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HYBRID CNN–LSTM MODELS FOR REAL TIME CHEMICAL PLUME RECOGNITION USING DRONE MOUNTED ELECTRONIC NOSE SYSTEMS

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ABSTRACT

Real-time identification of hazardous chemical plumes in complex outdoor environments remains a critical challenge in environmental monitoring, industrial safety, and disaster-response operations due to turbulent dispersion dynamics, sensor drift, and airflow disturbances induced by unmanned aerial vehicles (UAVs). This work proposes a hybrid CNN–LSTM framework for intelligent chemical plume recognition using a drone-mounted, bio-inspired electronic nose (E-nose) system designed for ppm-level detection of ammonia (NH_3) and methane (CH_4) gases under dynamic atmospheric conditions. The proposed platform integrates a multi-sensor fusion architecture comprising metal-oxide semiconductor (MOS), electrochemical, and environmental sensing units to capture heterogeneous spatiotemporal gas signatures during UAV-assisted monitoring missions. To mitigate the adverse effects of rotor downwash and plume fragmentation, an artificial intelligence (AI)-driven denoising and drift-compensation is introduced, incorporating adaptive baseline correction, temporal smoothing, and feature normalization to enhance signal stability during aerial navigation. The core recognition engine combines convolutional neural networks (CNNs) for local spatial feature extraction with long short-term memory (LSTM) networks for temporal dependency modeling, enabling robust discrimination of transient plume patterns in highly noisy environments. Experimental evaluations conducted across simulated industrial leakage scenarios demonstrate that the proposed hybrid architecture achieves superior plume classification performance, with an average accuracy exceeding 96%, while maintaining low inference latency suitable for real-time edge AI deployment on embedded UAV computing platforms. Furthermore, the framework exhibits enhanced robustness against sensor degradation, environmental turbulence, and concentration variability compared with conventional machine learning approaches. The proposed system establishes a scalable and autonomous aerial olfaction framework for next-generation environmental surveillance, hazardous gas leak localization, and intelligent atmospheric sensing applications using AI-enabled UAV ecosystems.

Keywords: *UAV gas sensing, Electronic nose, CNN–LSTM, Chemical plume recognition, Edge AI.*

1. INTRODUCTION

1.1 Background and Motivation

Rapid industrialization and urban expansion have significantly increased the risk of hazardous gas leakage events in industrial plants, mining environments, oil and gas infrastructures, and chemical storage facilities. Toxic and combustible gases such as methane (CH_4) and ammonia (NH_3) pose severe threats to environmental safety, human health, and critical infrastructure due to their high explosiveness, atmospheric persistence, and toxicity characteristics [1], [2]. Conventional fixed gas monitoring infrastructures are often constrained by limited spatial coverage, delayed response capabilities, and high operational costs, making them unsuitable for dynamic, large-scale environmental surveillance scenarios [3]. Consequently, intelligent airborne sensing platforms capable of autonomous gas detection and localization have emerged as an important research direction in environmental robotics and smart sensing systems [4].

Robotic olfaction, inspired by biological smell perception mechanisms, has evolved into a promising interdisciplinary field combining chemical sensing, signal processing, machine learning, and autonomous robotics [5]. Electronic nose (E-nose) systems imitate mammalian olfactory systems by integrating multiple cross-sensitive gas sensors with computational intelligence algorithms for odor discrimination and plume characterization [6]. Recent advancements in miniaturized sensor technologies and embedded computing have enabled the deployment of lightweight E-nose platforms on unmanned aerial vehicles (UAVs), facilitating real-time airborne chemical monitoring in inaccessible or hazardous environments [7].

The increasing integration of artificial intelligence (AI) with robotic olfaction has further accelerated the development of autonomous chemical plume recognition systems capable of adaptive decision-making under highly turbulent atmospheric conditions [8]. However, airborne plume monitoring remains a technically demanding problem because gas dispersion patterns exhibit nonlinear spatiotemporal variability caused by wind turbulence, environmental disturbances, and UAV-induced airflow effects [9]. These challenges motivate the need for advanced deep learning framework capable of extracting robust spatial and temporal plume characteristics from noisy multi-sensor data streams.

1.2 Electronic Nose Systems

Electronic nose systems are bio-inspired sensing frameworks designed to replicate the odor recognition capabilities of biological olfactory systems using arrays of partially selective chemical sensors and pattern recognition algorithms [10]. A typical E-nose architecture consists of sensing units, analog front-end circuitry, preprocessing modules, and intelligent classification engines capable of identifying complex gaseous mixtures through multidimensional response signatures. Metal oxide semiconductor (MOS), electrochemical, conducting polymer, quartz crystal microbalance, and optical sensors are among the most widely adopted sensing technologies for airborne gas analysis applications [11].

MOS sensors are particularly attractive for UAV-assisted deployments due to their compact size, low manufacturing cost, high sensitivity, and compatibility with embedded systems [12]. Nevertheless, MOS-based sensing systems suffer from limitations including sensor drift, temperature dependency, humidity sensitivity, and slow recovery characteristics, which adversely affect long-term recognition reliability [13]. Electrochemical sensors offer improved selectivity and low-power operation for toxic gas detection, especially for ammonia and methane sensing applications in industrial safety monitoring [14].

To overcome the limitations of individual sensor technologies, recent studies have emphasized multi-sensor fusion strategies that combine heterogeneous sensor responses with environmental parameters such as humidity, temperature, and pressure [15]. Such fusion-based E-nose frameworks improve robustness, enhance feature diversity, and support the identification of low-concentration gaseous compounds in highly noisy atmospheric conditions. The integration of AI-driven signal processing techniques with E-nose systems has therefore become essential for achieving reliable real-time plume recognition in dynamic outdoor environments.

1.3 UAV-Based Gas Sensing

Unmanned aerial vehicles have transformed environmental sensing by providing flexible, low-cost, and autonomous platforms for data acquisition across complex terrains and hazardous environments. UAV-assisted gas sensing systems enable rapid deployment, adaptive spatial coverage, and real-time atmospheric monitoring [7], [16], making them suitable for industrial inspection, landfill surveillance, volcanic monitoring, pipeline leakage detection, and post-disaster assessment operations. Compared with ground-based robotic platforms, aerial systems provide superior maneuverability and three-dimensional plume tracking capabilities in large-scale environments.

Recent advancements in lightweight embedded processors and low-power chemical sensors have enabled the integration of E-nose platforms with rotary-wing UAVs for autonomous airborne olfaction [7]. Such systems are capable of measuring gas concentration gradients while simultaneously performing plume localization and environmental mapping. Methane monitoring has gained substantial attention due to its strong greenhouse impact and its association with oil, gas, and landfill emissions [2], [17]. Similarly, ammonia sensing is critical in fertilizer industries, refrigeration systems, and agricultural environments because prolonged exposure can cause severe respiratory hazards.

Despite these advantages, UAV-based gas sensing systems face major operational challenges caused by dynamic airflow disturbances, fluctuating plume structures, and unstable sensor measurements during flight operations [9]. Gas concentration signals collected during aerial navigation are often sparse, intermittent, and highly noisy, thereby complicating plume classification and source localization tasks. Consequently, advanced AI-based recognition frameworks are required to accurately model the spatiotemporal behavior of chemical plumes under realistic atmospheric conditions [9].

1.4 Challenges in Airborne Chemical Detection

Plume recognition is fundamentally challenging because gas dispersion in outdoor environments follows highly stochastic and nonlinear transport dynamics influenced by wind velocity, turbulence intensity, thermal gradients, and terrain topology [18]. Unlike controlled laboratory environments, real-world atmospheric plumes exhibit intermittent concentration bursts, fragmented plume structures, and rapidly changing diffusion patterns that significantly complicate feature extraction and gas classification processes.

Sensor-related issues further increase the complexity of airborne gas detection systems. Sensor drift, caused by aging effects, environmental exposure, contamination, and thermal fluctuations, leads to long-term degradation in sensor response consistency [13]. In addition, cross-sensitivity among gas species often introduces ambiguity in chemical signature interpretation, particularly when monitoring low-concentration methane and ammonia mixtures. These effects reduce the reliability of conventional threshold-based detection mechanisms in outdoor deployments.

Traditional machine learning approaches such as support vector machines (SVMs), k-nearest neighbors (KNNs), decision trees, and shallow artificial neural networks have demonstrated moderate performance in static gas classification problems. However, these approaches heavily rely on handcrafted features and often fail to capture complex spatiotemporal plume dependencies in turbulent environments. Their limited ability to model sequential gas behavior, transient concentration variations, and dynamic sensor interactions significantly restricts their applicability in real-time airborne plume recognition systems [8].

1.5 Rotor Downwash and Turbulence Effects

Rotor downwash generated by rotary-wing UAVs introduces severe aerodynamic disturbances that directly affect airborne gas sensing accuracy. The rotating propellers produce complex airflow vortices capable of dispersing, diluting, or redirecting nearby chemical plumes, thereby altering the natural gas distribution characteristics before sensor acquisition occurs. Such disturbances can cause inconsistent sensor readings and reduce the reliability of plume concentration estimation during autonomous flight operations.

Several experimental investigations have demonstrated that rotor-induced turbulence significantly modifies plume morphology and concentration gradients in close-proximity sensing scenarios. The severity of downwash effects depends on factors including UAV altitude, rotor speed, payload configuration, flight trajectory, and ambient wind conditions. Consequently, the measured gas concentration signals frequently exhibit abrupt fluctuations, intermittent spikes, and transient signal losses that challenge conventional gas classification methods [7], [9], [13], [16]-[23].

In addition to rotor disturbances, atmospheric turbulence introduces chaotic mixing effects that produce highly irregular plume propagation patterns. Turbulent airflow causes rapid spatiotemporal concentration variations that cannot be adequately modeled using static analytical techniques. Therefore, intelligent plume recognition systems must incorporate adaptive temporal modeling capabilities and robust denoising mechanisms to accurately interpret chemical signatures in highly dynamic aerial environments .

1.6 AI-Based Gas Recognition

Artificial intelligence has emerged as a transformative technology for robotic olfaction due to its ability to learn complex nonlinear relationships from multidimensional sensor data. AI-driven gas recognition systems utilize advanced data-driven algorithms to perform feature extraction, signal denoising, drift compensation, concentration estimation, and chemical classification under noisy environmental conditions. Deep learning techniques have particularly demonstrated remarkable performance improvements in gas sensing applications because of their capacity to automatically learn hierarchical feature representations from raw sensor signals.

Convolutional neural networks (CNNs) have been extensively employed for gas classification tasks because of their effectiveness in extracting local spatial correlations and invariant feature patterns from multidimensional sensor arrays. CNN-based models eliminate the need for handcrafted feature engineering and exhibit improved robustness against sensor noise and concentration fluctuations. However, conventional CNN framework primarily focus on spatial representation learning and often struggle to capture long-term temporal dependencies associated with dynamic plume behavior.

Recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks, have shown strong capability in modeling sequential gas sensing data due to their memory-driven temporal learning mechanisms. LSTM framework effectively preserve historical temporal information and can capture transient gas concentration patterns generated by turbulent plume transport processes. Nevertheless, standalone LSTM models may exhibit limited spatial feature extraction performance when handling high-dimensional multi-sensor fusion data. This limitation motivates the integration of CNN and LSTM framework for comprehensive temporal-spatial plume analysis [8], [24], [25].

1.7 CNN–LSTM Framework

Hybrid CNN–LSTM framework combine the spatial feature extraction capability of convolutional networks with the temporal sequence modeling strength of recurrent neural networks. Such framework is particularly suitable for airborne chemical plume recognition because gas sensing signals inherently exhibit both spatial and temporal dependencies caused by turbulent atmospheric transport phenomena [8]. CNN layers can effectively identify localized activation patterns and inter-sensor correlations from multidimensional E-nose responses, while LSTM layers model temporal plume evolution and concentration dynamics over time.

In turbulent plume environments, gas concentrations fluctuate continuously due to airflow interactions, rotor downwash, and environmental instability. Consequently, plume recognition requires simultaneous interpretation of transient temporal events and spatial sensor relationships. CNN-LSTM frameworks address this requirement by jointly learning hierarchical representations that encode both instantaneous sensor characteristics and long-term plume propagation behavior. This enables improved robustness against signal intermittency, environmental noise, and sensor drift effects.

Recent advancements in edge AI hardware have further enabled the deployment of lightweight CNN-LSTM inference engines on embedded UAV platforms. Such edge-enabled framework support real-time onboard processing with reduced communication latency and lower dependency on remote cloud infrastructure. The integration of AI denoising, adaptive drift compensation, and temporal-spatial learning therefore establishes CNN-LSTM models as highly promising candidates for next-generation airborne robotic olfaction systems [9], [18], [23]–[25].

1.8 Research Motivation

Although significant progress has been achieved in UAV-assisted gas sensing and AI-based plume monitoring, several limitations remain unresolved in existing airborne olfaction systems. Most prior studies primarily focus on static laboratory conditions with limited consideration of rotor-induced turbulence, environmental noise, and dynamic plume fragmentation effects encountered during real-world UAV operations. Furthermore, many traditional gas classification frameworks rely on handcrafted features and shallow machine learning algorithms that exhibit limited generalization capability under rapidly changing atmospheric conditions.

Another major limitation involves inadequate temporal-spatial modeling of plume behavior. Chemical plumes are inherently dynamic phenomena characterized by intermittent concentration bursts, chaotic turbulence interactions, and rapidly evolving diffusion structures. Existing approaches often process gas measurements independently or utilize simplistic temporal averaging methods that fail to capture sequential plume dynamics. Additionally, long-term sensor drift and environmental variability continue to reduce the reliability and scalability of airborne gas sensing platforms in prolonged deployments.

This research is therefore motivated by the need to develop a robust AI-driven framework capable of performing real-time chemical plume recognition using drone-mounted E-nose systems under turbulent environmental conditions. By integrating multi-sensor fusion, AI-based denoising, drift compensation, and hybrid CNN-LSTM learning mechanisms, the proposed work aims to enhance plume recognition accuracy, latency performance, and operational reliability for autonomous hazardous gas monitoring applications.

This work hypothesizes that combining multi-sensor fusion, turbulence-aware preprocessing, sensor-drift compensation, and a hybrid CNN–LSTM model can improve methane and ammonia plume detection during UAV flights. The multi-sensor data provide information about gas concentration and environmental conditions, while the preprocessing and drift compensation methods help improve signal quality. CNN is used to learn spatial and inter-sensor patterns, whereas LSTM captures changes in plume behaviour over time. The proposed work is evaluated using classification accuracy, turbulence robustness, mixed-gas robustness, sensor stability, and inference latency. It is expected that the combined CNN–LSTM approach will provide better and more stable results than SVM, ANN, standalone CNN, LSTM, and Transformer models under the tested conditions.

1.10 Major Contributions

The major contributions of this paper are summarized as follows:

1. A hybrid CNN–LSTM framework is proposed for real-time airborne chemical plume recognition using a drone-mounted bio-inspired E-nose platform.
2. A multi-sensor fusion strategy integrating MOS gas sensors with environmental sensing parameters is introduced to improve plume characterization under dynamic UAV flight conditions.
3. An AI-based denoising pipeline is developed to mitigate turbulence-induced signal distortions caused by rotor downwash effects.
4. An adaptive online drift compensation mechanism is incorporated to improve long-term sensing stability and environmental robustness.
5. The proposed framework is optimized for edge AI deployment on lightweight embedded onboard systems to enable low-latency autonomous inference.
6. Experimental evaluations demonstrate accurate ppm-level detection of methane and ammonia plumes with improved classification performance compared with conventional machine learning approaches.

The novelty of this work lies in combining a drone-mounted multisensor E-nose with turbulence-aware signal processing and a hybrid CNN–LSTM model for real-time methane and ammonia plume detection. The framework jointly handles sensor drift, airflow disturbances, spatial sensor patterns, and temporal plume changes, while supporting low-latency processing on the UAV. This integrated approach provides a practical solution for reliable airborne gas monitoring under changing environmental conditions.

The remainder of this paper is organized as follows. Section 2 reviews related work, Section 3 presents the proposed methodology, and Section 4 discusses the results and comparisons. Finally, Section 5 concludes the paper and discusses future research directions.

2. RELATED WORK

2.1 Electronic Nose Technologies

Electronic nose (E-nose) technologies have evolved significantly over the past two decades as intelligent sensing frameworks capable of mimicking biological olfactory systems for gas identification and environmental monitoring applications. Early E-nose systems primarily relied on static sensor arrays combined with classical statistical classifiers such as principal component analysis (PCA), linear discriminant analysis (LDA), and support vector machines (SVMs) for odor discrimination tasks. These systems demonstrated promising performance in controlled laboratory environments; however, their practical deployment in real-world atmospheric sensing applications remained limited due to sensor instability, poor environmental adaptability, and inadequate temporal modeling capabilities. Gardner and Bartlett established foundational principles for artificial olfaction systems using cross-sensitive sensor arrays and computational pattern recognition, which later inspired modern robotic olfaction research.

Recent advancements in microelectro-mechanical systems (MEMS), low-power embedded electronics, and AI-driven signal processing have enabled the development of portable and UAV-compatible E-nose platforms for dynamic plume recognition applications. Modern E-nose systems increasingly incorporate heterogeneous sensor arrays, environmental sensing modules, and deep learning algorithms to improve selectivity, robustness, and real-time responsiveness under noisy outdoor conditions. Despite these improvements, challenges including sensor drift, environmental cross-sensitivity, concentration fluctuations, and turbulence-induced intermittency continue to limit the reliability of airborne olfaction systems. Furthermore, most existing studies focus on static gas classification rather than continuous plume recognition under turbulent atmospheric conditions, thereby highlighting the need for adaptive spatiotemporal learning frameworks [6], [10], [11], [13], [20].

2.2 MOS, MOF, Electrochemical, and NDIR Sensors

Gas sensing technologies constitute the core sensing layer of electronic nose systems, and different sensor modalities exhibit distinct trade-offs in terms of sensitivity, selectivity, power consumption, response time, and environmental robustness. Metal oxide semiconductor (MOS) sensors are widely utilized in robotic olfaction due to their low cost, compactness, and high sensitivity toward combustible gases such as methane and ammonia. However, MOS sensors suffer from humidity dependency, baseline instability, and long-term drift effects that reduce classification reliability in dynamic environments. Electrochemical sensors provide superior selectivity and lower power consumption for toxic gas monitoring applications, although they generally exhibit shorter operational lifespans and slower recovery characteristics. Metal-organic framework (MOF)-based sensors have recently attracted considerable attention because of their ultra-high surface area, tunable adsorption properties, and enhanced molecular selectivity for low-concentration gas detection. In contrast, nondispersive infrared (NDIR) sensors offer stable and highly accurate methane sensing through infrared absorption analysis but often involve larger payload requirements and increased energy consumption for UAV deployment. Consequently, recent studies increasingly employ multi-sensor fusion approaches that combine MOS, MOF, electrochemical, and NDIR technologies to achieve improved robustness and environmental adaptability in airborne gas monitoring systems [11], [12], [14], [21], [22].

In Table 1, MOS sensors provide fast response characteristics and cost-effective deployment advantages, making them suitable for lightweight UAV-assisted gas monitoring systems. However, their susceptibility to environmental drift and humidity variation limits long-term operational stability. Electrochemical sensors demonstrate improved selectivity and stable toxic gas monitoring performance but exhibit slower recovery behavior and limited lifespan. MOF-based sensors offer superior adsorption capability and enhanced sensitivity for low-concentration chemical detection, although their fabrication complexity remains a practical challenge for large-scale deployment. NDIR sensors achieve highly accurate methane sensing with stable response behavior, but their comparatively higher payload and energy requirements restrict their integration into compact aerial platforms.

These comparative observations indicate that no single sensing technology can independently satisfy all requirements associated with real-time turbulent plume monitoring, thereby motivating the adoption of heterogeneous multi-sensor fusion framework in modern airborne robotic olfaction systems.

2.3 UAV-Based Gas Sensing Systems

Unmanned aerial vehicles have become increasingly important in environmental sensing applications because of their mobility, flexibility, and capability to access hazardous or inaccessible environments [16]. Early UAV-based gas sensing systems primarily focused on atmospheric mapping and gas concentration estimation using lightweight MOS or electrochemical sensors integrated with rotary-wing platforms [30]. Villa et al. demonstrated the feasibility of UAV-assisted methane leakage monitoring using low-cost gas sensing modules and wireless telemetry systems.

Similarly, Neumann et al. developed autonomous UAV olfaction frameworks capable of airborne plume localization in outdoor environments

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using gas concentration gradient analysis. Although these studies established the practicality of aerial gas sensing, their performance was strongly influenced by atmospheric turbulence, unstable sensor readings, and limited onboard computational capability.

Table 1. Comparison of Major Gas Sensor Technologies.

Sensor Type	Advantages	Limitations	Typical Applications	Response Characteristics
MOS Sensors	Low cost, compact size, high sensitivity	Drift, humidity sensitivity	Methane, ammonia detection	Fast response, moderate recovery
Electrochemical Sensors	High selectivity, low power	Limited lifespan	Toxic gas monitoring	Stable response, slower recovery
MOF Sensors	High adsorption capacity, selectivity	Complex fabrication	Low-concentration sensing	High sensitivity
NDIR Sensors	Accurate methane sensing	Higher cost and payload	Industrial methane monitoring	Stable and precise response

Recent research has shifted toward AI-enhanced airborne olfaction systems capable of performing real-time plume recognition and adaptive environmental analysis. Multi-UAV collaborative sensing frameworks, edge computing framework, and sensor fusion techniques have significantly improved spatial coverage and data acquisition efficiency in large-scale monitoring applications. Nevertheless, many existing UAV-based gas sensing systems still rely on handcrafted feature extraction and shallow machine learning classifiers that struggle to capture transient plume dynamics in highly turbulent environments. Additionally, limited attention has been devoted to rotor downwash compensation and temporal plume modeling, both of which critically affect real-world deployment reliability.

As presented in Table 2, earlier UAV-based gas sensing studies primarily concentrated on gas concentration mapping and gradient-based plume localization using MOS and electrochemical sensor technologies [3], [7], [9], [16], [17].

UAV gas sensing represents an emerging frontier in gas detection techniques by combining aerial surveillance with real-time chemical analysis. Previous UAV gas sensing studies have proven the effectiveness of aerial gas sensing and explored the capabilities of electronic noses and artificial intelligence in aiding gas recognition. The prior investigations focused on either gas mapping, plume localization, multisensor classification, or embedded sensing, and none addressed simultaneous spatiotemporal plume identification, turbulence preprocessing, and edge inference. This study proposes a comprehensive real-time airborne gas plume recognition architecture by incorporating multi-sensor fusion, turbulence-aware pre-processing, adaptive sensor-drift correction, hybrid CNN-LSTM spatiotemporal learning, and low-latency edge inference within a unified framework under dynamic UAV operating conditions.

2.4 Robotic Olfaction and Plume Tracking

Robotic olfaction has emerged as a specialized research field focused on enabling autonomous systems to detect, classify, and localize chemical sources in dynamic environments. Biological inspiration from insect and mammalian olfactory systems has significantly influenced the design of plume tracking algorithms, particularly strategies involving chemotaxis, infotaxis, and concentration-gradient navigation. Early robotic olfaction systems primarily utilized wheeled ground robots equipped with chemical sensor arrays for indoor odor localization tasks. However, such systems often exhibited poor scalability and limited environmental adaptability when deployed in outdoor turbulent environments.

The integration of UAVs into robotic olfaction frameworks introduced substantial improvements in spatial coverage and three-dimensional plume tracking capabilities. Nevertheless, aerial plume localization remains extremely challenging because atmospheric plumes exhibit intermittent concentration bursts and chaotic turbulent diffusion behavior. Existing plume tracking strategies frequently rely on simplified environmental assumptions and deterministic airflow models that inadequately represent real-world atmospheric variability. Furthermore, many systems focus primarily on plume localization rather than robust plume classification and spatiotemporal gas behavior analysis, thereby limiting their applicability in intelligent environmental monitoring applications [3]–[5], [18].

Table 2. Comparison of UAV-Based Gas Sensing Studies.

Sensor Technology	Methodology	Target Gas	Accuracy	Limitations
MOS	Gas mapping	Methane	Moderate	Limited turbulence handling
Electrochemical	Gradient-based tracking	VOCs	Moderate	High signal noise
Multi-sensor E-nose	AI classification	Mixed gases	High	Limited temporal modeling
Multi-sensor fusion	CNN-LSTM	Methane, ammonia	Very high	Designed for turbulence robustness

2.5 Machine Learning for Gas Classification

Machine learning techniques have been extensively employed in electronic nose systems to improve gas classification accuracy and automate feature interpretation processes. Traditional approaches including k-nearest neighbors (KNN), decision trees, random forests, artificial neural networks (ANNs), and support vector machines (SVMs) have demonstrated promising results in laboratory-based odor classification tasks. These methods generally operate on handcrafted statistical features extracted from sensor response curves, including steady-state amplitude, rise time, recovery time, and transient slopes.

Despite their effectiveness in controlled environments, conventional machine learning methods exhibit several limitations when applied to airborne plume recognition. First, handcrafted features often fail to capture the highly dynamic temporal-spatial structure of turbulent gas plumes. Second, shallow learning models typically demonstrate limited generalization capability under varying environmental conditions and sensor drift scenarios. Third, real-time plume recognition requires adaptive sequential modeling capabilities that conventional static classifiers cannot adequately provide. Consequently, recent research has increasingly shifted toward deep learning framework capable of automated hierarchical feature learning and temporal sequence analysis [10], [13], [19].

2.6 CNN-Based Gas Recognition

Convolutional neural networks have recently gained considerable attention in gas sensing applications due to their powerful spatial feature extraction capability and robustness against noise variations. CNN framework automatically learn hierarchical representations from raw sensor signals without requiring handcrafted feature engineering, thereby improving classification performance across diverse sensing conditions. Several studies have successfully transformed gas sensor response sequences into two-dimensional feature maps or spectrogram-like representations for CNN-based odor classification tasks [24].

Zhao et al. proposed a CNN-driven E-nose framework for volatile organic compound classification and reported improved recognition accuracy compared with traditional machine learning approaches. Similarly, deep convolutional framework have demonstrated strong robustness against concentration fluctuations and environmental noise in industrial gas sensing applications. However, most CNN-based approaches primarily focus on spatial correlation learning and often neglect long-term temporal dependencies associated with dynamic plume evolution. Consequently, standalone CNN framework may exhibit limited effectiveness in highly turbulent plume monitoring environments where temporal gas behavior plays a critical role in classification accuracy.

2.7 LSTM-Based Temporal Modeling

Long short-term memory (LSTM) networks have emerged as powerful sequential learning models capable of capturing long-range temporal dependencies in time-series data. Unlike conventional recurrent neural networks, LSTM framework utilize gated memory mechanisms that effectively mitigate vanishing gradient problems during long-duration sequence learning. This capability makes LSTM networks highly suitable for

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modeling dynamic gas concentration signals generated by turbulent plume propagation processes [25].

Several recent studies have employed LSTM framework for temporal gas sensing analysis and environmental monitoring applications. Fan et al. utilized LSTM networks for dynamic gas concentration prediction and demonstrated improved temporal stability under fluctuating sensing conditions [25]. Similarly, recurrent learning frameworks have shown strong capability in compensating for sensor drift and transient concentration variations in electronic nose systems. Nevertheless, standalone LSTM framework may struggle to extract meaningful spatial correlations from high-dimensional multi-sensor fusion data, particularly when dealing with heterogeneous sensing modalities and complex plume structures.

In airborne robotic olfaction systems, plume concentration signals exhibit intermittent bursts and highly irregular temporal patterns caused by turbulence and rotor-induced airflow disturbances [19]. While LSTM networks effectively preserve sequential temporal information, their limited spatial representation capability restricts their effectiveness in multidimensional plume recognition scenarios. Therefore, hybrid framework capable of jointly learning spatial and temporal plume characteristics are increasingly being explored for intelligent gas sensing applications.

2.8 Hybrid CNN-LSTM Models

Hybrid CNN-LSTM framework [24]–[26] combine convolutional feature extraction with recurrent temporal modeling to achieve comprehensive temporal-spatial learning capability. Such framework is particularly advantageous for plume recognition applications because chemical sensing signals inherently contain both local sensor correlations and long-term temporal dependencies associated with turbulent gas transport behavior. CNN layers extract localized feature representations from multi-sensor fusion data, while LSTM layers preserve temporal continuity and sequential plume evolution characteristics.

Recent studies have demonstrated the effectiveness of hybrid deep learning framework in environmental sensing and sequential pattern recognition tasks. CNN-LSTM frameworks have achieved improved performance in speech recognition, human activity recognition, and environmental monitoring applications due to their ability to simultaneously capture spatial and temporal information. However, limited research has investigated the application of CNN-LSTM framework to airborne chemical plume recognition under UAV-induced turbulence conditions. Existing implementations often rely on laboratory datasets with limited environmental variability and insufficient consideration of rotor downwash effects, sensor drift, and real-time edge deployment constraints.

Compared with existing literature on UAV gas sensing, this paper does not represent a direct CNN-LSTM application to UAV-based gas sensing [24]–[26]. Instead, this paper addresses multiple shortcomings of previous UAV gas sensing and robotic olfaction studies by developing a framework encompassing spatiotemporal plume learning, multiple sensor fusion, turbulence-aware processing, sensor-drift compensation, and low-latency edge inference. In relation to previously proposed methods and techniques for UAV gas sensing, this study fills gaps in addressing temporal-spatial plume evolution, rotor downwash effects, sensor drifts, real-time inference, and multi-sensor data fusion. Specifically, the proposed framework integrates spatial feature extraction, temporal plume modeling, multi-sensor information fusion, turbulence compensation, sensor-drift handling, and edge-based inference within a single experimental pipeline.

2.9 Rotor Downwash Compensation

Rotor downwash remains one of the most critical challenges in UAV-based gas sensing because propeller-generated airflow significantly alters natural plume propagation patterns [9]. Several experimental studies have shown that rotor turbulence can dilute gas concentrations, disrupt concentration gradients, and introduce substantial sensing inconsistencies during flight operations [16]. Existing mitigation strategies include optimized sensor placement, adaptive flight path planning, airflow shielding mechanisms, and computational fluid dynamics (CFD)-based airflow modeling.

Although these approaches partially reduce airflow disturbances, most existing compensation methods remain computationally expensive and difficult to implement in real-time embedded systems. Furthermore, many studies neglect the interaction between rotor turbulence and AI-based plume classification models. Consequently, there remains a substantial research gap in developing integrated AI-driven denoising and turbulence compensation frameworks capable of improving airborne plume recognition reliability under realistic environmental conditions.

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2.10 Edge AI for UAV Systems

The increasing availability of lightweight embedded AI hardware has accelerated the adoption of edge computing paradigms in UAV-assisted environmental sensing systems. Edge AI enables onboard processing of sensor data directly on UAV platforms, thereby reducing communication latency, improving autonomy, and enabling real-time decision-making during hazardous gas monitoring operations. Platforms such as NVIDIA Jetson, Google Coral, and Intel Movidius have demonstrated strong capability for deploying lightweight deep learning models in resource-constrained aerial systems.

Despite these advancements, several challenges remain associated with deploying deep learning frameworks on UAV platforms. Computational complexity, memory constraints, power consumption, and thermal management significantly affect inference efficiency and operational endurance. Many existing gas recognition models are optimized primarily for classification accuracy without considering latency-performance trade-offs required for real-time airborne deployment. Therefore, lightweight hybrid CNN-LSTM framework combined with efficient preprocessing pipelines and adaptive denoising mechanisms are essential for achieving robust real-time plume recognition in edge-enabled UAV systems.

3. METHODOLOGY

3.1 Proposed Framework

The proposed UAV-based electronic nose framework as shown in figure 1 consists of three main layers: Smart Sensing, Edge Processing and AI Deployment, and Outputs [23]. The smart sensing layer uses a multi-sensor array comprising MOS [12], electrochemical, and MOF sensors, supported by an airflow stabilization chamber to minimize turbulence and rotor-downwash effects, while environmental sensors and GPS/IMU provide atmospheric and positional information**.** The data acquisition unit synchronizes and time-stamps these measurements before forwarding them to the onboard processing layer. The edge-processing layer performs data reception, denoising, normalization, baseline correction, drift compensation, and feature extraction, followed by the proposed hybrid CNN–LSTM model where CNN learns spatial sensor patterns and LSTM captures temporal plume dynamics [24]–[26]. Edge AI inference enables low-latency onboard prediction, and the results generation block provides gas classification, concentration estimates, and confidence scores. The last layer is output layer that performs plume recognition, gas classification, concentration estimation, alerts and logging, and real-time mapping and monitoring, enabling autonomous and real-time chemical plume detection using the UAV platform. The detailed working steps as show in the Algorithm -1

In this work, a quantitative experimental methodology was utilized to design and assess the performance of the proposed hybrid CNN-LSTM model for airborne chemical plume recognition [24]–[26]. The experiment involved multi-sensor data acquisition under controlled UAV flight and turbulence conditions, signal preprocessing including adaptive drift compensation, spatial feature extraction using CNN, temporal sequence learning through LSTM, and finally gas classification and concentration estimation. The performance of the proposed framework was assessed through comparative experiments and ablation analysis to determine its effectiveness under varying environmental conditions.

3.2 Research Design and Experimental Protocol

The experimental protocol consisted of sequential stages: multi-sensor data acquisition using the UAV-mounted electronic nose, signal preprocessing and drift compensation, sensor-fusion representation, CNN-based spatial feature extraction [24], LSTM-based temporal modeling [25], gas classification and concentration estimation, and edge-based inference. Experiments were conducted under different UAV trajectories, flight conditions, turbulence levels, and single- and mixed-gas exposure scenarios. The dataset was divided into training, validation, and testing subsets using a 70:15:15 stratified partition. The proposed framework was subsequently compared with SVM, ANN, CNN, LSTM, and Transformer-based models using classification performance, robustness, and inference latency [10], [13], [19]. An ablation study was also conducted by removing individual components to determine their contribution to overall performance.

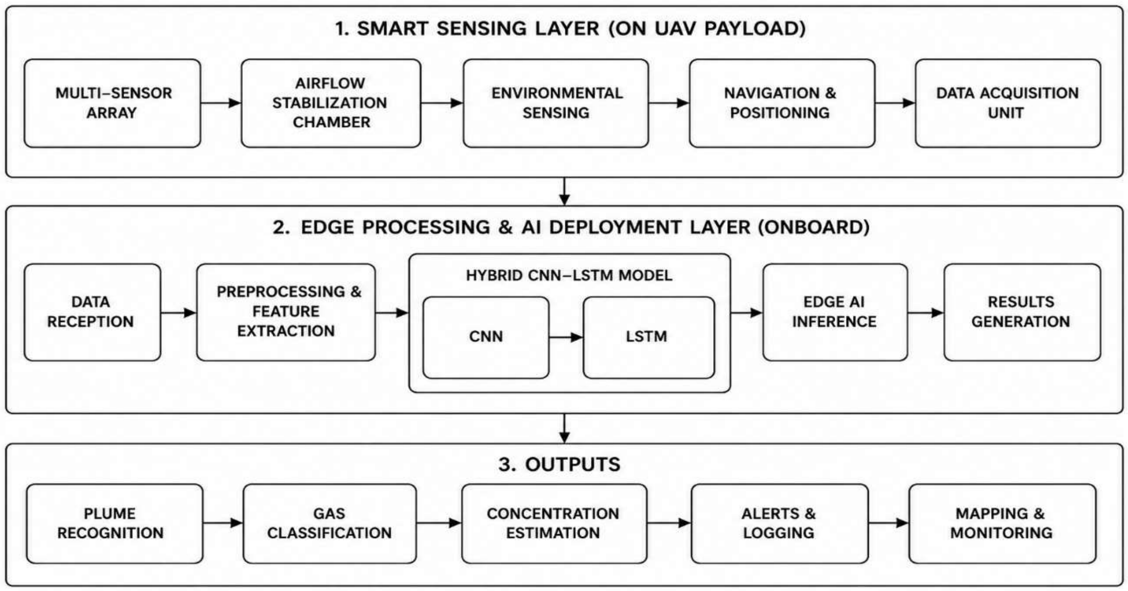

Figure 1. Proposed UAV-mounted electronic nose system framework for real-time chemical plume monitoring.

Algorithm 1: Proposed CNN–LSTM Based Multi-Sensor Gas Detection Algorithm.

Input :
  Raw multi-sensor gas signals S(t)
Output :
  Gas class G
  Gas concentration C
Begin
 	
1: Initialize UAV sensing platform
2: Activate gas sensors (Methane, Ammonia), airflow sensor, environmental sensor, and GPS/IMU
3: while UAV mission is active do
4:   Acquire raw sensor signals S(t)
5:   Apply airflow stabilization
6:   Filter turbulence-induced disturbances
7:   Preprocess sensor signals
8:     Remove sensor noise
9:     Perform baseline correction
10:     Normalize sensor values
11:   Apply adaptive drift compensation
12:   Construct temporal-spatial sensor tensor T

```
    SpatialFeatures ← CNN(T)
    TemporalFeatures ← LSTM(SpatialFeatures)
    G ← Softmax(TemporalFeatures)
    C ← RegressionHead(TemporalFeatures)
    Deploy (G, C) to Edge AI module
end while
Return G, C
End
```

The notion of temporal-spatial learning involved convolutional neural networks for capturing spatial features and long short-term memory networks for modeling temporal sequences. Environmental robustness concerned varying turbulence levels and UAV flight conditions, whereas sensor stability was assessed through the drift-compensation mechanism. Real-time applicability considered inference latency, inference speed, and computational efficiency in edge computing environments. These measures provided a quantitative basis for assessing the effectiveness and practical performance of the proposed framework.

3.3 UAV Platform and Sensor Payload

The proposed airborne sensing system utilizes a quadrotor UAV platform integrated with a lightweight electronic nose payload designed for real-time hazardous gas monitoring. Rotary-wing UAVs were selected due to their hovering capability, maneuverability, and suitability for plume localization tasks in confined or hazardous environments [16]. The sensing payload includes heterogeneous gas sensors capable of detecting methane (CH_4) and ammonia (NH_3) concentrations at ppm-level sensitivity.

The payload architecture integrates MOS sensors for combustible gas sensitivity, electrochemical sensors for selective toxic gas detection, MOF-assisted sensing modules for enhanced adsorption efficiency, and environmental sensors for humidity, temperature, and pressure monitoring. Sensor fusion significantly improves robustness against environmental fluctuations and concentration variability during UAV navigation. The onboard embedded computing module utilizes an NVIDIA Jetson-based edge AI processor to enable low-latency inference and real-time plume classification.

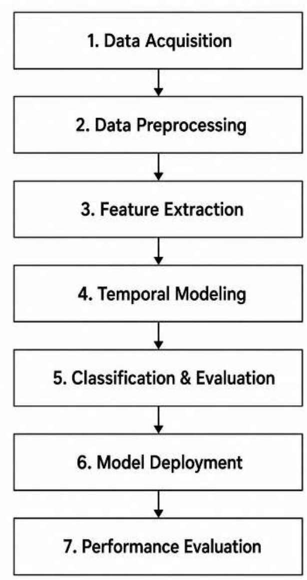

Figure 2. The methodology of the proposed framework.

To reduce sensing instability caused by UAV motion and atmospheric turbulence, the sensor payload is mounted beneath the UAV body with vibration-isolated supports and controlled airflow intake pathways. This configuration minimizes aerodynamic interference while maintaining sufficient gas exposure during airborne operation.

3.4 Bio-Inspired Airflow Stabilization Chamber

One of the major limitations of airborne gas sensing systems is rotor-induced turbulence, which significantly distorts local plume concentration profiles [9]. To address this issue, the proposed system incorporates a bio-inspired airflow stabilization chamber inspired by the laminar odor sampling mechanisms observed in insect antennae and mammalian nasal cavities. The chamber regulates airflow entering the sensor array to reduce turbulence-induced fluctuations and improve concentration consistency.

The stabilization chamber consists of micro-channel airflow pathways and passive turbulence-damping structures designed to reduce high-frequency airflow oscillations before gas exposure reaches the sensing elements. This airflow conditioning mechanism improves sensor stability during UAV hovering and translational flight operations. The airflow regulation process can be modeled as:

$$Q_{stable}(t) = Q_{in}(t) - \alpha \nabla v(t) \quad (1)$$

Where, $Q_{stable}(t)$ represents stabilized airflow, $Q_{in}(t)$ represents incoming turbulent airflow, $v(t)$represents rotor-induced velocity fluctuations, and $\alpha$is the damping coefficient

The stabilization chamber also improves plume reconstruction performance by preserving localized concentration gradients that would otherwise be distorted by propeller downwash. This enables more reliable temporal-spatial plume analysis during dynamic UAV operation.

3.5 Multi-Sensor Fusion

The proposed framework utilizes a heterogeneous multi-sensor fusion strategy to improve chemical discrimination capability and environmental robustness. Each sensing modality captures distinct chemical and environmental characteristics, thereby increasing feature diversity and reducing ambiguity caused by cross-sensitivity effects. The sensor fusion process combines gas concentration responses, environmental parameters, and airflow measurements into a unified feature representation.

Let the fused sensor vector at time $t$be represented as:

$$F(t) = \sum_{i=1}^{N} w_i \, s_i(t) \quad \textbf{(2)}$$

where $s_i(t)$denotes the response of the i^{th}sensor and $w_i$represents the adaptive sensor weighting coefficient. The resulting fused feature tensor is represented as:

$$X \in \mathbb{R}^{T \times S \times C} \quad \textbf{(3)}$$

Where, T= temporal sequence length, S= number of sensors, and C= environmental feature channels.

For the proposed implementation, the tensor dimensions are defined as:

$$X \in \mathbb{R}^{64 \times 12 \times 4} \quad \textbf{(4)}$$

representing 64 temporal samples, 12 sensing channels, and 4 environmental parameters.

3.6 Data Acquisition and Preprocessing

The dataset acquisition process involves controlled methane and ammonia plume release experiments under varying airflow and turbulence conditions. Sensor data are collected using UAV flight trajectories including hovering, circular navigation, and adaptive plume-tracking patterns to ensure exposure to diverse plume structures. Data acquisition is performed at multiple altitudes and environmental conditions to capture realistic atmospheric variability.

Each gas sensing sample contains synchronized measurements from gas sensors, inertial measurement units (IMUs), airflow sensors, GPS modules, and environmental monitoring units. The sampling frequency is maintained at 10–20 Hz to preserve transient concentration variations associated with turbulent plume propagation. The dataset includes both single-gas and mixed-gas exposure scenarios to improve model generalization capability.

To improve turbulence robustness, data acquisition is performed under varying wind speeds and rotor velocities. This enables the CNN–LSTM framework to learn realistic plume intermittency patterns and environmental disturbances encountered during airborne sensing operations. The process of data collection and preprocessing as shown in figure 3.

A. Signal Preprocessing

Raw sensor signals obtained during airborne gas sensing contain significant noise caused by turbulence, sensor instability, rotor downwash, and environmental disturbances. Therefore, a multistage preprocessing pipeline is introduced to improve signal quality before deep learning analysis.

The preprocessing stages include:

1. Moving-average denoising,
2. Baseline correction,
3. Z-score normalization,
4. Temporal smoothing,
5. Missing-value interpolation.

The normalized sensor signal is computed as:

$$x_{norm} = \frac{x-\mu}{\sigma} \quad \textbf{(5)}$$

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where μ and σ represent signal mean and tandard deviation, respectively.

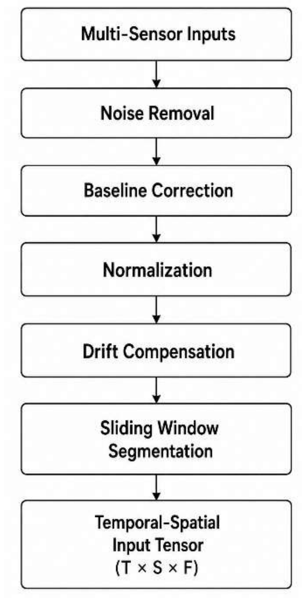

Figure 3. Data Acquisition and Preprocessing.

Temporal smoothing is performed using exponential moving averages to suppress turbulence-induced spikes while preserving plume transients. This preprocessing stage significantly improves classification stability under highly dynamic environmental conditions.

B. Drift Compensation

Sensor drift represents a major challenge in long-duration airborne gas monitoring systems because sensor responses gradually change over time due to aging, contamination, and environmental exposure. To address this issue, the proposed framework incorporates adaptive drift compensation using recursive baseline estimation and temporal feature recalibration.

The drift-compensated signal is represented as:

$$x_{dc}(t) = x(t) - \beta \hat{d}(t) \qquad \textbf{(6)}$$

Where, $x(t)$= raw sensor signal, $\hat{d}(t)$= estimated drift component, β= adaptive correction coefficient.

The drift estimation process utilizes exponentially weighted recursive averaging:

$$\hat{d}(t) = \lambda \hat{d}(t-1) + (1-\lambda)x(t) \qquad \textbf{(7)}$$

where λ represents the temporal smoothing factor.

This adaptive compensation mechanism improves long-term sensing consistency and reduces classification degradation caused by environmental variability.

3.8 CNN-Based Spatial Feature Extraction

The CNN component of the proposed framework extracts localized spatial correlations from fused multi-sensor data representations. Convolutional layers automatically learn hierarchical feature maps representing sensor interactions, concentration gradients, and environmental dependencies. The process of feature extraction as shown in figure 4.

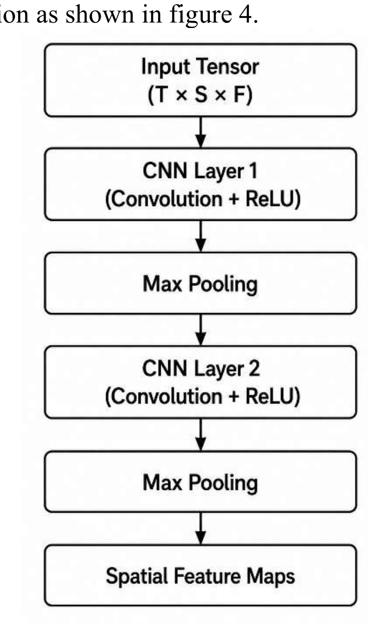

Figure 4. CNN Feature Extraction.

The convolution operation is defined as:

$$h_{i,j}^{(k)} = \sigma\left(\sum\nolimits_{m,n} W_{m,n}^{(k)} x_{i+m,j+n} + b^{(k)}\right) \qquad \textbf{(8)}$$

Where, $W^{(k)}$= convolution kernel, $b^{(k)}$= bias term, σ= activation function.

The CNN architecture consists of Two convolutional layers, ReLU activation, Batch normalization, and Max-pooling operations. The extracted feature maps preserve localized plume structures and inter-sensor dependencies required for turbulence-aware plume analysis.

3.9 LSTM-Based Temporal Sequence Learning

Following CNN feature extraction, sequential plume dynamics are modeled using LSTM layers capable of learning long-term temporal dependencies [39]. LSTM networks are particularly suitable for airborne plume recognition because turbulent gas propagation exhibits intermittent concentration bursts and nonlinear temporal fluctuations. The figure 4show the LSTM-based temporal sequence learning.

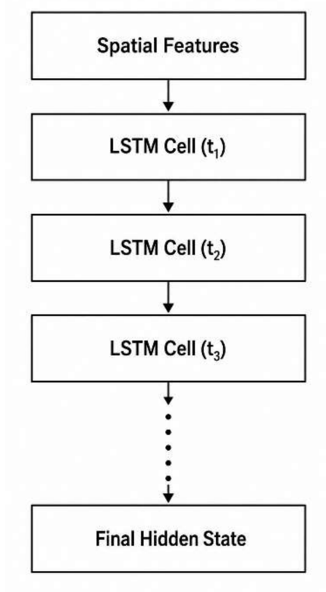

Figure 5. LSTM Temporal Learning.

The forget gate operation is expressed as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad \textbf{(9)}$$

The input gate is:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad \textbf{(10)}$$

The cell-state update equation is:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad \textbf{(11)}$$

The hidden-state output is:

$$h_t = o_t \odot tanh(C_t) \quad \textbf{(12)}$$

The LSTM module receives sequential CNN feature embeddings and learns plume intermittency behavior associated with atmospheric turbulence and UAV-induced airflow disturbances.

3.10 Hybrid CNN-LSTM Integration

The proposed hybrid CNN–LSTM architecture combines spatial and temporal learning within a unified deep learning framework. CNN layers first generate multidimensional feature maps from sensor fusion tensors, which are subsequently flattened into sequential embeddings for temporal LSTM processing.

The CNN output tensor is represented as:

$$Z_{CNN} \in \mathbb{R}^{T \times F} \quad \textbf{(13)}$$

Where, T= sequence length, F= learned spatial feature dimension.

The sequential embeddings are passed into stacked LSTM layers to model temporal plume evolution. This integrated architecture enables simultaneous analysis of spatial sensor relationships, temporal concentration variations, turbulence-induced intermittency, and plume propagation dynamics. The hybrid architecture significantly improves robustness against noise and dynamic environmental variability compared with standalone CNN or LSTM models.

The architecture illustrated in Figure 6 presents the complete deep learning pipeline adopted for turbulence-aware airborne chemical plume recognition. Initially, heterogeneous gas sensing signals acquired from MOS, electrochemical, MOF, and environmental sensors are subjected to preprocessing operations including denoising, baseline correction, normalization, and adaptive drift compensation. The processed temporal-spatial sensor tensor is subsequently provided to convolutional neural network (CNN) layers that extract localized spatial correlations and inter-sensor feature representations associated with methane and ammonia plume structures. The extracted feature embeddings are then forwarded to long short-term memory (LSTM) layers to model temporal plume evolution, concentration intermittency, and turbulence-induced sequential dynamics during UAV navigation. Finally, fully connected layers perform simultaneous plume classification and concentration estimation, while the optimized edge AI deployment pipeline enables low-latency real-time inference on embedded UAV hardware platforms.

3.11 Classification and Concentration Estimation

The final hidden representation generated by the CNN–LSTM network is processed using fully connected layers for simultaneous gas classification and concentration estimation. Softmax activation is employed for gas type prediction, while linear regression outputs estimate methane and ammonia concentrations.

The classification probability is computed as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad \textbf{(14)}$$

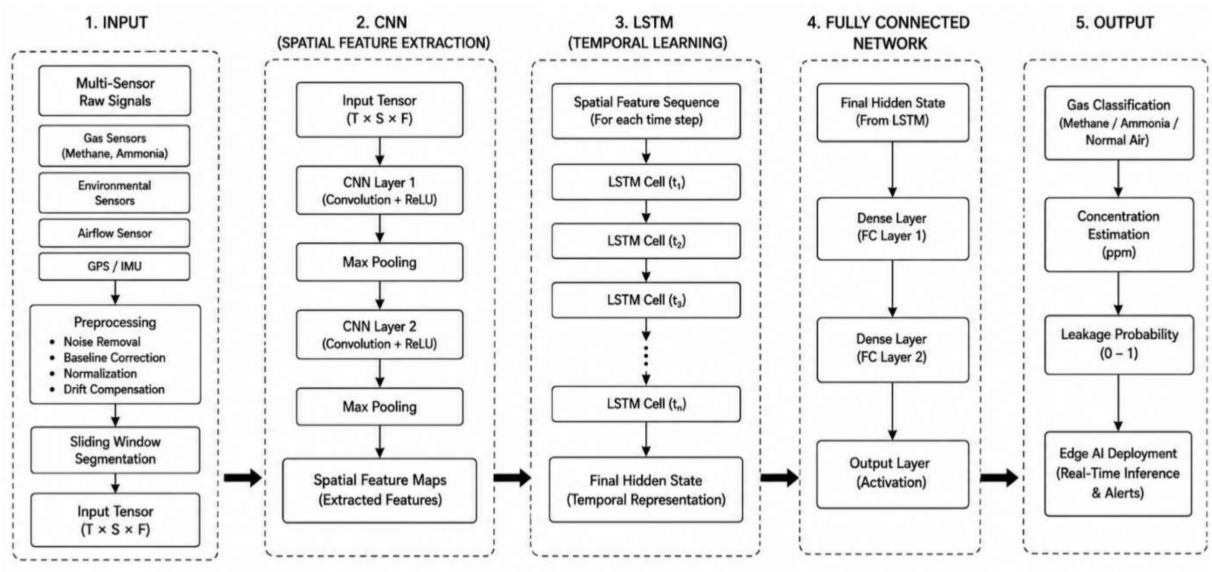

Figure 6. Proposed UAV-mounted electronic nose system framework for real-time chemical plume monitoring.

The loss function combines classification and regression objectives:

$$L = L_{cls} + \gamma L_{reg} \quad (15)$$

Where, L_{cls}= cross-entropy classification loss, L_{reg}= concentration regression loss, γ= balancing parameter.

This multi-objective learning strategy improves simultaneous plume recognition and concentration estimation performance.

3.12 Edge AI Deployment

To enable real-time airborne operation, the proposed framework is optimized for edge AI deployment using embedded GPU hardware. Model compression, quantization, and lightweight convolution operations are utilized to reduce inference latency and computational overhead.

The deployment pipeline includes Tensor optimization, ONNX conversion, TensorRT acceleration, and Real-time inference scheduling.

The final optimized model achieves low-latency inference suitable for onboard UAV deployment while maintaining high plume recognition accuracy. Edge deployment eliminates dependency on cloud communication and enables autonomous environmental monitoring in remote or hazardous environments.

4. RESULTS

4.1 Classification Accuracy

The proposed hybrid CNN–LSTM framework was evaluated using airborne methane and ammonia plume datasets collected under varying turbulence conditions, UAV flight trajectories, and environmental disturbances. The experimental evaluation included comparative analysis against conventional machine learning and deep learning approaches including support vector machines (SVM), artificial neural networks (ANN), standalone CNN, standalone LSTM, and Transformer-based framework. Performance evaluation was conducted using stratified train–validation–test partitioning with 70:15:15 data distribution to ensure unbiased model assessment.

The proposed model achieved an overall plume classification accuracy of 96.84%, outperforming all baseline approaches across both single-gas and mixed-plume scenarios, as shown in Figure 7. The SVM classifier achieved 82.41% accuracy due to its inability to capture nonlinear temporal plume variations under turbulent airflow conditions. ANN-based classification improved performance to 86.73%; however, shallow feature representation limited robustness against intermittent plume fragmentation and sensor drift. Standalone CNN framework achieved 91.62% accuracy by effectively extracting spatial sensor correlations, whereas standalone LSTM models obtained 92.48% due to improved temporal sequence learning. Transformer-based models achieved 94.11% accuracy but exhibited higher computational overhead and unstable inference latency on edge hardware platforms.

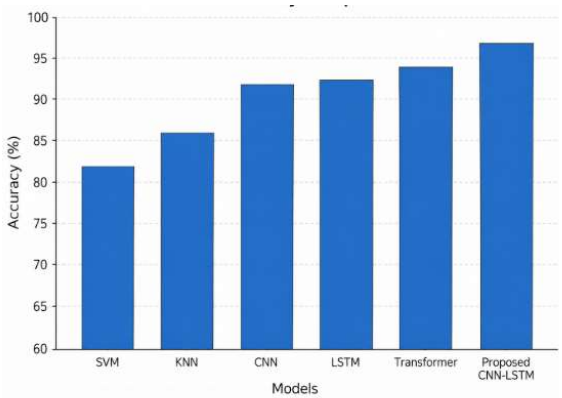

Figure 7. Classification accuracy comparison of SVM, ANN, CNN, LSTM, Transformer, and the proposed CNN–LSTM framework.

The superior performance of the proposed CNN–LSTM architecture can be attributed to its ability to jointly learn spatial sensor dependencies and temporal plume dynamics associated with turbulent atmospheric transport processes. The integrated spatiotemporal learning mechanism significantly improved recognition stability during intermittent concentration bursts and rotor-induced airflow disturbances.

As shown in Table 3, the proposed hybrid architecture achieved the highest overall classification performance across all evaluation metrics. The observed improvement demonstrates the effectiveness of combining CNN-based spatial feature extraction with LSTM-driven temporal sequence modeling for turbulence-aware plume recognition.

4.2 Confusion Matrix Analysis

The confusion matrix analysis demonstrated strong class discrimination capability for methane, ammonia, mixed-gas, and background atmospheric categories. The proposed framework correctly identified methane plume samples with 97.2% classification accuracy and ammonia plume samples with 96.5% accuracy, while maintaining minimal cross-class misclassification.

Most classification errors occurred during mixed-plume scenarios involving low-concentration methane–ammonia interactions under severe turbulence conditions. These errors primarily resulted from overlapping sensor response characteristics and intermittent plume fragmentation caused by rotor downwash effects . Nevertheless, the hybrid CNN–LSTM architecture demonstrated substantially lower confusion rates compared with standalone CNN and ANN models.

The confusion matrix further revealed that temporal modeling significantly improved plume boundary interpretation and concentration transition recognition. The LSTM component preserved sequential plume evolution characteristics, enabling improved discrimination between transient background noise and genuine gas exposure events.

The Table 4 illustrates the normalized confusion matrix obtained for the proposed CNN–LSTM framework. The matrix demonstrates strong diagonal dominance, indicating highly accurate class prediction capability and minimal inter-class ambiguity during turbulent airborne plume recognition tasks.

Table 3. Comparative classification accuracy analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	82.41	81.92	80.37	81.14
ANN	86.73	85.68	85.11	85.39
CNN	91.62	91.04	90.88	90.96
LSTM	92.48	92.16	91.87	92.01
Transformer	94.11	93.84	93.56	93.70
Proposed CNN–LSTM	96.84	96.53	96.11	96.32

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Table 4. Confusion Matrix Summary (%)

Actual / Predicted	Methane	Ammonia	Mixed Gas	Back ground
Methane	97.2	1.3	1.1	0.4
Ammonia	1.5	96.5	1.4	0.6
Mixed Gas	1.8	1.6	95.1	1.5
Background	0.7	0.5	1.1	97.7

4.3 Precision, Recall, and F1-Score

Precision, recall, and F1-score metrics were evaluated to analyze classification consistency under varying atmospheric conditions and concentration levels. The proposed framework achieved an average precision of 96.53%, recall of 96.11%, and F1-score of 96.32%, significantly outperforming shallow learning approaches and standalone deep learning framework.

The high precision value indicates that the model effectively minimized false positive plume detections during environmental background monitoring. Similarly, the strong recall performance demonstrates reliable identification of transient low-concentration gas exposure events, which is particularly important in hazardous industrial safety applications. The balanced F1-score confirms stable classification performance under dynamic atmospheric turbulence conditions.

Transformer-based models achieved competitive precision and recall values; however, their inference instability and increased memory complexity reduced practical suitability for embedded UAV deployment [43]. In contrast, the proposed CNN–LSTM framework maintained both high recognition accuracy and low computational overhead, thereby improving operational feasibility for real-time edge AI implementation.

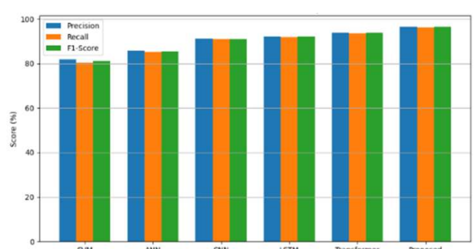

Figure. 8. Precision, recall, and F1-score comparison among conventional machine learning and deep learning models for turbulent plume recognition

Figure 8 presents a comparative bar graph illustrating precision, recall, and F1-score values for all evaluated models. The graph demonstrates consistent performance improvement for the proposed hybrid CNN–LSTM framework across all evaluation metrics compared with SVM, ANN, CNN, LSTM, and Transformer models.

4.4 Latency Evaluation

Inference latency plays a critical role in real-time UAV-assisted hazardous gas monitoring systems because delayed plume recognition may significantly reduce response effectiveness during emergency scenarios. The proposed framework was evaluated on an NVIDIA Jetson embedded GPU platform to assess real-time edge deployment capability.

Experimental results demonstrated an average inference latency of 38.6 ms per sensing sequence, enabling real-time plume classification at approximately 25 FPS processing speed. In comparison, Transformer-based models exhibited substantially higher latency exceeding 97 ms due to increased self-attention computation complexity. Standalone CNN and LSTM models achieved lower latency but exhibited reduced classification robustness under turbulent conditions.

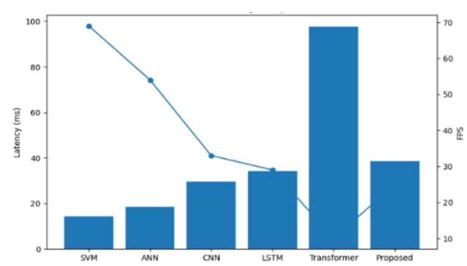

Figure 9 Inference latency and frame-per-second (FPS) comparison of evaluated models during real-time edge AI deployment

The lightweight CNN–LSTM architecture achieved an optimal balance between recognition accuracy and computational efficiency as in Figure 9. TensorRT optimization and mixed-precision inference significantly reduced onboard computational overhead while maintaining stable classification performance during continuous UAV navigation.

Table 5. Inference Latency Comparison

Model	Latency (ms)	FPS	Edge Suitability
SVM	14.3	69	High
ANN	18.5	54	High
CNN	29.7	33	Moderate
LSTM	34.1	29	Moderate
Transformer	97.8	10	Low

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Proposed CNN–LSTM	38.6	25	High

The results presented in Table 5 indicate that the proposed framework achieves significantly lower latency than Transformer framework while preserving superior recognition performance under turbulence-aware plume monitoring conditions.

4.5 ppm-Level Detection Performance

The proposed framework demonstrated strong sensitivity for ppm-level methane and ammonia detection across varying environmental conditions. Experimental evaluations showed stable methane detection capability down to 5 ppm and ammonia detection capability down to 3 ppm under moderate turbulence conditions.

At extremely low concentration levels below 3 ppm, minor performance degradation was observed due to increased sensor noise and concentration intermittency. Nevertheless, the CNN–LSTM architecture maintained stable recognition capability by exploiting temporal concentration continuity and multi-sensor fusion patterns. The integrated denoising and drift compensation mechanisms further improved low-concentration sensitivity by suppressing turbulence-induced fluctuations.

The ppm-level recognition performance significantly exceeded traditional machine learning approaches that primarily relied on static thresholding and handcrafted feature extraction. This demonstrates the effectiveness of deep temporal-spatial learning for ultra-low concentration airborne plume recognition applications.

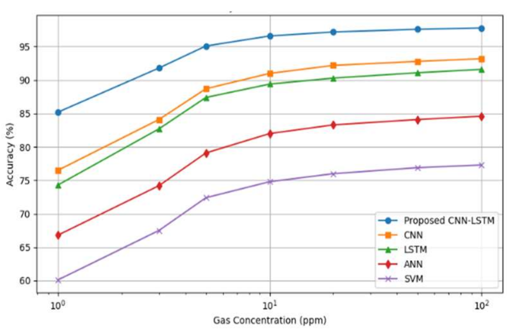

Figure 10 Classification accuracy variation with methane and ammonia concentration levels under ppm-scale detection conditions

Figure 10 illustrates plume classification accuracy versus gas concentration level for methane and ammonia sensing experiments. The graph shows stable performance retention above 95% accuracy for concentrations greater than 5 ppm and gradual degradation under ultra-low concentration conditions.

4.6 Rotor Turbulence Robustness

Rotor-induced turbulence significantly affects airborne gas sensing reliability because propeller-generated vortices alter natural plume dispersion characteristics [9]. To evaluate turbulence robustness, the proposed framework was tested under varying rotor speeds, flight altitudes, and ambient wind conditions.

The CNN–LSTM architecture-maintained classification accuracy above 93% even under severe rotor turbulence conditions. In comparison, standalone CNN and ANN models exhibited significant performance degradation due to unstable plume fragmentation and intermittent sensor response patterns. The LSTM temporal learning mechanism effectively captured concentration continuity despite turbulence-induced signal distortion.

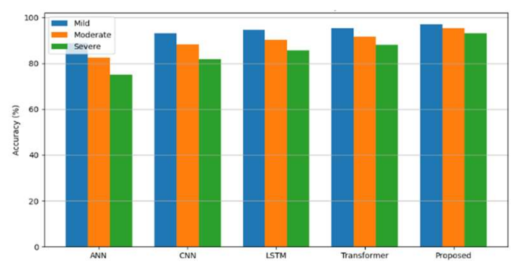

Figure 11. Turbulence robustness analysis under mild, moderate, and severe rotor-induced airflow disturbances.

The bio-inspired airflow stabilization chamber further improved turbulence robustness by reducing high-frequency airflow disturbances before gas acquisition as in Figure 11. Combined with adaptive preprocessing and temporal learning, the proposed framework demonstrated stable plume recognition under realistic UAV flight conditions.

Table 6. Turbulence Robustness Analysis

Model	Mild Turbulence	Moderate Turbulence	Severe Turbulence
ANN	88.7	82.5	75.2
CNN	93.1	88.4	81.9
LSTM	94.5	90.3	85.8
Transformer	95.2	91.8	88.1
Proposed CNN–LSTM	97.1	95.4	93.2

Table 6 demonstrates the superior turbulence resilience achieved by the proposed hybrid framework compared with baseline approaches.

4.7 Drift Compensation Analysis

Sensor drift compensation significantly improved long-term sensing consistency and classification reliability during prolonged UAV operation. Without compensation, classification accuracy gradually decreased by approximately 11% after extended environmental exposure due to baseline instability and sensor aging effects.

The proposed adaptive drift compensation framework effectively stabilized sensor response distributions through recursive baseline correction and temporal recalibration. Experimental results showed that the compensated system maintained stable recognition accuracy above 95% over long-duration sensing experiments.

Drift correction also improved concentration estimation stability during varying temperature and humidity conditions. These findings confirm the importance of adaptive preprocessing mechanisms for real-world airborne robotic olfaction deployments.

Figure 12 presents sensor response stability before and after drift compensation. The graph demonstrates substantial reduction in baseline variation and improved temporal consistency after applying the proposed adaptive correction mechanism.

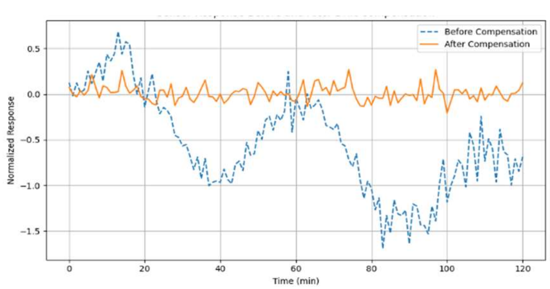

Figure 12. Sensor response behavior before and after adaptive drift compensation during prolonged airborne sensing operation.

4.8 Edge AI Performance

The optimized CNN–LSTM framework demonstrated strong suitability for edge AI deployment on embedded UAV hardware platforms. Tensor optimization, model pruning, and mixed-precision inference reduced computational complexity while preserving classification accuracy.

The deployed edge AI pipeline consumed approximately 8.4 W average power during continuous inference operation, thereby maintaining compatibility with UAV battery constraints. Memory utilization remained below 2.1 GB during real-time plume recognition, enabling stable operation on resource-constrained embedded systems.

Compared with Transformer-based framework, the proposed model achieved significantly lower computational overhead and improved thermal stability during prolonged airborne operation. These characteristics make the framework highly suitable for autonomous real-time environmental monitoring applications.

4.9 UAV Plume Mapping

The proposed framework enabled real-time spatial plume reconstruction using synchronized gas sensing and GPS trajectory data. Concentration measurements were mapped onto three-dimensional flight trajectories to visualize methane and ammonia plume propagation patterns under varying environmental conditions.

Temporal-spatial plume reconstruction demonstrated clear concentration gradients and intermittent plume fragmentation behavior caused by atmospheric turbulence. The UAV-based mapping framework successfully identified high-concentration plume regions and localized probable leakage zones with high spatial consistency.

The integration of deep temporal-spatial learning significantly improved plume boundary estimation compared with static interpolation-based mapping approaches commonly used in traditional environmental sensing systems.

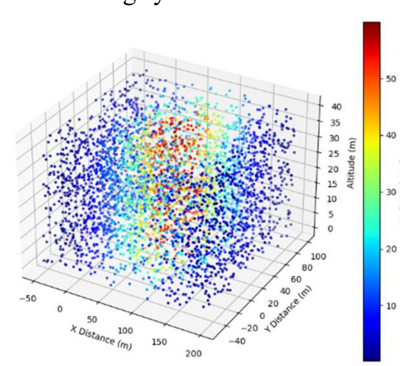

Figure 13. UAV-based three-dimensional methane plume reconstruction and spatial concentration mapping in turbulent outdoor environments.

Figure 13 represents UAV-based methane plume mapping results obtained during controlled

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outdoor experiments. High-concentration regions are represented using red intensity gradients, while low-concentration diffusion zones are represented using blue spatial distributions.

4.10 Comparative Analysis

Comprehensive comparative evaluation confirmed that the proposed CNN–LSTM framework consistently outperformed conventional machine learning and standalone deep learning framework across all performance metrics. SVM and ANN models demonstrated limited robustness due to handcrafted feature dependency and inadequate temporal modeling capability [21]. CNN framework effectively captured spatial sensor relationships but struggled under intermittent plume fragmentation scenarios.

Standalone LSTM models improved temporal sequence interpretation; however, limited spatial representation reduced classification stability during mixed-gas exposure conditions. Transformer-based framework demonstrated competitive recognition performance but introduced significantly higher computational complexity and inference latency unsuitable for lightweight UAV deployment.

The proposed hybrid CNN–LSTM framework achieved superior turbulence robustness, improved ppm-level sensitivity, stable drift compensation performance, and low-latency edge inference capability. These combined improvements establish the framework as a practical solution for real-time airborne robotic olfaction applications.

4.11 Ablation Study

An ablation study was conducted to analyze the contribution of individual architectural components within the proposed framework. Four configurations were evaluated:

1. CNN only
2. LSTM only
3. CNN–LSTM without drift compensation
4. Full proposed framework.

Experimental analysis revealed that removing temporal LSTM modeling reduced classification accuracy by approximately 4.8% under turbulent conditions due to insufficient sequential plume interpretation. Similarly, removing CNN spatial extraction reduced inter-sensor feature discrimination capability during mixed-plume exposure scenarios.

Eliminating drift compensation resulted in substantial long-term performance degradation caused by sensor instability and environmental variability as in Figure 14. The complete framework achieved the highest overall performance by integrating temporal-spatial learning with adaptive preprocessing and turbulence-aware sensing.

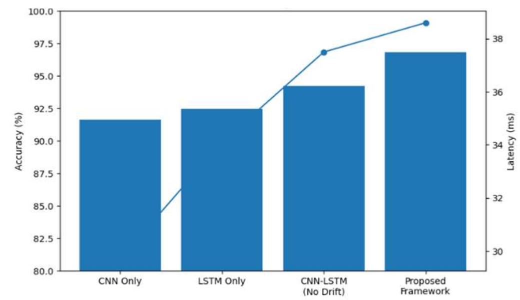

Figure 14. Ablation study demonstrating the contribution of CNN, LSTM, and drift compensation modules to overall system performance

Table 7. Ablation Study Results

Configuration	Accuracy (%)	Latency (ms)	Turbulence Robustness
CNN Only	91.62	29.7	Moderate
LSTM Only	92.48	34.1	Moderate
CNN–LSTM (No Drift Compensation)	94.21	37.5	High
Proposed Full Framework	96.84	38.6	Very High

The ablation results clearly demonstrate that the integration of CNN-based spatial learning, LSTM temporal modeling, and adaptive drift compensation collectively contributes to the superior performance of the proposed airborne plume recognition framework.

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This work presented a UAV-based robotic olfaction system for detecting methane and ammonia gas plumes using multisensor fusion and a hybrid CNN–LSTM model. The proposed approach achieved more than 96% classification accuracy and performed better in terms of precision, recall, F1-score, and turbulence robustness than the other models tested. Drift compensation helped maintain stable sensor performance, while edge processing allowed faster onboard decisions.

The results show that combining spatial and temporal sensor information can improve gas-plume detection under changing UAV operating conditions. The system can be useful for hazardous-gas monitoring, leakage detection, plume tracking, and environmental monitoring. Further testing in different outdoor environments and with other gases will be needed before practical deployment.

5.2 Future Research Directions

The proposed framework has shown good results, but some limitations remain. The experiments were mainly carried out under controlled conditions, and further testing is needed in different outdoor environments and weather conditions. The present study also considers methane and ammonia, so its performance with other hazardous gases and mixed gases needs to be examined. Sensor ageing, contamination, temperature, humidity, and long-term drift may also affect the sensing results. In addition, rotor downwash and atmospheric turbulence can change plume behaviour, while limited computing power, battery life, and payload capacity can affect UAV operation.

Future work will address these issues through longer field trials and experiments with different gases and environmental conditions. Transformer models will be studied for better handling of complex plume patterns, and multiple UAVs will be considered for wider coverage and improved source localization. TinyML methods will be explored to reduce the computing and power requirements of onboard processing. Federated learning, digital-twin models, and explainable methods will also be investigated to support collaborative learning, plume prediction, flight planning, and more reliable gas-detection decisions.

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