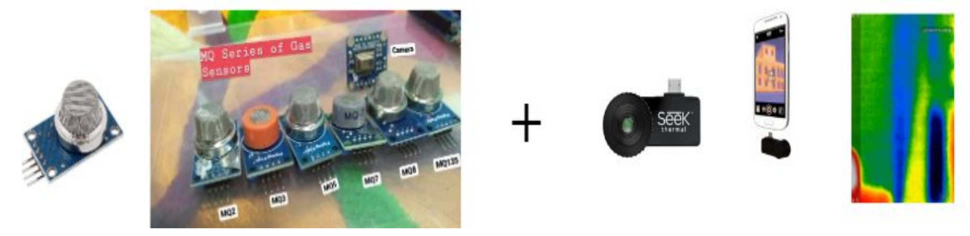
AIM

We propose a novel approach to detect and identify the gaseous emissions using the multimodal AI fusion techniques.

Data Fusion

Combining sensor data from different sources to produce more consistent, accurate, and useful information than individual sensors to reduce false positives and false negatives..

The **main contributions** of our research are -
Using Multimodal Sensor Fusion and Deep Learning Architectures (Thermal CNN + Sensor Sequence LSTM)



(MQ2, MQ3, MQ5, MQ6, MQ7, MQ8, MQ135) (Seek Thermal Camera)

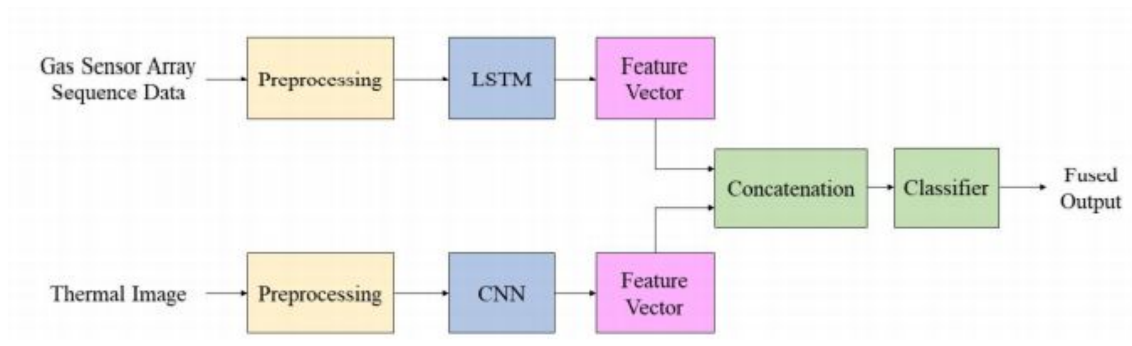
Fusion of **7 MQ Gas Sensor Data** and **Gas Thermal Image**-
- To detect whether gas is leaking or not.
- To detect which gas is leaking.
- Multiple sensors outperfrom single sensor

BACKGROUND

Multimodal Fusion Methods -

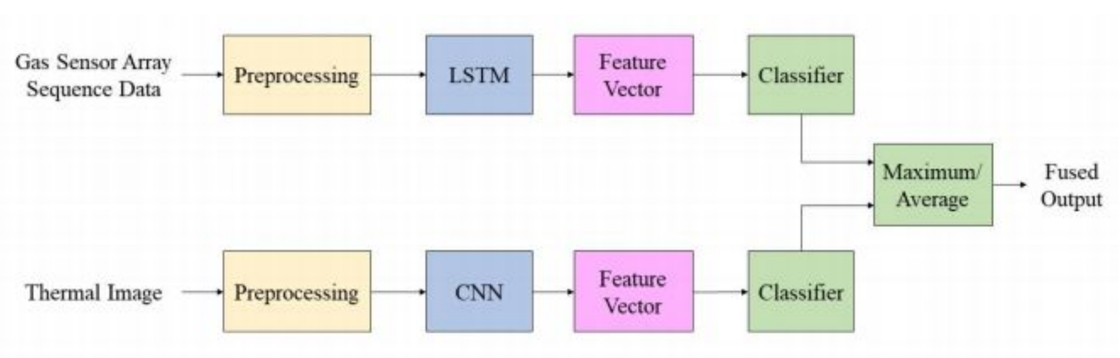
Early Fusion -

Combines features extracted from raw data which have high correlation between them, which are passed through **Concatenate** layer and final predictions are made.



Late Fusion -

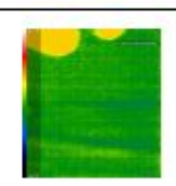
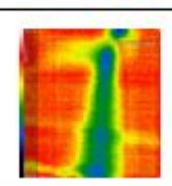
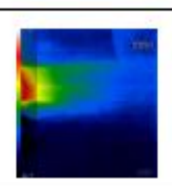
Decisions are taken based on the individual modalities separately. Predictions from individual modalities are then combined the using statistical method like mean, mode, median.

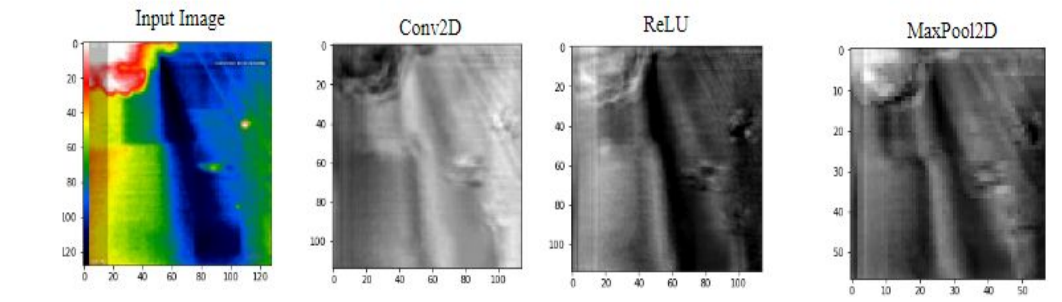


DATASET

- **Data Collection (Balanced) –**
  - 4800 Gas Sensor Output Sequences + 4800 Gas Thermal Images
- **3 Labels** –
  - No Gas (Class 0)
  - Alcohol/Perfume Fumes (Class 1)
  - Smoke (Class 2)
- **1600 Samples** of Each Class (Sequence + Image)

- Collected at a time interval of 2 seconds continuously for one and a half hours.
- Gas was sprayed with an interval of 15 sec for the first 30 minutes, with 30-sec intervals for the next 30 minutes and 45-second intervals for the next 30 minutes.

No Gas	Perfume (Alcohol)	Smoke
		
[558 516 376 336 665 450 415]	[808 520 515 485 692 754 513]	[550 343 371 400 572 583 304]



AUGMENTATION

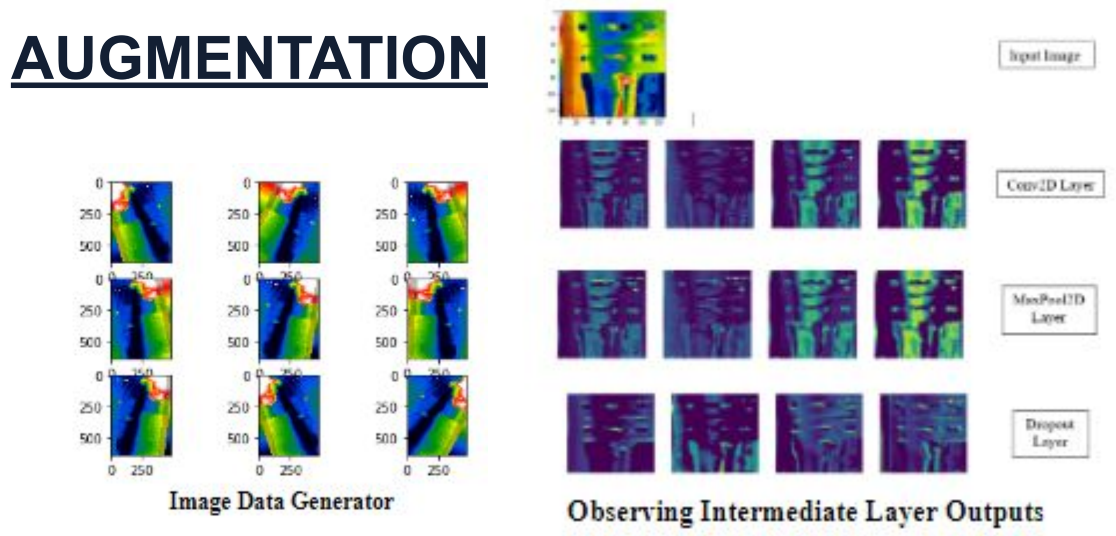
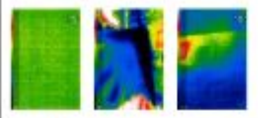
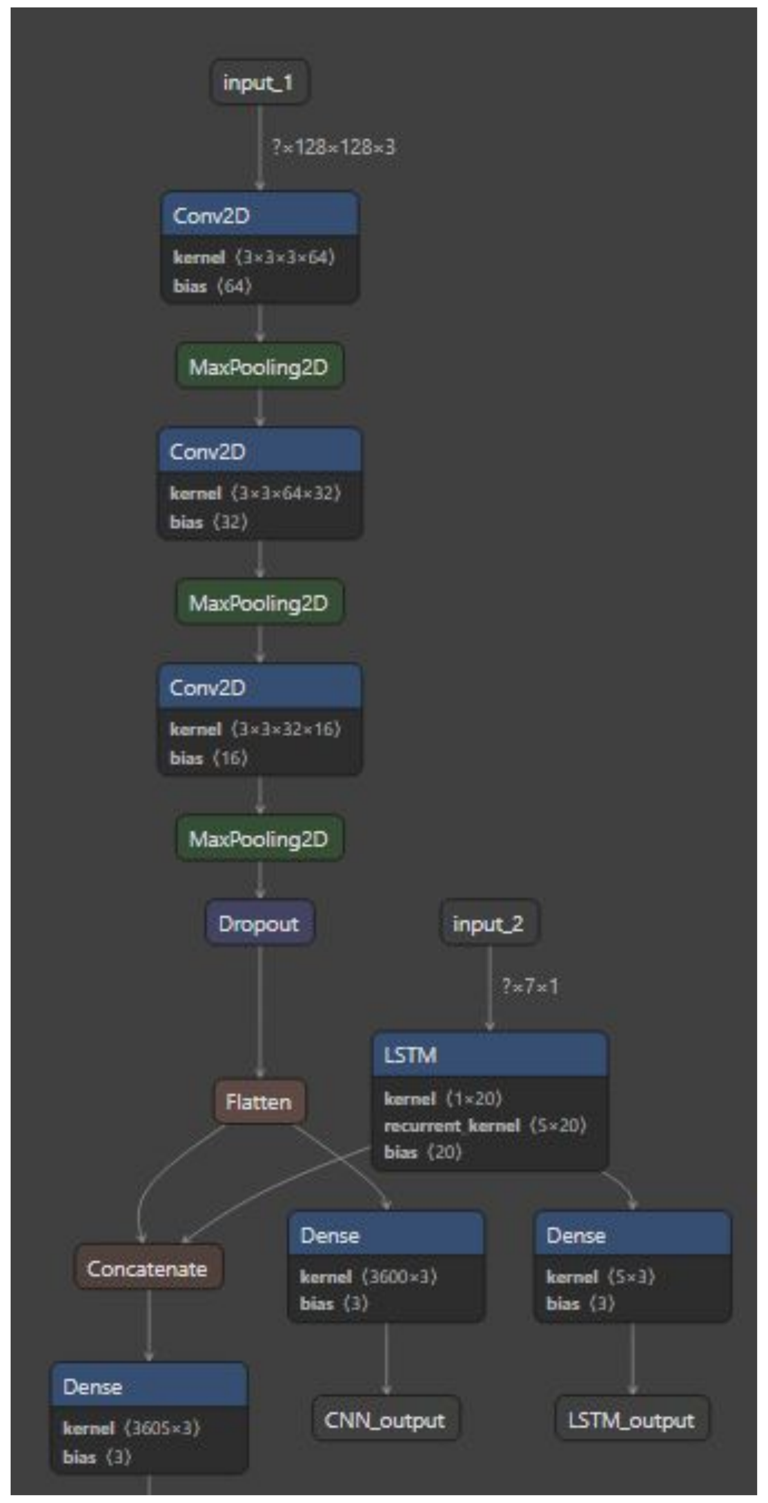


Image Data Generator

Observing Intermediate Layer Outputs

		Train	Validation	Test
Data	[RGB] – 4800 Images + 4800 Labels 	3840	768	192
	• Input Image Size – 128 x 128 x 3 • **Data Augmentation** from Original Dataset such as flipping and rotation. • Learning Rate – 0.001, Decay – 1e^-3 • Loss – Sparse Categorical Cross Entropy • Optimizer – Adam • Batch Size – 20 • Number of Epochs - 100 • Metrics – Accuracy			

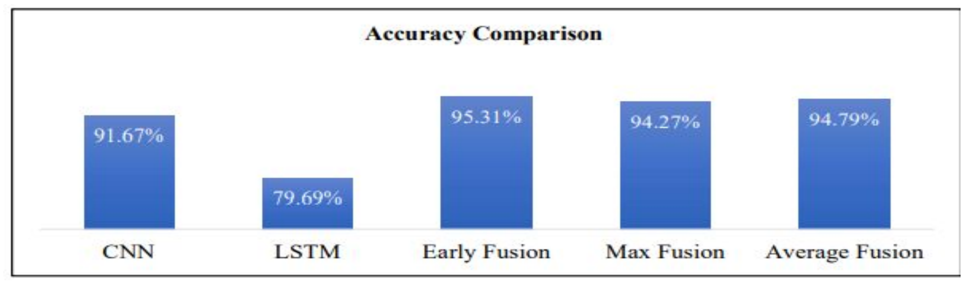
FUSION ARCHITECTURE

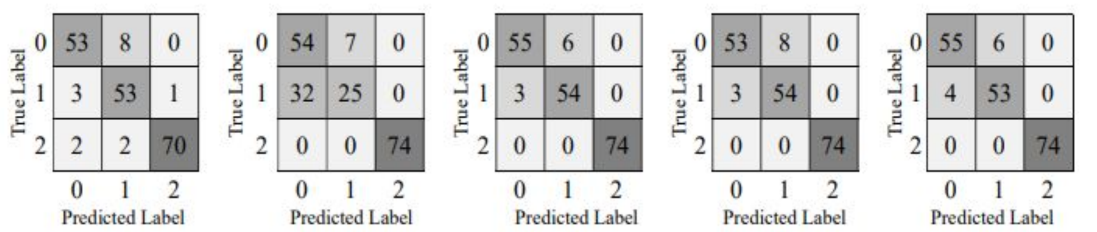


RESULTS

Accuracy -

CNN Thermal Images - 91.67 % Early Fusion - 95.31%
LSTM Gas Sequence - 79.69 % Late Fusion - 94%





(a) CNN (b) LSTM (c) Early Fusion (d) Max Fusion (e) Average Fusion

	Training Accuracy	Testing Accuracy	Training Loss	Testing Loss	Class	Precision	Recall	F1
LSTM Model only	74 %	79 %	0.4455	0.4747	No Gas	0.63	0.89	0.73
					Perfume	0.78	0.44	0.56
					Smoke	1.00	1.00	1.00
CNN Model only	92 %	91 %	0.1786	0.2604	No Gas	0.91	0.87	0.89
					Perfume	0.84	0.93	0.88
					Smoke	0.99	0.95	0.97
Early Fusion Model	94 %	95 %	0.1256	0.1942	No Gas	0.95	0.90	0.92
					Perfume	0.90	0.95	0.92
					Smoke	1.00	1.00	1.00

CONCLUSIONS

Contribution of this work -

solving a real world problem by developing a more reliable gas detection method involving two modalities and fusing them to achieve better results.

1. Accuracy of **Early Fusion** is larger than Late Fusion.
2. The multimodal model outperforms the individual models by supporting or opposing the individual modalities.
3. In case if one modality fails, the other modality can work alone until repair takes place.
4. This is essential in **high-risk applications** such as leak detection in chemical plants, identification of explosives.