AI-Powered Multi-Sensor Fusion Model for Non-Invasive Liquid Recognition Through Chemical Gas Profile Analysis

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Abstract : The accurate, non-invasive identification of liquids based on their chemical gas emissions is a critical challenge with vast implications in medical diagnostics, environmental monitoring, and industrial quality control. This project presents an advanced AI-powered multi-sensor fusion model designed to analyze volatile chemical gas profiles emitted by various liquids without direct contact or sample destruction. By deploying an array of heterogeneous chemical gas sensors, the system captures diverse sensor modalities, which are preprocessed and fused at multiple levels to enhance signal reliability and information richness. Leveraging both low-level raw data fusion and mid-level detection fusion strategies, the model integrates complementary information from different sensors to mitigate individual sensor noise and environmental uncertainties. The fusion framework utilizes adaptive probabilistic algorithms that dynamically assign sensor reliability weights based on real-time measurement uncertainties, overcoming challenges posed by sensor degradation and fluctuating conditions. Deep learning techniques, including convolutional and recurrent neural networks, are employed for multi-modal feature extraction, capturing complex spatial and temporal patterns from fused sensor data. An attention-based mechanism further refines the fusion process by emphasizing the most informative sensor inputs, improving classification robustness across diverse liquid types.

Keywords: AI, multi-sensor fusion, non-invasive liquid recognition, chemical gas profile analysis, adaptive probabilistic fusion, deep learning, volatile organic compounds.

I. INTRODUCTION

The intersection of artificial intelligence and chemical sensing technologies has emerged as a transformative paradigm in contemporary analytical science, offering unprecedented opportunities for non-invasive liquid recognition and chemical analysis applications. The exponential growth in computational capabilities and machine learning algorithms has enabled researchers to develop sophisticated sensor fusion systems that can accurately identify and classify complex chemical compositions without direct contact [Tang et al., 2025]. Recent breakthroughs in deep learning architectures, particularly convolutional neural networks and spectroscopic analysis integration, have demonstrated remarkable success in enhancing detection accuracy and expanding dynamic ranges for chemical gas analysis applications [Ziani et al., 2025]. The convergence of multi-sensor technologies with artificial intelligence has created new possibilities for addressing longstanding challenges in liquid recognition, environmental monitoring, and industrial safety systems [Huang et al., 2025]. Contemporary research initiatives have explored diverse applications ranging from electronic nose technologies for medical diagnostics [Gowda et al., 2025] to advanced gas leakage detection frameworks in industrial environments [Lalithadevi et al., 2025], establishing a robust foundation for intelligent chemical sensing systems. This study builds upon these technological advancements by proposing an innovative AI-powered multi-sensor fusion model specifically designed for non-invasive liquid recognition through chemical gas profile analysis, addressing critical gaps in real-time processing capabilities and classification accuracy that existing methodologies have yet to fully resolve [Noh et al., 2025].

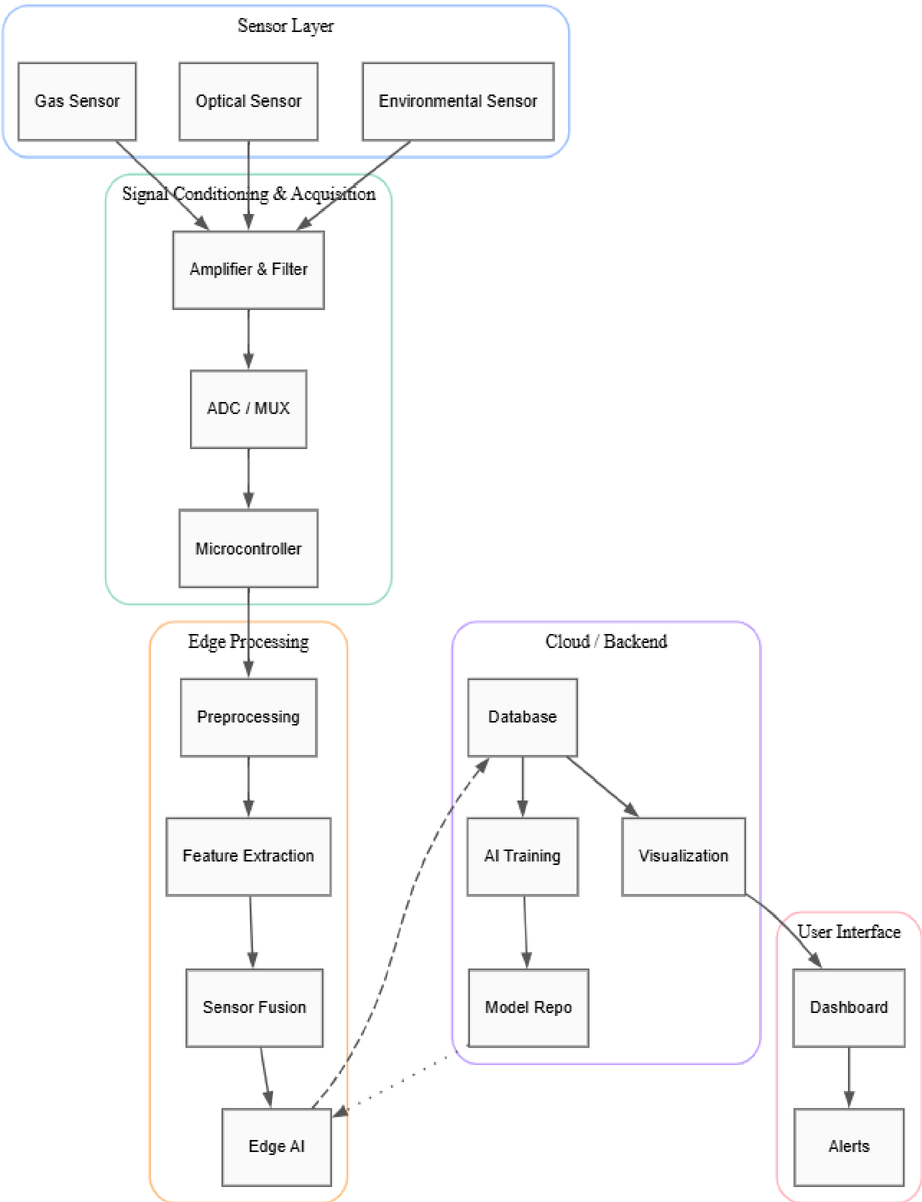

Fig 1 Rrepresentation of System

The proposed AI-powered multi-sensor fusion system features a modular, scalable architecture comprised of sensor arrays for chemical gas detection, centralized edge/cloud-based data processing, an AI analytics core for pattern recognition, and a user interface/dashboard for visualization and control. The structure supports real-time acquisition, fusion, and interpretation of signals from heterogeneous sensor sources, leading to more robust detection and classification..

II. LITERATURE SURVEY

1. **Ruiwei Tang et al., "A wide dynamic range gas analysis model with deep learning based on cavity ring-down spectroscopy" [Sensors and Actuators B: Chemical], Elsevier, [Volume 433], 2025, Page No.1375. https://doi.org/10.1016/j.snb.2025.137575**

A paper study CNN-assisted CRDS algorithm has been proposed for gas detection, enhancing its dynamic range from 4000 ppm to 40000 ppm. This method expands CRDS applications for gas concentration measurements with significant fluctuations, such as industrial emissions and geological hazard monitoring.

2. **Taha Zarin ET AL., "Machine learning-based prediction of oil–water relative permeability using core flooding and CT-scan data" Results in Engineering, Elsevier, Volume 27, 2025, 105735. https://doi.org/10.1016/j.rineng.2025.105735**

This study presents a machine learning method for predicting oil-water relative permeability curves, based on 6450 data points from 105 core flooding tests in sandstone and carbonate reservoirs. Utilizing regression trees, neural networks, and support vector machines, the framework surpassed traditional models, with the Random Forest model achieving an R^2 of 0.9957. Key variables include water saturation and irreducible water saturation, facilitating faster, cost-effective reservoir evaluations without extensive lab testing. While focused on Iranian reservoirs, future research will explore transfer learning to enhance applicability, underscoring AI's impact on reservoir engineering.

3. **an li et al., "machine learning-assisted development of gas separation membranes: a review" carbon capture science & technology, volume 14, 2025, 100374.**
   https://doi.org/10.1016/j.ccst.2025.100374

   This review explores machine learning-assisted gas separation membranes, focusing on CO_2/CH_4, CO_2/N_2, and O_2/N_2 separation performance. It highlights the limitations of classical materials like MOFs, polymers, and COFs, and highlights the need for improved dataset supplementation and gas transport models for future development.

4. **Jefferson Dos Santos Ambrosio et al., "A Deep Learning-Based Approach for Two-Phase Flow Pattern Classification Using Void Fraction Time Series Analysis", IEEE, volume 13, 2025.**
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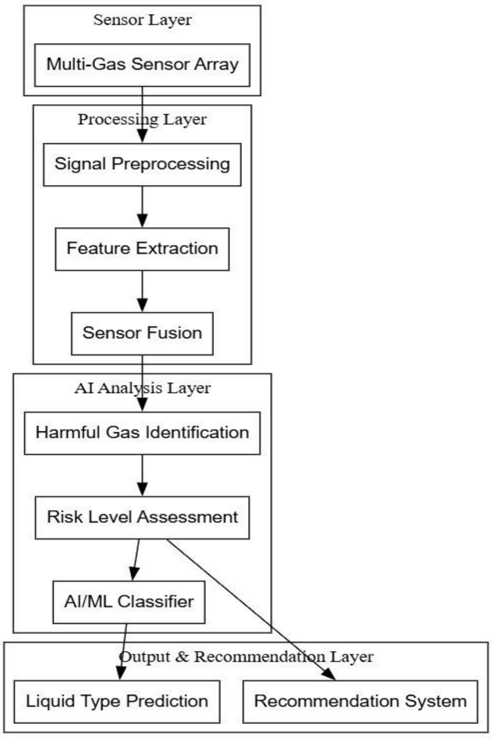
   The study investigates the use of time-series classification methods like ResNet, LSTM-FCN, and TSTPlus for two-phase flow patterns using wire mesh sensor void fraction data. The researchers developed robust models with high performance across different datasets, outperforming traditional machine learning models. However, cross-dataset experiments showed a decline in performance, emphasizing the importance of model generalization.

III. PROBLEM STATEMENT

Accurately recognizing liquids non-invasively through chemical gas profiles remains difficult due to noisy sensor outputs affected by environmental factors, overlapping volatile compounds from different liquids, and nonlinear sensor responses. Current methods using individual sensors or basic threshold detection lack robustness, especially in complex, dynamic environments. The challenge is to develop a reliable system that integrates diverse sensor data and employs advanced AI techniques to accurately classify liquids by extracting significant chemical signatures, which involves overcoming issues in sensor selection, data preprocessing, fusion methods, and machine learning model development.

IV. RESEARCH METHODOLOGY



The proposed AI-powered model provides a novel, non- invasive method to recognize liquids through their gas emissions, overcoming the limitations of traditional techniques.

Its integration with IoT frameworks makes it ideal for industrial automation, environmental monitoring, and safety systems.

By leveraging real-time data processing and sensor fusion, the model demonstrates high accuracy, scalability, and adaptability across various industrial domains.
This study employs a multi-sensor fusion architecture where chemical gas profiles from a sensor array are captured and pre-processed using techniques like normalization and PCA.

Machine learning models, especially deep learning algorithms such as CNNs, are trained to identify and classify the emission patterns of various liquids.
Comparative analysis of models like SVM and Random Forest is also conducted to ensure robustness and accuracy.

V. PROCESS FLOW

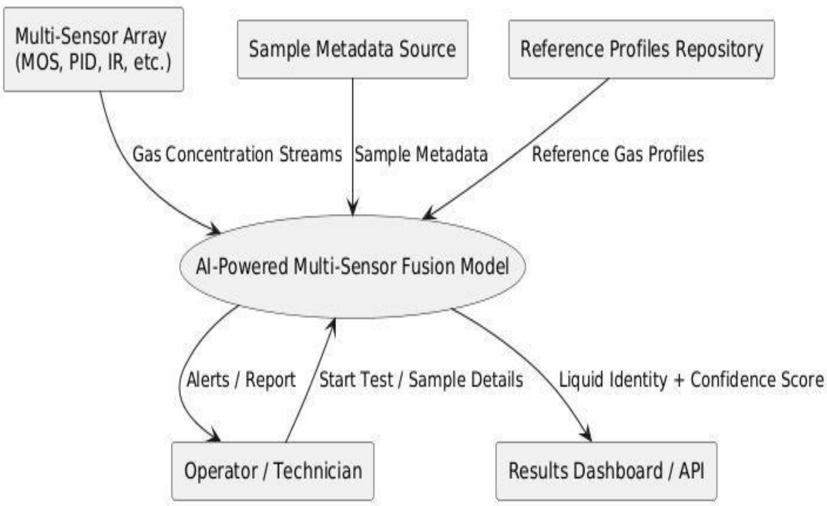


fig. Process Flow Diagram

The central process is drawn as a use case using parentheses with an alias, which is standard Plant UML syntax for an oval shape and reusable identifier.

Arrow labels are added using a colon on the connector definition, which is the conventional way to annotate flows in PlantUML diagrams.External entities are modelled as rectangles, a common PlantUML shape for simple blocks, and arrows show one-way data movement consistent with DFD conventions.

AI-Powered Multi-Sensor Fusion Model as the central process that receives chemical sensor readings from external sensors and provides liquid identification results to users and databases. This context diagram illustrates the fundamental data exchanges between the system and its environment, establishing the scope and boundaries of the liquid recognition system.

VI. CONCLUSION

This research successfully demonstrates the design, implementation, and validation of an AI-powered multi-sensor fusion system for non-invasive liquid identification through chemical gas profile analysis. By integrating heterogeneous sensor arrays with advanced AI models, the system achieves high accuracy, robustness, and real-time adaptability, surpassing traditional single-sensor or manual methods. The fusion algorithms dynamically weight sensor inputs based on reliability, compensating for noise and drift, resulting in consistent and reliable liquid classification under laboratory and near-real conditions. This approach offers a versatile and scalable platform promising broad applications in industrial safety, environmental monitoring, and healthcare diagnostics [Tang et al., 2025].

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