

MACHINE LEARNING APPROACHES IN ODOUR CLASSIFICATION ALGORITHM: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Odour classification using electronic nose (e-nose) has gained increasing importance due to its wide range of applications in environmental monitoring, food safety, and medical diagnostics. Recent advances in sensor technology and machine learning have significantly improved odour profiling capabilities; however, variations in methodology and evaluation approaches across studies remain a challenge. This systematic literature review aims to evaluate and synthesize existing classification algorithms applied in odour analysis, with particular emphasis on recent trends, limitations, and research opportunities. Following PRISMA guidelines, 27 primary studies published between 2020 and early 2024 were selected from IEEE Xplore, Scopus, and ScienceDirect for detailed analysis. This review examines key aspects of odour classification research, including sensor types, performance metrics, application domains, and machine learning algorithms. The findings show that traditional machine learning models such as Support Vector Machines (SVM) and Random Forest continue to be widely adopted due to their robustness, interpretability, and reliable performance when dealing with high-dimensional sensor data. In comparison, deep learning approaches such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models demonstrate promising performance in more complex and large-scale classification tasks, although their use is often limited by higher computational requirements and data dependency. Feature extraction and feature selection are identified as critical factors influencing classification accuracy across different studies. This review further provides a structured synthesis linking sensor configurations, algorithm selection, and application domains, highlighting why certain approaches outperform others under specific constraints. Based on these insights, the study emphasizes the need for closer interdisciplinary collaboration between sensor developers and algorithm designers to support the development of scalable and real-world-ready odour classification systems.

Keywords: *Odour Profiling; Classification Algorithms; Electronic Nose (e-nose); Volatile Organic Compounds (VOCs); odour Detection.*

1.0 INTRODUCTION

Odour profiling traditionally relied on human sensory panels, which, despite their high sensitivity, are subjective and prone to variability. The introduction of electronic noses (e-noses) and other sensor-based technologies has revolutionized the field, providing objective, reproducible, and high-throughput alternatives. These devices typically consist of an array of chemical sensors that respond to volatile organic compounds (VOCs), producing complex data patterns that require sophisticated algorithms for interpretation and classification [1].

Classification algorithms are essential for converting raw sensor data into meaningful odour profiles. These algorithms are generally categorized into supervised and unsupervised learning methods [2]. Supervised learning algorithms, such as Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN),

require labelled training data to learn the mapping between sensor responses and odour classes. These methods have shown high accuracy in various studies due to their ability to handle high-dimensional data and learn complex patterns from the sensor responses [4].

Unsupervised learning algorithms, like Principal Component Analysis (PCA) and k-means clustering, do not require labelled data and are used to identify natural groupings within the sensor responses. PCA is particularly useful for dimensionality reduction and feature extraction, facilitating more efficient classification processes [5][6].

Recent advancements have highlighted the potential of deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have demonstrated remarkable success in learning hierarchical features from sensor data and classifying complex odour mixtures. Despite the progress, the efficacy of these algorithms heavily depends on the quality and quantity of training data and the robustness of the features extracted from sensor responses [7][8].

Despite significant advancements, several challenges persist in odour profiling. One major limitation is the high dimensionality and variability of sensor data, which complicates the classification process. Odour sensor arrays often produce multivariate time-series data influenced by environmental factors such as temperature, humidity, and the presence of interfering substances. Moreover, sensor drift over time can affect the reproducibility and stability of odour profiles. Current algorithms struggle to maintain accuracy under varying conditions and often require recalibration, which can be resource-intensive [9][10].

Another limitation is the lack of standardized datasets and evaluation metrics. The absence of universally accepted benchmarks makes it difficult to objectively compare the performance of different algorithms. Researchers often rely on proprietary datasets, which limits the generalizability of their findings. Standardized datasets and evaluation protocols are essential for meaningful comparisons and the development of more robust classification algorithms [11][12].

Furthermore, many existing studies focus on specific applications or limited sets of odours, reducing the breadth of their applicability. The generalization of algorithms across different domains and odour types remains a significant challenge. Additionally, while hybrid approaches combining multiple algorithms such as PCA for feature reduction with SVM for classification have shown promise, their implementation is often complex and computationally demanding [13]. The integration of machine learning with domain knowledge, such as chemical and sensory information, has been relatively unexplored. This integration could potentially lead to more sophisticated and interpretable models, but it requires interdisciplinary expertise that is not always readily available.

2.0 MOTIVATION AND RELATED WORKS

The classification of odours has become an increasingly important research area, particularly in applications such as environmental monitoring, food safety, and medical diagnostics. Odour classification systems play a crucial role in detecting hazardous substances, assessing air quality [14], and enabling non-invasive disease diagnosis through breath analysis [15]. Despite substantial advancements in sensor technologies and machine learning algorithms, the inherent complexity of odour data and the variability of sensor responses continue to pose significant challenges in developing reliable and generalizable classification systems [16]. Motivated by these challenges, this systematic literature review aims to examine the current state of odour classification research, identify methodological and technological gaps, and explore opportunities for future development. By synthesizing findings across a diverse range of studies, this review seeks to provide clearer insight into effective practices and unresolved issues affecting classification accuracy and system robustness.

Early work by Teng et al. investigated machine olfaction technologies using electronic nose (e-nose) systems for gas-odour concentration estimation. Their study evaluated multiple algorithms, including quadratic multivariate logarithmic regression, tapped delay lines, and Support Vector Machine-based methods, and reported superior performance from radial neural network approaches for concentration estimation tasks. The authors highlighted the need for continued research on odour characterization and reproduction to enhance the functional capabilities of e-nose systems [17].

In contrast, Alessandra et al. examined odour perception from a human sensory perspective by investigating the effects of smoking on smell and taste among adult populations. Their systematic review revealed consistent improvements in olfactory performance following smoking cessation and emphasized the importance of standardized experimental protocols to ensure reliable and comparable results across studies [18]. Although not focused on sensor-based systems, this work underscores the variability and subjectivity of olfactory responses, which remain relevant considerations when designing and evaluating algorithmic odour classification models.

From an environmental engineering standpoint, Krzysztof et al. provided a comprehensive review of biological odour treatment technologies, including biofilters, biotrickling filters, and bioscrubbers. Their analysis demonstrated the maturity of biological treatment methods as effective and sustainable solutions for industrial odour control, particularly under moderate operating conditions. However, the authors identified the need for improved mathematical modelling, simulation frameworks, and optimization strategies to support large-scale and efficient deployment [19].

Addressing odour classification from a perceptual and cognitive perspective, Kathrin et al. reviewed psychological odour classification studies conducted over the past five decades. Their work highlighted the influence of linguistic, perceptual, and cognitive factors on odour categorization outcomes and demonstrated that classification reliability is strongly affected by experimental design and subject variability. The authors suggested that future research should adopt more systematic approaches to better model human odour perception and classification processes [20].

More closely aligned with the objectives of this review, the systematic literature review by Usman et al. focused on the application of machine learning techniques to enhance gas sensor performance, particularly in terms of selectivity and long-term stability. Their findings demonstrated that machine learning-based feature extraction methods, including static, dynamic, and frequency-domain features, can significantly improve classification performance and compensate for sensor drift. The study also emphasized the growing demand for intelligent sensor systems capable of balancing accuracy, robustness, and computational efficiency [21]. A summary of related systematic literature review studies is presented in Table 1.

Taken together, these studies highlight the multidisciplinary nature of odour-related research, spanning sensor technology, human perception, environmental treatment, and machine learning-based analysis. However, most existing works remain domain-specific and application-driven, with limited emphasis on cross-study comparison of algorithms, sensor configurations, or evaluation methodologies. This fragmentation underscores the need for a systematic and analytical review that integrates sensor design, feature extraction strategies, and algorithm performance across diverse application contexts, thereby motivating the present study.

Table 1: Summary of related SLR studies.

Study References	Study Focus	Contribution	Future Work
[17]	- Machine olfaction using e-nose - Challenges in odour reproduction - Applications: medical, advertisement, VR	- Emphasizes e-nose for odour characterization - Reviews gas sensor-based odour studies	- Investigate molecular feature separation via biological imitation - Develop nano filters for complex molecular profiles
[18]	- Smoking effects on smell & taste (1980–2014) - Sensory improvements post-cessation	- Systematic review on tobacco's impact on sensory capability - Highlights research gaps in olfactory studies	- Adopt standardized methods in future studies - Explore smoking–olfaction association
[19]	- Biological odour treatment in waste gas - Techniques: biofiltration, biotrickling, bioscrubbing	- Overview of biological odour removal methods - Compares advantages & disadvantages	- Develop new biofilter applications - Enhance mathematical models - Investigate biodegradation mechanisms
[20]	- Psychological studies on odour classification - Factors: subjects, stimuli, analysis - Language influence on categorization	- Identifies perception factors - Highlights language impact on classification	- Investigate evolutionary functions of odour perception - Apply object categorization principles - Assess language–olfaction interaction
[21]	- Smart gas sensors with ML for selectivity - Limitations of chemiresistive & FET sensors	- Discusses sensor performance & limitations - Highlights ML potential for selectivity	- Investigate novel materials for stability - Develop ML models for selective sensors - Explore feature extraction techniques

Based on previous studies, this SLR will explore how different classification algorithms impact the accuracy and reliability of odour profiling systems. This SLR also aims to identify which algorithms have been commonly used, examining their performance and the contexts in which they have been applied. Within this review, this SLR study will take a closer look at how these algorithms have been fine-tuned for specific odour datasets and sensor

setups. Additionally, this work delves into the challenges, limitations, and potential areas for future research to further enhance odour classification accuracy. Next chapter is the methodology section.

3.0 RESEARCH METHODOLOGY

For this study, the SLR methodology has been selected to guide the review process. The approach, illustrated in Fig. 1, is based on the systematic literature review guidelines provided by Kitchenham and Charters [22]. The methodology is structured into three key phases: 1) Preparation, 2) Organization, and 3) Results and Discussion. The Preparation phase is centered on identifying the need for the review and formulating the Research Questions (RQs). The Organization phase covers crucial steps like the search process, screening strategy, and data extraction and synthesis. Lastly, the Results and Discussion phase focuses on a detailed evaluation and discussion of the findings. Each phase, along with its specific steps, is explained in the following subsections.

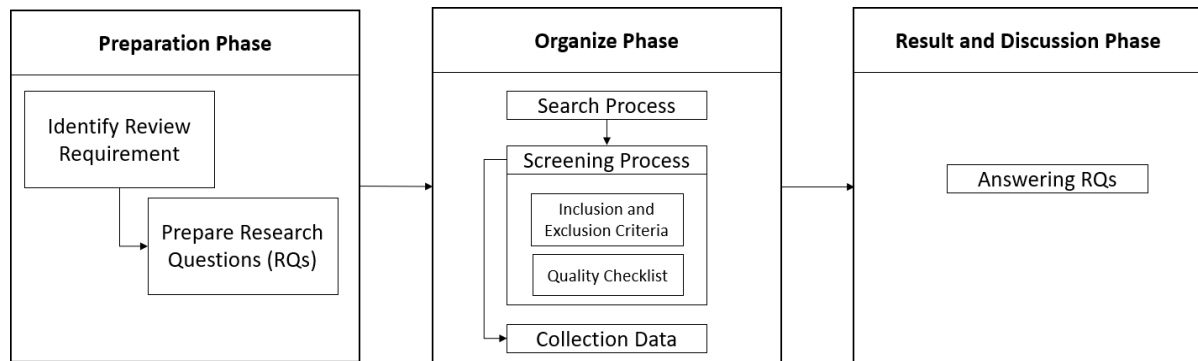


Fig. 1: Review Research Methodology

2.1 Preparation Phase

The justification for this review was outlined in the previous section, where the motivation and related work were discussed, including an examination of prior review articles and their findings. The analysis revealed that many existing systematic literature reviews do not sufficiently address the complexities of odour classification algorithms, particularly in relation to sensor variability and methodological differences. This systematic literature review aims to address these gaps by providing a more structured and analytical synthesis of recent studies. Accordingly, the research questions were formulated to align with the study's objectives, support comparative analysis, and facilitate a clearer synthesis of existing literature. The Research Questions (RQs) are presented below, with their rationale summarized in Table 2.

Table 2: Research Questions (RQs)

Research Questions (RQs)	Motivations
<i>RQ1: What are the dominant application domains and types of studies addressed in recent odour classification research?</i>	To identify the different sets of the finding studies in the domain.
<i>RQ2: Which algorithms are most commonly used for odour classification?</i>	To identify the algorithms that have been most frequently applied or compare for odour profiling.
<i>RQ3: How many sensors are utilized in classification tasks, and what types of sensors are employed?</i>	To determining the number of sensors and its type typically employed in odour classification systems.
<i>RQ4: What evaluation metrics, methodological challenges, and limitations are consistently reported across existing studies?</i>	To evaluate the performance of classification algorithms in odour profiling is essential to determine their effectiveness, reliability, and applicability.
<i>RQ5: What kind of field odour has been done, critical research gaps, challenges and prioritized future research directions can be identified from current odour classification?</i>	To determine the field of research in odour. the gaps, limitations and future work for the odour classification.

2.2 Organize Phase

This phase focuses on carrying out the key stages: a systematic method for identifying relevant studies, the approach used for selecting articles, and the process of data collection and analysis. The following subsections will provide more detail on how each of these stages is implemented.

2.3 Searching Process

Defining the search process carefully is crucial for achieving high-quality and reliable results. In this SLR, the identification and selection of sources are carried out systematically to ensure that all relevant studies in the specified domain are captured. This process is based on two key elements: 1) using a variety of search strings and 2) utilizing different resources. The search terms in this SLR are formulated based on the listed Research Questions (RQs) and follow a standard procedure that includes the following steps. These steps are designed to ensure that the search terms accurately reflect the research focus:

1. Identifying the relevant keywords for the Research Questions (RQs).
2. Incorporating synonyms and alternative spellings of the terms.
3. Verifying the suitability of the search terms for the study.
4. Combining the search terms using Boolean operators like OR and AND.

The search strings obtained after following the steps are listed below:

- “Odour Profiling” OR “Scent Profiling” OR “Smell Classification” OR “Odour Classification”
- “Odour Profiling” OR “Odour Profiling” OR “Scent Profiling” OR “Smell Classification” OR “Odour Classification”
- “Odour Classification Algorithm” OR “Smell Classification” OR “Machine Learning” OR “Odour Pattern Recognition”
- “Odour Classification Algorithm” OR “Odour Machine Learning” OR “Odour Pattern Recognition”

In this SLR, the search was carried out using three electronic libraries: Scopus, IEEE, and ScienceDirect. These well-regarded resources were chosen for their comprehensive coverage of both empirical studies and literature surveys in the field of Odour Classification. First, Scopus is a comprehensive international database that indexes peer-reviewed literature, including scientific journals, books, and conference proceedings. It is owned by Reed Elsevier, a leading publisher in the fields of scientific, technical, and medical literature. [23], [24]. Second, IEEE Xplore is an online resource for accessing technical information and documents. Developed and maintained by the Institute of Electrical and Electronics Engineers (IEEE) along with other partners, it provides access to a wide range of materials, including patents and standards. [25]. The third search engine is ScienceDirect. ScienceDirect is a major full-text scientific database that offers a vast amount of scientific and technical information. It is managed by Elsevier, a prominent academic publishing company. [26]. To ensure the results are accurate and up-to-date, the searches are restricted to studies published within the last five years, from 2019 through December 2024.

2.4 Screening Strategy

Another important part of the research methodology is the study selection strategy, which helps determine the most relevant studies for the topic. Initially, 111 papers were retrieved using the defined search process. To refine this selection, the process was carried out in two stages: 1) applying inclusion and exclusion criteria, and 2) filtering based on Quality Standard Questions (QSQ). Table 3 details these criteria.

Table 3: Inclusion and exclusion standard.

Inclusion standard	Exclusion standard
Studies must be written in the English language.	Studies that are not written in English language
Studies have potential to answer the Research Questions (RQs) based on keywords, title, and abstract.	Duplicate copies and incomplete versions were excluded; only complete papers were included in this SLR
Studies focusing on odour classification	Studies that are not focussing on Odour Classification
Studies that are reporting the issues, problems and future enhancement of Odour Classification	Studies that are not clearly defined the concern of Odour Classification
	Gray Studies (Study that non-publish, non-peer reviewed and work in progress)

Each study was reviewed according to these standards. Papers that focused on classification in Odour problem and answered at least one of the research questions were included. Papers in languages other than English and those outside the specific domain of interest were excluded. The process also involved removing duplicates to ensure that only the most recent versions of the articles were considered.

Inclusion and exclusion standards were applied to enhance the quality of the search and ensure the relevance of the final studies. Each study was carefully reviewed, including the title, abstract, and full content, and assessed based on the Quality Standard Questions (QSQ) listed in Table 4. The studies were scored as follows: "Yes" received 3 points, "Moderately" received 2 points, and "No" received 1 point. The overall score for each study was determined by summing the answers to all the questions.

Table 4: Quality Standard Question (QSQ)

ID QSQ	Question	Score
QSQ1	Are the aims of studies clearly stated?	Yes= 3 / moderate = 2 / no = 1
QSQ2	Are the context of studies well defined?	Yes= 3 / moderate = 2 / no = 1
QSQ3	Does the study answer the RQs?	Yes= 3 / moderate = 2 / no = 1
QSQ4	Are the proposed classification algorithms in studies well explained?	Yes= 3 / moderate = 2 / no = 1
QSQ5	Is the proposed classification algorithm can classify the odour pattern?	Yes= 3 / moderate = 2 / no = 1
QSQ6	Is the proposed classification algorithm compared with other classification algorithm?	Yes= 3 / moderate = 2 / no = 1
QSQ7	Is the result well explained?	Yes= 3 / moderate = 2 / no = 1

All the authors of this study discussed and compared the results to resolve any contradictions and reach a consensus. To ensure the reliability of the findings, only studies with a quality rating of 14 or higher (more than half of the maximum quality rating score of 21) were included in this SLR. As a result, 27 studies were selected as the primary studies for this review. Fig. 2 illustrates the outcome of the screening strategy.

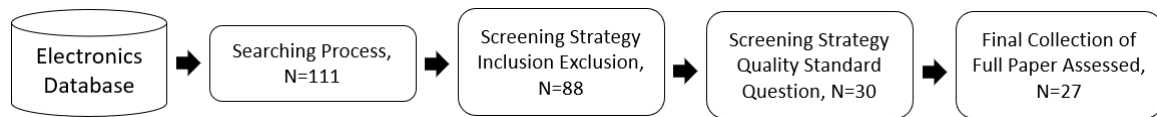


Fig. 2: Result of Screening Strategy

Table 4 presents the Quality Standard Question (QSQ) scores for all studies. Figure 2 also outlines the screening process from the three electronic databases to the final selection of studies. Table 5 shows the Quality Standard Question (QSQ) scores of the 27 selected studies after being filtered by the questions in Table 4.

Table 5: Quality Standard Question (QSQ) scores of the 27 studies

Reference	QSQ1	QSQ2	QSQ3	QSQ4	QSQ5	QSQ6	QSQ7	Score
[27]	3	3	2	3	3	3	3	20
[28]	3	3	2	3	3	3	3	20
[29]	3	3	2	2	3	2	2	15
[30]	3	3	2	2	2	2	3	17
[31]	3	3	3	3	3	3	2	20
[32]	3	3	2	2	2	2	3	17
[33]	3	3	2	3	2	2	3	18
[34]	3	3	2	3	3	2	3	19
[35]	3	3	2	3	2	2	3	18
[37]	3	3	2	3	3	3	3	20
[38]	3	3	2	3	3	3	3	20
[39]	3	3	2	3	3	3	3	20
[41]	3	3	2	3	2	3	3	19
[42]	3	3	3	3	2	2	3	19
[43]	3	3	3	3	2	2	3	19
[44]	3	3	3	3	3	3	3	21
[45]	3	3	2	2	2	2	3	17
[46]	3	3	3	2	2	2	3	10

Table 5: Continued

Reference	QSQ1	QSQ2	QSQ3	QSQ4	QSQ5	QSQ6	QSQ7	Score
[47]	3	3	2	2	2	2	3	17
[48]	3	3	2	2	2	2	3	17
[49]	3	3	2	3	3	2	3	19
[50]	3	3	2	3	3	2	3	19
[51]	3	3	2	3	2	3	3	19
[52]	3	3	2	2	2	2	3	17
[53]	3	3	2	2	2	2	3	17
[54]	3	3	2	3	2	2	3	18
[55]	3	3	2	3	2	3	3	19

4.0 RESULT AND DISCUSSION

4.1 RQ1: What are the dominant application domains and types of studies addressed in recent odour classification research?

The total papers discussed are 27 studies from three electronic libraries which are Scopus, IEEE and Science Direct as a final screening for this SLR. These final studies consist of 27 journal papers which are from the final selected studies.

Table 6: Number of Studies after Screening Strategies

Electronic Library	Searching Process	Screening Strategy		Screening Strategy Quality	
		Exclusion	Including	Standard Question (QSQ)	
		Included	Excluded	Included	Excluded
IEEE	47	30	17	14	16
SCOPUS	54	34	20	13	21
Science Direct	10	5	5	0	5
Total	111	69	42	27	42

Table 6 displays this SLR screening process. During the initial search process, 111 studies were screened using all three electronic libraries. Through "Screening Strategy Exclusion and Including" process, 69 studies are included and 42 studies are excluded. Subsequently, "Screening Strategy Quality Standard Question (QSQ)" filtering the studies resulted in only 27 studies included and another 42 studies excluded. Fig. 3 illustrates the percentage of included studies IEEE is around 55%, Scopus is around 45% and Science Direct is around 0%.

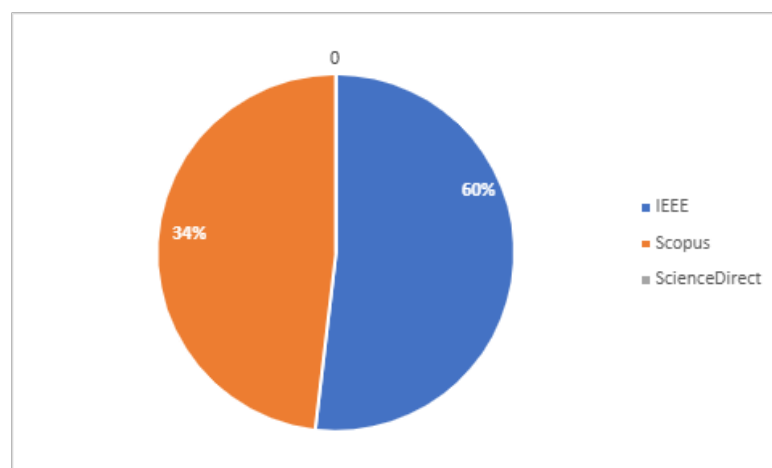


Fig. 3: Percentage of the inclusion rates by Electronic Library

Fig. 4 shows the quantity of last collected studies during the year. The line graph with increase from year 2019 to June 2024. The trendline shows a steady increase, indicating that odour classification remains an active research issue.

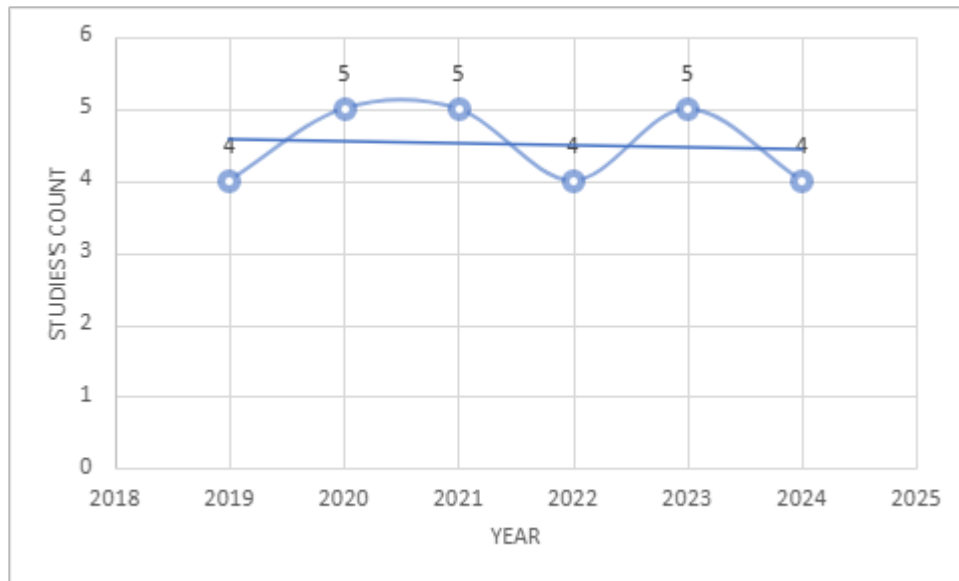


Fig. 4: Count of studies over the years.

The 27 selected studies span diverse application domains. The most frequent domain is environmental monitoring and air quality assessment (13 studies) [32],[34],[37],[39],[42],[43],[45],[46],[47],[48],[51],[53],[54],[55], reflecting the global urgency in pollution control and hazardous gas detection. The health domain (6 studies) [27],[30],[33],[35],[50],[52] highlights the growing role of odour profiling in medical diagnostics and non-invasive disease detection. Applications in food safety (4 studies) [31],[38],[41],[44] and agriculture (3 studies) [28],[49],[49] remain comparatively underexplored, despite their direct relevance to food security and sustainable farming.

4.2 RQ2: Which algorithms are most commonly used for odour classification?

Based on the final collection of 27 studies, the bar chart illustrates the distribution of classification algorithms employed in odour profiling, revealing clear trends in algorithm selection based on both classical machine learning and advanced deep learning techniques. This section delves into the reasons behind the popularity and effectiveness of each algorithm in the context of odour data, which is often characterized by high dimensionality, sensor noise, and non-linear relationships.

Table 7 provides a synthesized overview of the frequency distribution of classification algorithms adopted in odour profiling research. The data reveals diverse methodological approaches across studies, with both traditional machine learning techniques and contemporary deep learning architectures being employed. This variation reflects the multidisciplinary and evolving nature of electronic nose (e-nose) systems and odour classification tasks, which often require adaptive strategies depending on data complexity, sensor modality, and intended application. Among the 27 final studies, Support Vector Machine (SVM) based classifiers are the most extensively utilized, reported in eight (8) studies. The sustained prominence of SVM in odour classification can be attributed to its strong generalization capabilities, particularly in high-dimensional feature spaces typical of sensor array outputs. Moreover, SVM's ability to manage non-linear decision boundaries through kernel functions makes it well-suited for handling overlapping or noisy odour data, a common challenge in practical e-nose applications.

Closely following SVM are k-Nearest Neighbour (kNN), Random Forest, and Artificial Neural Network (ANN) based approaches, each appearing in seven (7) studies. The frequent use of kNN suggests that simplicity and interpretability remain valuable in odour profiling, particularly in scenarios involving low computational resources or real-time inference. Random Forest, an ensemble method known for its robustness and capacity to mitigate overfitting, has gained traction as a reliable baseline classifier, especially when handling sensor noise and imbalanced data distributions. The consistent presence of ANN-based models underscores the field's shift toward biologically inspired computation, especially when coupled with preprocessed or engineered feature sets. Interestingly, deep learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models, though less prevalent, are increasingly employed. CNNs were cited in four studies, indicating a growing interest in applying spatial feature extraction even in non-image sensor data by treating temporal or spatially correlated sensor readings analogously to pixel data. This suggests an ongoing paradigm shift towards hierarchical feature learning in olfactory signal processing. Similarly, Bidirectional LSTM (BiLSTM) and Spiking Neural Networks (SNN), albeit less common, represent exploratory forays into temporally-aware and

neuromorphic modelling techniques, respectively both promising for modelling the dynamic nature of odour signatures.

Other notable algorithms include Decision Trees, Discriminant Analysis, and XGBoost, each cited in four instances. These methods are known for their performance in structured datasets and have been reported to yield high accuracy in various classification tasks. XGBoost, in particular, stands out for its efficiency and scalability, making it a preferred choice in competitive odour profiling scenarios where speed and accuracy are critical. Less frequently used techniques such as the Bio-inspired Spike Algorithm (BSA), Gaussian Deep Belief Classification Network (GDBCN), and e-rTPNN decision systems appear only once in the corpus. While their adoption is limited, their presence reflects ongoing experimentation with novel algorithmic paradigms, potentially inspired by neurobiological or probabilistic reasoning frameworks. These methods may offer unexplored advantages, especially in specific niche applications or with complex sensor fusion strategies.

Overall, the algorithmic landscape suggests a dual trend: continued reliance on established classifiers like SVM, Random Forest, and kNN for their interpretability and stability, and a gradual transition toward more complex, data-driven deep learning approaches. As odour datasets become larger, more diverse, and less structured especially with advances in multi-sensor arrays and IoT-enabled systems future research is expected to increasingly leverage deep learning architectures, hybrid models, and automated feature engineering frameworks. These trends not only reflect technological advancement but also the growing need for scalable, generalizable solutions in real-world odour profiling deployments. The broad spectrum of algorithms employed underscores the multifaceted nature of odour classification problems and reflects the absence of a universally dominant technique. Algorithm selection appears to be guided by the specific characteristics of the application domain, including data dimensionality, the temporal nature of signals, computational constraints, and the desired trade-offs between accuracy, interpretability, and generalizability.

Across the selected studies, Support Vector Machines (SVM) and Random Forests (RF) remain the most widely adopted due to their robustness and interpretability. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models are increasingly applied in complex odour mixtures, showing superior performance in feature learning but requiring larger datasets. Hybrid approaches combining PCA for feature reduction with SVM or RF for classification are also reported, demonstrating improved accuracy in high-dimensional sensor data.

Table 7: Classification algorithms for odour profiling

References	Algorithm	Count
[34], [37], [41], [42], [44], [46], [49], [52]	Support Vector Machines (SVM) Based	8
[28], [41], [46], [50], [51], [52], [55]	NN Based	7
[37], [41], [44], [45], [46], [49], [54]	Random Forest	7
[30], [31], [34], [38], [42], [46], [54]	k-Nearest Neighbour (kNN)	7
[32], [41], [44], [45]	XGBoost (EXtreme Gradient Boosting) algorithm	4
[34], [41], [51], [52]	Discriminant Analysis	4
[34], [38], [44], [46], [54]	Decision Tree	4
[39], [41], [44], [47]	Convolutional Neural Network (CNN) based	4
[34], [46]	Logistic Regression	2
[43], [53]	Spiking Neural Network (SNN)	2
[45], [46]	AdaBoost	2
[45], [46]	Multi-Layer Perceptron (MLP)	2
[46], [49]	Radial Basis Function (RBF) based	2
[27]	Gaussian Deep Belief Classification Network (GDBCN)	1
[30]	Vector Machines	1
[33]	Correlative Weight Elimination Algorithm	1
[34]	Naïve Bayes	1
[35]	e-rTPNN decision system	1
[37]	Extreme Learning Machine (ELM)	1
[41]	Long Short-Term Memory (LSTM)	1
[41]	Bidirectional Long Short-Term Memory (BiLSTM)	1
[46]	Linear Discriminant Analysis (LDA)	1
[48]	Step-wise Function (SF) Encoding	1
[48]	Bio-inspired Spike Algorithm (BSA)	1

4.3 RQ3: How many sensors are utilized in classification tasks, and what types of sensors are employed?

Less The performance and dependability of scent classification systems rely heavily on the features and arrangement of the sensors used. In e-nose systems, sensor placement has a direct effect on system sensitivity, specificity, and discrimination power for intricate mixtures of scents [48]. Therefore, understanding the number and types of sensors used in odour profiling studies is essential in estimating the validity, reproducibility, and generalizability of existing research outcomes. Different sensor technologies such as metal oxide semiconductors (MOS), conducting polymers (CP), quartz crystal microbalance (QCM) sensors, as well as optical and biosensors, respond differently to volatile compounds due to their different transduction mechanisms [40]. Moreover, the number of sensors used in a sensor array directly relates to the data's dimensionality; this directly influences the difficulty of the classification algorithm needed and the basic structure of the system. Therefore, this scientific question aims to comprehensively analyze the diversity and prevalence of sensors used in the literature on scent classification systems with the goal of determining best practices, underlying patterns, gaps for future work, and possible frameworks that could aid in designing systems to identify scents.

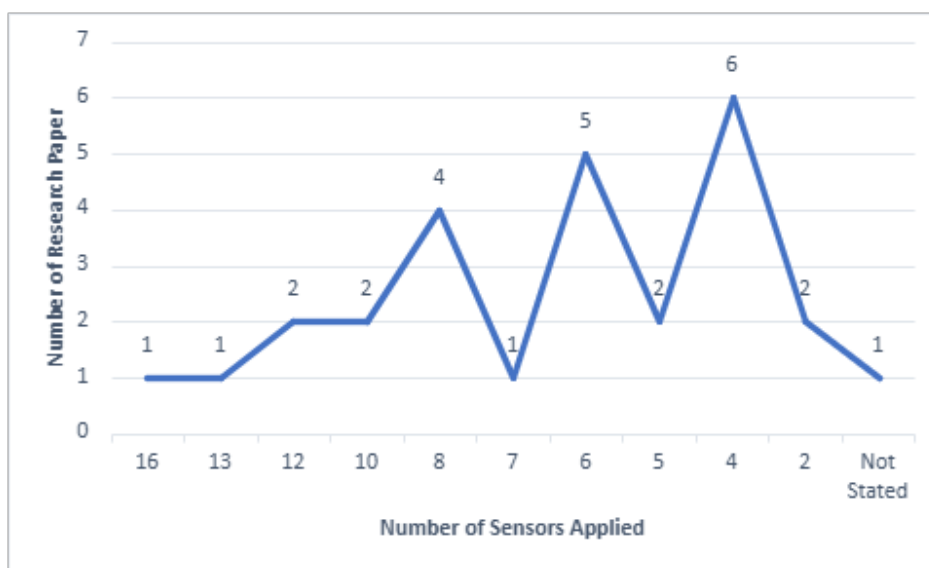


Fig. 5: Number Sensors Applied compare to Collected Research Paper

Investigating from Fig. 5, shows that the configuration with four sensors is the most common, as illustrated by six other works with this configuration. This tendency is clear due to quite a number of studies preferring this middle ground between system ease and performance. Four sensors are adequate to provide the appropriate diversity of chemicals and selectivity of response needed to identify several classes of odours while avoiding excessive overlap and noise that sensor arrays may bring. Compared to bigger arrays, a four-sensor configuration is relatively cheap and computationally inexpensive, which is most advantageous in systems with limited resources like portable or embedded e-nose systems. Moreover, smaller arrays mitigate the effects of sensor drift which allows for easier calibration and maintenance, important factors to reliable long-term operational availability. Using four sensors may also indicate that the design is based on targeted sensing approaches where the sensors are strategically chosen to target particular volatile compounds pertaining to the focus area of the study. This demonstrates the focus on practicality, which is increasingly prevalent and supports the objective of moving odour classification systems built in controlled lab environments.

Table 8 shows that there is inconsistency in the number and types of sensors used for odour classification tasks. The most common configuration consists of four sensors, used in at least six studies which is consistent with the earlier frequency analysis. Furthermore, these studies frequently make use of TGS-series sensors like TGS2600, TGS2602, TGS2610 and TGS2620 because of their availability, stability, and sensitivity to many volatile organic compounds (VOCs). Researchers who use four sensors tend to focus on achieving non-redundant complementary profiles with minimum spatial squinting. More complicated sensor arrays, including those with 8 to 16 sensors, are detected less frequently. These include MOX (metal oxide) sensors like the MQ-series, DHT11, and custom fabricated arrays containing cadmium sulfide (CdS), molybdenum oxide (MoO₃), tin oxide (SnO₂), and zinc oxide (ZnO). Such configurations are developed for high-resolution odour profiling in complex multi-source environments.

Table 8: Type of Sensors Applied

References	Number Sensor Applied	Type of Sensor
[27]	4	TGS2600, TGS2602, TGS2610 and TGS2620
[28]	Not stated	Not stated (Bioaromatic lab UMPISA)
[49]	8	TGS 2600, TGS 2602, TGS 2603, TGS 2610, TGS 2611, TGS 2612, TGS 2020, TGS 2630
[30]	5	MP503, BME680, MQ3, MQ5, WSP2110
[31]	4	TGS 2602, TGS 2610, TGS 2600, TGS 2611
[32]	2	TGS2600 and TGS2611
[33]	2	MQ-135, Humidity sensor
[34]	4	TGS2600, TGS2602, TGS2610, TGS2620
[35]	6	MQ-3, MQ-4, MQ-6, TGS 800, TGS 813, TGS 822
[37]	8	MQ-2, MQ-3, MQ-137, TGS-813, TGS-821, TGS-825, TGS-830, TGS-2610
[38]	6	Alphasense, H ₂ S, MembraporNH ₃ , MembraporH ₂ S, SGX NH ₃ , SGX H ₂ S, SGX SO ₂
[39]	4	SnO ₂ powder doped with CdS, SnO ₂ powder doped with MoO ₃ , Undoped SnO ₂ Powder, SnO powder with ZnO
[41]	6	TGS2602, TGS813, TGS2610, MQ-137, MQ-5, MQ-2
[42]	7	TGS826, TGS2611, TGS2603, TGS2602, TGS2600, TGS2610, TGS2620
[43]	12	Not Stated (combination of distinct sensitivity and selectivity characteristics)
[44]	8	TGS2600, TGS2602, TGS2610, TGS2611, TGS2620, MQ135, MQ3, MQ7
[45]	8	MQ2, MQ3, MQ5, MQ6, MQ7, MQ8, MQ135, DHT11
[46]	4	Integrated four-sensing elements (tin-oxide, molybdenum oxide, cadmium sulfide, and zinc oxide)
[47]	8	Mox based gas sensor
[48]	12	Not Stated
[49]	6	TGS 2600, TGS 2602, TGS 2603, TGS 2610, TGS 2611, TGS 2620
[50]	10	W1C, W5S, W3C, W6S, W5C, W1S, W1W, W2S, W2W, W3S R
[51], [52]	13	TGS880 (2), TGS822 (2), TGS2611 (2), TGS2620 (2), TGS2602 (2), TGS825 (1), TGS826 (1)
[52]	6	MQ-3 , MQ-5 , MQ-9 , MQ-131 , MQ-135, MQ-136
[53]	16	4 × 4 SnO ₂ gas sensor array
[54]	5	MQ-7, MQ-135, MQ-136, SO ₂ -D4, NO ₂ -D4.
[55]	4	Four-element gas sensor array fabricated using different sensing materials, specifically cadmium sulfide (CdS), molybdenum oxide (MoO ₃), tin oxide (SnO ₂), and zinc oxide (ZnO)

More challenging environments require higher energy consumption, precision calibration, and hardware strain. As reported in some studies, the applications of specialized and bioinspired sensors such as biosensors, Alphasense, and Membrapor were noted which indicates, though limited, a growing interest in biomimetic sensing that requires greater focus and precision targeting. In addition, at least two studies did not clearly describe the number of sensors, preferring instead to the types of sensors in vague terms which demonstrates a gap in the reporting procedures that is likely to affect reproducibility.

In general, the conclusions indicate that there is a strong preference for low-cost and miniaturized sensor arrays (especially those containing four sensors) which appears to strike a balance between sought-after outcomes and practical implementation. On the other hand, high density sensor arrangements increase the variety of measurements within a single system. However, such configurations are usually reserved for sophisticated or exploratory work.

Most odour classification systems employ sensor arrays of 6–12 chemical sensors, typically based on metal-oxide semiconductor (MOS) or conducting polymer sensors. Some studies integrate hybrid sensor arrays combining MOS with quartz crystal microbalance (QCM) or surface acoustic wave (SAW) sensors to improve selectivity. The number of sensors varies depending on application domain: food and agriculture studies often use larger arrays (≥ 10 sensors), while medical diagnostics tend to employ smaller, specialized arrays optimized for volatile organic compounds (VOCs).

4.4 RQ4: Evaluation Metrics, Methodological Challenges, and Limitations

From the 27 studies reviewed, several evaluation metrics were consistently used to measure the performance of odour classification algorithms. The most common were accuracy, precision, recall, and F1-score, which together provide a balanced view of how well models perform. A few studies also reported confusion matrices and ROC curves, offering deeper insights into misclassification trends and overall robustness.

Beyond metrics, researchers highlighted recurring methodological challenges. The most critical issues include:

- Sensor drift over time, which reduces reproducibility and often requires recalibration.
- Environmental variability such as humidity and temperature, which can distort sensor readings.
- Data imbalance in odour datasets, leading to biased training and weaker generalization.
- Limited reproducibility, since many studies rely on proprietary datasets that are not publicly available.

Limitations were also widely acknowledged. These include the absence of standardized datasets and evaluation protocols, which makes it difficult to compare algorithms fairly; heterogeneity in sensor platforms, which complicates replication; and the heavy reliance on handcrafted features, which restricts scalability. While deep learning approaches show promise, their high computational cost remains a barrier for real-time or resource-constrained applications.

Taken together, these findings show that machine learning has strong potential in odour classification, but its success depends heavily on dataset quality, sensor stability, and methodological rigor. Moving forward, the field would benefit from standardized benchmarks, improved sensor technologies, and hybrid algorithmic approaches that balance accuracy with efficiency.

The most common evaluation metrics are accuracy, precision, recall, and F1-score, with some studies also reporting confusion matrices and ROC curves. Methodological challenges include sensor drift, environmental variability (humidity, temperature), and data imbalance. Limitations include the lack of standardized datasets, platform heterogeneity, and the computational cost of deep learning approaches. These findings emphasize the need for standardized benchmarks and more efficient algorithms.

4.5 RQ5: Field of odour, critical research gaps, challenges and prioritized future research directions

Fig. 6 shows the distribution of research fields across the final set of studies, with environmental monitoring dominating (14 papers), [32],[34],[37],[39],[42],[43],[45],[46],[47],[48],[51],[54],[53],[55]. This reflects the global urgency in air quality assessment and hazardous gas detection, where E-nose and multi-sensor systems are widely applied. The health domain (6 papers), [27],[30],[33],[35],[50],[52] highlights the growing role of odour profiling in medical diagnostics and non-invasive disease detection. Meanwhile, food applications (4 papers), [31],[38],[41],[44] and agriculture (3 papers), [28],[49],[49] remain comparatively underexplored, despite their direct relevance to food security and sustainable farming.

The distribution reveals clear gaps in the food and agriculture sectors, where odour classification could play a vital role in spoilage detection, crop monitoring, and disease prevention. The limited number of studies suggests that these domains have not yet received sufficient attention, possibly due to technical barriers, lack of standardized datasets, and lower funding priority compared to environmental and health research.

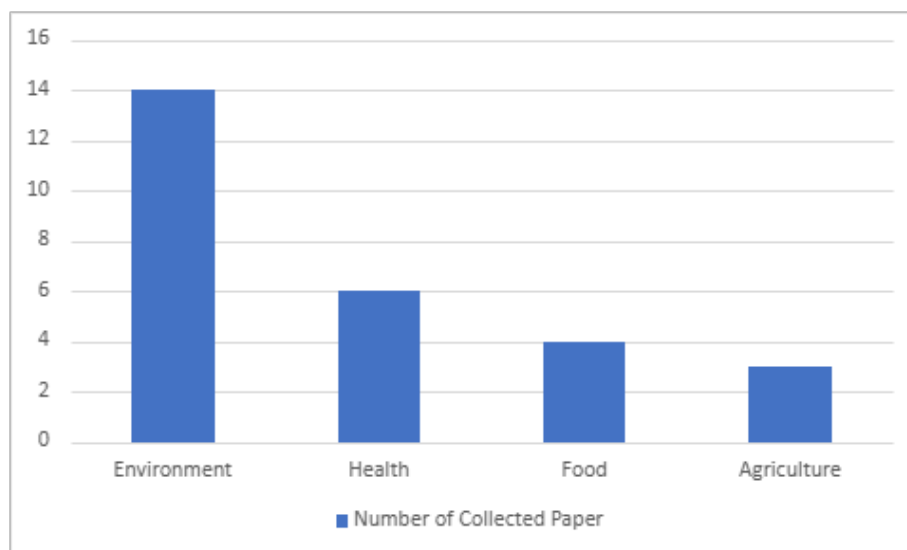


Fig. 6: Research Field of Final Collected Paper

Several challenges cut across all domains stated in Table 9. These include sensor drift and environmental variability, which reduce reproducibility; data imbalance and inconsistency, which limit model robustness; and platform heterogeneity, which makes cross-study comparison difficult. In food and agriculture, additional challenges arise from the complexity of natural odour mixtures and the absence of large, labelled datasets.

Looking ahead, future research should expand odour classification into food and agriculture, given their direct relevance to food security and sustainable farming. Developing bio-inspired sensor arrays with higher specificity will be crucial for handling complex odour mixtures, while IoT-based frameworks can enable continuous monitoring across farms and food supply chains. At the same time, multi-sensor fusion and adaptive learning models offer promising solutions to manage environmental fluctuations and improve long-term robustness. Finally, establishing standardized datasets and evaluation protocols remains a priority, as these will allow fair benchmarking across domains and accelerate the development of scalable, real-world odour classification systems.

The reviewed studies reveal critical gaps in dataset standardization, cross-domain generalization, and integration of chemical knowledge into machine learning models. Future research directions include:

- Development of bio-inspired sensor arrays for improved selectivity.
- IoT-based monitoring frameworks for scalable deployment.
- Adaptive and hybrid algorithms that balance accuracy with computational efficiency.
- Establishment of open, standardized odour datasets to enable fair benchmarking.

5.0 CRITICAL ANALYSIS AND IMPLICATIONS

5.1 Comparative Analysis of Algorithms and Sensor Configurations

A comparative examination of the reviewed studies reveals that the effectiveness of odour classification systems is highly dependent on the interaction between algorithm choice, sensor array configuration, and data characteristics rather than on algorithm sophistication alone. Traditional machine learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbour (kNN), and Artificial Neural Networks (ANN) continue to dominate the literature due to their robustness, interpretability, and consistent performance in handling high-dimensional sensor data derived from electronic nose systems [27], [34], [37], [41]. These algorithms are particularly effective in scenarios involving small to medium-sized datasets and controlled experimental environments, which remain common in odour classification research. Their widespread adoption also reflects lower computational requirements and ease of implementation compared to deep learning approaches.

In contrast, deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks demonstrate superior performance when applied to complex odour patterns, dynamic sensor responses, and large-scale datasets [39], [47], [50]. Studies employing CNN-based approaches reported improved feature learning capabilities by exploiting temporal or spatial correlations within sensor signals, especially when combined with data augmentation or upscaling strategies [39], [55]. However, these advantages are counterbalanced by challenges related to data scarcity, higher computational cost, and increased sensitivity to sensor drift, limiting their applicability in real-time and resource-constrained deployments. This comparison

highlights that deep learning methods offer performance gains primarily under favorable data and hardware conditions rather than serving as universally optimal solutions.

Sensor configuration analysis further indicates a clear trade-off between system complexity and classification reliability. Compact sensor arrays, typically comprising between three to six gas sensors, are widely favored due to lower calibration effort, reduced power consumption, and improved stability, making them well suited for practical and portable applications [31], [41], [46]. These configurations often achieve competitive accuracy when paired with appropriate feature extraction and traditional machine learning algorithms. Conversely, larger sensor arrays provide richer feature representations and improved discrimination capability but introduce challenges such as increased dimensionality, redundancy, hardware complexity, and susceptibility to long-term sensor drift [38], [46], [54]. As a result, large arrays are more commonly employed in laboratory-based or exploratory studies rather than operational environments.

A cross-study comparison also reveals that performance improvements are strongly influenced by feature extraction strategies rather than algorithm selection alone. Static, dynamic, and frequency-domain features have been shown to significantly enhance classification accuracy when appropriately matched to both the sensor characteristics and the learning algorithm [21], [32], [42]. For instance, machine learning models trained on transient or frequency-modulated sensor responses consistently outperformed those relying solely on steady-state signals, particularly in applications requiring rapid detection or drift compensation [34], [46]. This observation underscores the importance of aligning feature extraction techniques with both sensor behavior and algorithmic capabilities.

Overall, this comparative analysis demonstrates that no single algorithm or sensor configuration guarantees optimal performance across all odour classification scenarios. Instead, effective system design emerges from a balanced and context-aware integration of sensor selection, feature extraction, and learning algorithm choice. These findings support a system-level perspective in which algorithm performance is conditioned by sensor design and application constraints, reinforcing the need for integrated and adaptive approaches rather than isolated optimization of individual components. Such synthesis provides a clearer foundation for guiding future odour classification research and practical system development.

5.2 Conceptual Framework for Odour Classification

The conceptual framework for odour classification systems, structured into two main phases: the training phase and the classification (inference) phase. In the training phase, raw sensor data obtained from electronic nose systems undergo feature extraction to generate discriminative feature representations, which are subsequently used together with labeled data to train the classification model. This phase reflects common practices identified across the reviewed studies, particularly in supervised learning-based odour classification, where labeled datasets play a crucial role in establishing reliable decision boundaries.

The classification phase represents the operational deployment of the trained model, where unseen raw sensor data are processed using the same feature extraction strategies before being passed to the trained classification algorithm for label prediction. This separation between training and classification highlights an important distinction observed in the literature: while algorithm performance is often evaluated during training, real-world effectiveness is primarily determined during inference under practical constraints such as noise, sensor drift, and environmental variability. By explicitly distinguishing these phases, the framework enables clearer comparison between traditional machine learning approaches and deep learning-based models across different deployment scenarios.

Overall, the framework emphasizes that odour classification performance is influenced not only by the choice of learning algorithm, but also by how feature extraction strategies, data characteristics, and application requirements interact within the system pipeline. Unlike prior studies that describe individual components in isolation, Figure 7 provides a holistic and operational synthesis that integrates data processing, model learning, and application context within a single structure. This system-level perspective supports deeper comparative analysis and serves as a practical reference for designing, evaluating, and benchmarking future odour classification systems.

6.0 CONCLUSION

This systematic literature review provides a comprehensive and structured synthesis of recent research on odour classification using electronic nose (e-nose) systems and machine learning techniques. Based on the analysis of 27 primary studies, it is evident that traditional machine learning algorithms such as Support Vector Machines (SVM), Random Forest, and Neuro Network based algorithm remain the most widely adopted approaches due to their robustness, interpretability, and consistent performance in handling high-dimensional sensor data. In terms of sensor configurations, compact and low-cost sensor arrays particularly those consisting of a limited number of gas sensors are commonly preferred, as they offer a practical balance between classification accuracy, system complexity, and deployment feasibility. Fig. 8 shows the summary of the result and discussion.

The findings of this review indicate that effective odour classification is not determined by algorithm selection alone. Instead, performance is strongly influenced by the combined interaction between sensor type, sensor array design, feature extraction strategies, and application context. While deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks demonstrate strong potential in complex and data-rich scenarios, their usage remains constrained by computational cost, sensor data availability, and limited benchmarking across studies.

Several persistent challenges were identified across the reviewed literature, including sensor drift, lack of standardized datasets, inconsistent evaluation metrics, and limited cross-study comparability. These issues restrict the generalizability and reproducibility of existing odour classification systems and highlight the need for more systematic experimental designs and reporting practices.

Based on these observations, future research should prioritize three key directions. First, the development of standardized datasets and evaluation frameworks is essential to enable fair and meaningful comparison across studies. Second, adaptive and drift-aware learning approaches should be explored to improve long-term system stability in real-world deployments. Third, closer integration between sensor design and machine learning algorithms through interdisciplinary collaboration has the potential to enhance both performance and scalability. Overall, this review establishes a clearer understanding of the current landscape of odour classification research and provides practical guidance for advancing intelligent and real-world-ready olfactory systems.

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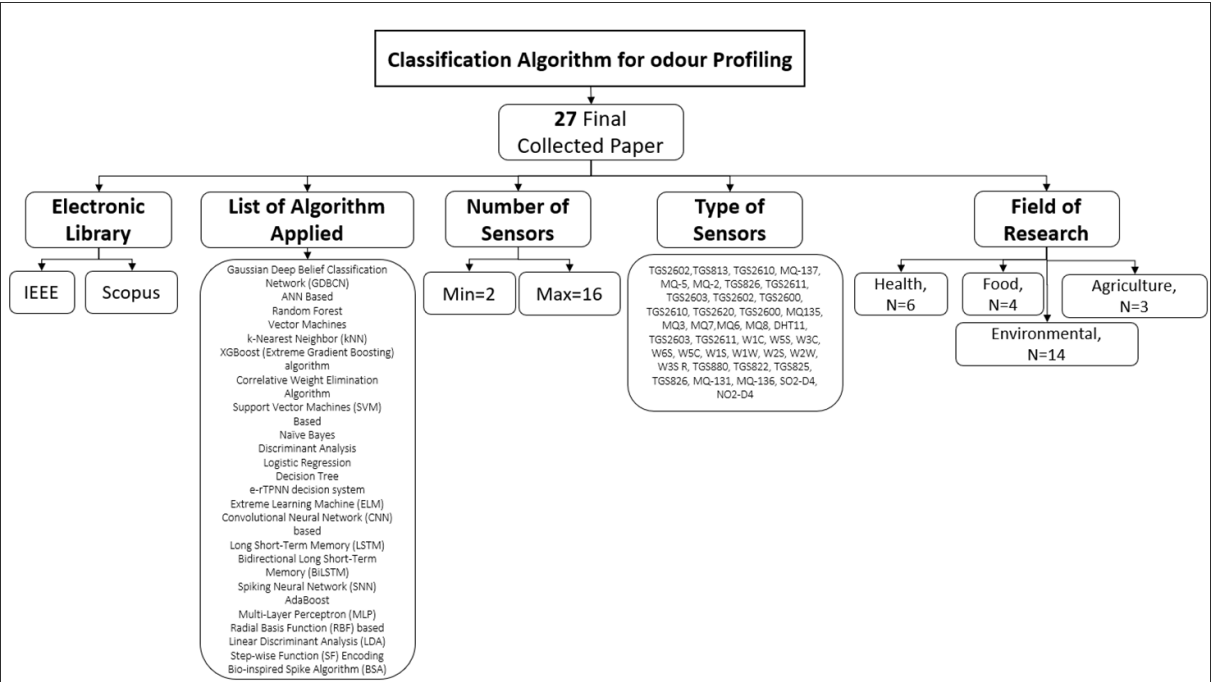


Fig. 8: Summary of Results and Discussion based on RQ

Appendix B

Table 9: Summary of Final Collected Paper for Metric, Field, Limitation and Future Trend

References	Metric	Field	Limitation	Future Trend
[27]	Accuracy	Distinct odours (Health)	Gaussian-Bernoulli RBM: Limited application due to its binary unit structure, especially in gas data analysis. Sensor drift: Caused by various factors, leading to distorted data and degraded E-nose performance. Deep learning models: Underperform in drift compensation when compared to traditional methods. Assumption in studies: Most prior research assumed no drift in E-nose systems, which is unrealistic. Drift causes: Include sensor ageing, poisoning, and environmental changes, all affecting sensitivity and accuracy.	Research focus: E-noses and their capability to identify odours, with emphasis on gas sensor drift compensation. Proposed model: Introduces the Gaussian Deep Belief Classification Network (GDBCN) for drift compensation at the decision level. Experimental scope: Uses datasets involving multiple chemical analytes (e.g., acetone, ethanol, ammonia), covering a wide odour spectrum. Challenges addressed: Examines the effects of sensor ageing, environmental fluctuations, and other factors on E-nose sensitivity and accuracy.

[28]	-Mean Squared Error (MSE) -Correlation coefficient (R) -Confusion matrices -Accuracies -Sensitivities - Specificities -Precisions.	Agarwood (Agriculture)	Slow convergence: Error backpropagation in neural networks has limited effectiveness due to slow convergence rates. Overreliance on ANN: May ignore other potentially effective methods for agarwood grading. Focus on computation: Emphasis on efficiency might overlook important qualitative factors like aroma complexity. Conventional grading: Subjective and inefficient, depending heavily on human judgment. Lack of standardization: No established grading system for agarwood oil, resulting in inconsistent evaluations.	Research focus: Identifying and classifying agarwood oil quality based on characteristics like intensity, aroma, texture, and weight. Grading system: Agarwood oil is categorized into four grades—low, medium-low, medium-high, and high. Limitations of traditional methods: Conventional grading is subjective and time-consuming, relying on human sensory evaluation. Use of ANN: Applies Artificial Neural Networks with the Levenberg-Marquardt algorithm to improve classification accuracy. Contribution: Proposes a more systematic and objective method for agarwood oil classification based on chemical and sensory data.
[49]	Accuracy	Detection of forest tree pathogens (Agriculture)	Lab limitations: The method is typically restricted to controlled laboratory environments. Design constraint: Most low-cost E-noses lack support for temperature modulation mode. Measurement challenges: Biological sample variability and external conditions impact accuracy.	Future trend: Development of E-noses with advanced sensor heater modulation to improve gas detection, including forest tree pathogens. Modulation profiles: Recommends exploring various heater voltage amplitudes and frequencies for better sensor adaptability. Machine learning: Highlights the potential of Random Forest and PCA for improved data visualization and classification. High accuracy: Achieved 97% classification accuracy using multi-sensor data fusion, suggesting further research into optimizing sensor combinations and fusion techniques.

[30]	Accuracy	Investigates the use of aromatic oils (Health)	Sensitivity and specificity: E-nose has lower sensitivity and specificity compared to DAPCI-MS, limiting its application in certain areas. Real-time limitation: DAPCI-MS lacks real-time data access, reducing its suitability for immediate odour detection. Chemical pretreatment: Some tasks with E-nose require pretreatment of samples, increasing system complexity. Participant reliability: Use of untrained individuals in odour discrimination experiments may affect result accuracy. Distance effect: E-nose performance decreases with increased distance from the odour source, limiting effective range.	Artificial synesthesia: Suggests enhancing human-machine interfaces with multisensory integration for better user interaction. Pattern recognition: Calls for broader odour diversity and specific sensor calibration to improve discrimination accuracy. Odour intensity: Highlights the role of intensity in detection and visualization; recommends optimizing intensity for better classification. Machine learning trend: Indicates growing use of algorithms like Random Forest, SVM, and k-NN to improve odour classification performance.
[31]	Accuracy	Various fruit juices (Food)	Sensor sensitivity: Notes that increased temperature or humidity reduces sensor performance, necessitating environmental compensation. Device limitations: Points out that long response times and large sizes of earlier E-noses hinder integration into humanoid robots. Temperature compensation: Emphasizes the need for integrated temperature sensors to maintain reading accuracy under varying conditions. Sensor combination: Stresses that individual sensors perform poorly alone, advocating for sensor fusion to enhance accuracy.	Compact integration: Indicates a trend toward developing small electronic noses for embedding in humanoid robots to detect volatile and nonvolatile odours. Performance enhancement: Suggests ongoing efforts to improve sensitivity and response time as key areas for future development. Environmental challenges: Highlights 3D mapping, source detection, and airflow perturbations as critical issues for advancing odour profile classification. Advanced algorithms: Points to increasing use of methods like K-Nearest Neighbors (KNN) to boost classification accuracy and efficiency.

				Future direction: Recommends focusing on expanding E-nose applications in robotics and environmental monitoring.
[32]	Root Mean Square Error (RMSE)	Predicting gas types and concentrations (Environmental)	Sensor selectivity: Notes that metal oxide gas sensors have low selectivity, limiting their effectiveness across different gases. Temperature modulation: Highlights that this method captures limited features, thereby reducing overall accuracy. Mixture complexity: Indicates that analyzing gas mixtures is more complex than anticipated, posing interpretation challenges.	Application expansion: Highlights potential for electronic noses in medical diagnostics, food safety, and environmental monitoring, signaling a move toward versatile gas-sensing systems. Selectivity improvement: Suggests enhancing metal oxide sensor selectivity through advanced temperature modulation for better odour classification and concentration prediction. Waveform diversification: Recommends exploring combinations of heating waveforms (e.g., square, triangular) to enrich feature datasets and improve gas detection performance. Algorithm advancement: Points to the use of sophisticated models like neural networks for improved classification and prediction of gas types and concentrations. Future outlook: Emphasizes the need for innovative methods to advance odour profile classification and electronic nose technology.
[33]	Accountability	Detect various substances that may contribute to illnesses (Health)	Hardware limitations: States that achieving perfect selectivity through hardware modifications alone is nearly impossible. Chemical complexity: Notes that target chemicals often consist of compound mixtures, making detection more challenging.	Sensor advancement: Highlights a shift toward high-speed response sensors using nanotechnology and 2-D materials to improve efficiency and odour classification in medical diagnostics. Algorithmic enhancement: Suggests using advanced methods like the Correlative Weight Elimination Algorithm (CWEA) to boost accuracy by filtering out weak signals.

			Detection accuracy: Indicates that some samples exceed normal substance limits, revealing potential limitations in detection precision.	Detection range: Recommends expanding the spectrum of detectable substances and improving sensor integration for better health-related odour classification. Medical focus: Emphasizes a growing trend toward using enhanced sensor technologies and algorithms for improved diagnostic applications in healthcare.
[34]	-Accuracy -Sensitivity -Specificity -Error -Precision -F1_Score -False Positive Rate -Kappa -Matthews Correlation Coefficient	Focus of detection ethanol (Environmental)	Sensor drift: Notes that long-term sensor drift degrades machine learning model performance, reducing classification accuracy. Latency issues: Highlights that classical ML models depend on steady-state responses, leading to delays in time-sensitive applications. Algorithm limitations: Points out challenges such as computational complexity and hyperparameter tuning in some ML approaches. Sensor generalization: Indicates that models trained on new sensors often fail when applied to data from older sensors. System limitation: Mentions that the proposed fast gas recognition system overlooks the impact of long-term sensor drift.	Drift robustness: Reports that the proposed model, trained on 36 months of drifted data, achieves a robust classification accuracy of 87.34%. Multi-classifier strategy: Introduces a multi-classifier tree approach using initial transient sensor responses to reduce response time and handle long-term sensor drift. Feature selection: Emphasizes the critical role of selecting suitable transient features to compensate for drift and enhance discrimination. Real-time feasibility: Highlights the model's reliance on transient features for fast response, making it suitable for real-time ENS applications despite long-term drift.
[35]	-Accuracy -Recall -Specificity -F1 scores -Matthews Correlation Coefficient (MCC)	Medical diagnosis (Health)	Data collection cost: Notes that gathering large datasets for ML systems is resource-intensive, affecting their generalization ability. Training limitations: Indicates that offline training may not achieve sufficient generalization or specialization for specific applications.	Future work: Suggests that future research will focus on implementing and testing the e-rTPNN decision system in real-time experiments using actual E-Nose hardware.

			Dataset imbalance: Highlights that the COPD dataset's sample imbalance led to the adoption of a binary classification approach. System consistency: Points out challenges due to limited datasets collected on the same E-Nose system under consistent environmental conditions. Evaluation constraints: Observes that performance of the e-rTPNN system is based on existing datasets, which may not reflect real-world conditions.	
[37]	-Predicted score -Regression	Odour intensity in ABS (Environmental)	Traditional methods: Acknowledges that traditional analysis methods suffer from slow response times and strict operational requirements. Cross-sensitivity: Points out that selected sensors may exhibit cross-sensitivity, impacting their overall performance. Sensor exclusions: Notes that some sensors were excluded due to poor stability and repeatability, limiting the effectiveness of the sensor array. Evaluation standard: Emphasizes the need for a unified standard in odour intensity evaluation, as current methods show variability. Generalizability limitations: Highlights that reliance on specific sensors may limit the applicability of the findings to other contexts.	Olfactory bionics: Highlights the advancement of olfactory bionic technology, combining signals from olfactory cells with advanced recognition methods, pointing to a trend towards sophisticated sensor arrays and algorithms for odour classification. Odour evaluation system: Proposes a novel system for measuring the odour intensity of acrylonitrile butadiene styrene (ABS), suggesting further research into standardized methods for evaluating odour intensity across materials. AI integration: Emphasizes the trend of using machine learning models like ELM, RF, and SVM to predict odour intensity, enhancing the accuracy and efficiency of odour profile classification systems. Future directions: Suggests future research into optimizing sensor arrays and applying diverse machine learning techniques to improve the reliability and accuracy of odour classification systems.
[38]	-Accuracy -macro F1 score (M-F1)	Derived odour (Food)	Feature significance: Notes that JMIM may overestimate feature importance due to cumulative summation, presenting a limitation of the JMI method.	Integrated e-nose systems: Indicates that future trends in odour profile classification may involve deploying integrated e-nose systems with selected sensors for

			Filter methods: Points out that filter methods, while efficient, may not select the optimal feature subset as they are not model-specific. System performance: Highlights that redundant or irrelevant features can impact e-nose system performance and increase computational complexity. Malodour detection: Acknowledges the limited research on e-nose applications for malodour detection in uncontrolled environments, presenting a challenge. Detection limitations: Indicates that certain odours, like detergent, may not trigger sensor responses, limiting detection capabilities.	real-world applications, especially in sanitation settings. Performance enhancement: Suggests that future research will focus on improving e-nose solutions through sophisticated approaches to enhance odour detection technologies. Machine learning potential: Highlights the potential of machine learning techniques for sensor selection and odour classification, with an emphasis on exploring advanced algorithms to improve classification accuracy. Malodour classification: Points out the successful classification of malodours using classifiers like decision trees and logistic regression, suggesting further exploration of various machine learning models for odour classification. Research outlook: Suggests a promising future for odour profile classification research, particularly in sanitation and waste management.
[39]	-Mean Squared Error (MSE) -Cohen's kappa coefficient.	Hazardous gases (Environmental)	CNN application limitations: Notes that the proposed approach cannot apply CNN on initially captured 1D or 2D steady-state sensor responses with a small number of sensor elements. Steady-state incompatibility: Highlights that steady-state samples from a sensor array are incompatible with 2D-CNN in its current form. Feature size constraint: Points out that the limited feature vector size restricts the conversion into a sufficient 2D array for 2D-CNN.	CNN potential: Highlights the potential of convolutional neural networks (CNNs) to enhance the accuracy of gas sensor array responses, pointing to a trend towards integrating advanced machine learning techniques for odour profile classification. Modular ANN advantage: Indicates that modular artificial neural networks (ANNs) may outperform traditional statistical methods like PCA and LDA, suggesting future research into hybrid models for improved classification accuracy. Spatial upscaling: Mentions the use of spatial upscaling techniques to enhance sensor data, inspiring

			Upscaling limitations: Indicates that the upscaling approach is limited to non-perfect square feature numbers, complicating the conversion process. Data length requirement: Emphasizes the need for sufficient data length to enable effective CNN analysis.	future research into optimizing data preprocessing for better odour classification performance. System adaptability: Points out that the proposed system's generic design allows for adaptation to various gases and odours, suggesting future research on its applicability in different contexts and environments.
[41]	-Accuracy -Precision -Recall -F1-measure.	Baking cookies (food)	Color-based method: Points out that using color to determine cooking levels is problematic due to similar colors across different stages. Spectroscopy limitations: Highlights that high operational costs and the need for trained personnel limit the use of spectroscopy for quality analysis. Gas sensor usage: Notes that while commercial gas sensors can enhance oven features, they are primarily intended for safety, not for comprehensive monitoring. Optimization trade-off: Mentions that the optimization process required eliminating several sensors, which may affect overall system performance.	Electronic noses in food control: Indicates a growing trend in using electronic noses for food quality control, particularly for distinguishing cooking levels of baked goods through aroma profiles, suggesting further research in enhancing accuracy and efficiency. Sensor array optimization: Suggests exploring the optimization of gas sensor arrays, as the current research achieved high accuracy with only 6 out of 20 sensors, potentially leading to more compact and efficient systems. Advanced classification algorithms: Highlights the opportunity to integrate advanced classification algorithms like convolutional neural networks for improving odour profile classification, a direction for future research. AI potential: Emphasizes the potential for artificial intelligence to enhance aroma pattern detection, suggesting a promising avenue for future exploration in odour profile classification.
[42]	Accuracy	Environment	Feature extraction limitation: Notes that traditional feature extraction methods do not fully utilize the information embedded in the original response curve. Detection method drawbacks: Highlights that existing gas detection methods are labor-intensive, time-consuming, and costly.	Feature extraction focus: Emphasizes that optimizing feature extraction and pattern recognition could improve odour analysis accuracy, suggesting that future research should focus on these aspects rather than solely on hardware optimization.

			Data challenges: Points out that the sparse and high-dimensional data from the gas acquisition system complicates obtaining satisfactory results.	Weighted summation (WS) method: Introduces the WS method for feature extraction, indicating a trend toward using more data to enhance classification accuracy, which could lead to further exploration of novel feature extraction techniques. E-nose applications: Highlights the effectiveness of electronic noses (e-noses) in environmental control and odour analysis, suggesting that future research could expand these applications to improve real-time odour classification systems. WS method advantage: Points out that the WS method outperformed traditional methods, suggesting a trend toward developing advanced algorithms that leverage comprehensive data for better classification outcomes. Research direction: Suggests a direction toward enhancing feature extraction methods and exploring broader e-nose applications in odour classification.
[43]	Accuracy	Chemical compounds (Environmental)	Computational limitations: Notes that neuromorphic olfactory systems face high computational and power requirements, limiting their real-world application integration. Traditional system drawbacks: Highlights that traditional electronic nose systems suffer from significant latency and poor accuracy in classification. Spike-based system constraints: Points out that many spike-based olfactory systems only provide results under specific operating conditions, making them impractical.	AERO development: Highlights the development of AERO, an AER-based data-to-spike encoder for olfaction data, opening avenues for future research in encoding multi-dimensional data and enhancing odour profile classification systems. System interfacing: Suggests future research directions that include interfacing electronic nose systems with AER-based neuromorphic hardware for more efficient processing and classification of olfactory data. Latency reduction: Emphasizes the need for further exploration into reducing processing latency to support real-time applications, pointing to a trend in improving odour classification system responsiveness.

			Processing latency: Mentions that the processing latency for classification results can range from 2.5 to 3 seconds, affecting real-time applications. Research need: Suggests further research on reducing processing latency to improve real-time application performance.	Unsupervised learning: Introduces the implementation of unsupervised spike-timing-dependent plasticity (STDP) for learning in spiking neural networks (SNNs), suggesting a novel approach that could significantly impact future odour classification research.
[44]	-Stacked mean values -Accuracy	Aroma and taste of coffee (Food)	Technical limitations: Notes that the electronic nose has limitations, particularly in understanding odourant receptors and the organization of the olfactory system. Sample set limitations: Highlights that limited sample sets can lead to misleading initial results in aroma recognition. Black box issue: Points out that existing e-nose applications are often treated as black boxes, lacking insight into the underlying chemical processes. Environmental sensitivity: Emphasizes that the e-nose's performance is sensitive to environmental factors like humidity and temperature. GC-MS drawbacks: Acknowledges that while GC-MS methods are effective, they are expensive and time-consuming compared to electronic noses.	Advancements in e-nose technology: Highlights significant advancements in electronic nose technology, particularly for quality assessment and aroma identification of products like coffee and beverages, suggesting a trend towards more precise aroma profiling and classification. Feature extraction development: Indicates the need for developing efficient coffee aroma feature extraction methods, pointing to future research in improving the accuracy and reliability of aroma classification systems. Digital aroma fingerprints: Emphasizes creating digital aroma fingerprints for specific coffee beans, which could serve as biochemical markers for aroma characteristics, inspiring research into standardization and database creation for aroma profiles. Machine learning integration: Suggests that integrating advanced machine learning techniques with e-nose technology could lead to new trends in odour profile classification and open up further research opportunities in this field.
[45]	-Accuracy -Mean squared error (MSE)	Environmental	Airborne hazard monitoring: Highlights the possibility of widespread monitoring of airborne hazards across remote locations by creating a network of gas sensors using Internet connectivity, though this consumes significant power.	VOCs and odour monitoring expansion: Indicates that future work could scale up to monitor a wide range of VOCs, gases, smokes, and odours by training the AI model appropriately.

			LoRa-based networks: Points out that long-range (LoRa)-based wireless networks do not require Internet connectivity and can operate independently, offering a more power-efficient solution.	Wide area network creation: Suggests the creation of a wide area network of N-IGSS, covering entire hospitals, malls, industrial settings, or smart cities, with thousands to millions of sensor nodes providing real-time data 24/7 to a command-and-control center. Scalability for AQI and climate change: Highlights the potential for further scaling the N-IGSS with more sensors for short-term AQI monitoring and long-term climatic change detection.
[46]	Accuracy	General gas environmental	High power consumption: Notes that the use of multiple gas sensors leads to high power consumption and increased complexity in circuitry. Recalibration challenges: Highlights that frequent recalibration of numerous sensor elements is tedious and time-consuming. Dataset drift: Points out that a large number of sensors can cause extensive drift in captured datasets. Lack of optimization rule: Mentions the absence of an established rule for determining the optimal number of sensors in a gas sensor array. Hardware redundancy: Warns that the unconstrained use of sensors can lead to hardware redundancy in gas sensor arrays.	Virtual sensor responses (VSRs): Highlights the potential of enhancing VSRs through the three-input and three-output (TITO) technique, suggesting a trend towards developing more sophisticated data-driven techniques for gas sensor responses, leading to improved odour classification accuracy. Partial-selective gas sensors: Indicates that partial-selective gas sensors in electronic noses (e-Noses) have been effective, hinting at future research focused on optimizing sensor arrays for better selectivity and sensitivity in odour detection. Machine learning integration: Emphasizes the potential of various machine learning algorithms in classifying gases/odours, suggesting that future research could focus on integrating advanced machine learning techniques to enhance classification performance. Sensor materials and algorithms: Suggests that ongoing exploration of sensor materials and the development of innovative algorithms will likely shape future research directions in odour profile classification.

[47]	Accuracy (OCA) -Kappa coefficient (K) -Mean squared error (MSE)	General gas environmental	Real-time challenges: Highlights that high-performance detection and estimation of gases/odours are challenging, especially in real-time gas sensing applications. CNN integration: Points out the recent development of efficient electronic noses (e-noses) using convolutional neural networks (CNNs). Optimized CNN performance: Mentions that CNNs perform better when operating on a minimal size of vector response.	AI-based methods: Highlights the potential of using convolutional neural networks (CNNs) for real-time gas/odour classification, suggesting a trend towards AI-based methods over traditional statistical approaches, which have limitations in real-time applications. Hybrid sensor responses: Introduces a novel approach combining physical sensor responses with virtual sensor responses derived from principal components, suggesting future research directions to enhance dimensionality and accuracy in odour classification systems. Mirror mosaicking technique: Presents the use of mirror mosaicking for upscaling input sample vectors as an innovative technique, which could be further explored to improve CNN performance in gas detection. Hybrid dataset success: Notes that the achievement of 100% correct classification in experimental settings with the proposed hybrid dataset suggests future research could focus on optimizing and validating this approach across different gas types and real-world conditions.
[48]	-RMSE -Accuracy	General gas environmental	Sparse spike-based representation: Highlights that while transformation is pivotal for sparse spike-based odour data representation, classification techniques based on bio-computations of higher brain areas for odour identification remain largely unexplored. SNN model performance: Mentions that the classification performance of the Spiking Neural Network (SNN) model was limited to a maximum of 84% for the 4-class dataset.	Biologically plausible algorithms: Highlights the need for further exploration of biologically plausible algorithms for mapping, learning, and interpreting odour data, suggesting they could enhance odour profile classification in future studies. Neuromorphic hardware potential: Emphasizes the potential of implementing these algorithms on highly parallel and low power-consuming neuromorphic hardware devices, which could enable real-world applications in odour classification systems.

			Lower classification rates: Attributes lower classification rates to a lack of differentiating features between the classes. BSA encoding issues: Points out that BSA encoding led to higher RMSE and average firing rate, causing errors in sensor signal characteristics. Need for improved strategies: Indicates that achieving high accuracy would require alternate strategies or enhanced datasets. Impact of dynamic responses: Notes that factors like inhibitory behavior and exposure to dynamic sensor responses directly impacted pattern recognition capabilities.	Exploring bio-computations: Indicates that while existing methods focus on data transformation based on the neurobiological architecture of the olfactory pathway, there is an opportunity to investigate classification techniques leveraging the bio-computations of higher brain areas, which remain largely unexplored. Future trend: Suggests that the future of odour profile classification will likely integrate advanced spiking neural network methods and deep machine learning systems to improve the efficiency and effectiveness of odour data processing.
[49]	Principal Component Analysis	Forest Agriculture	Limited dataset: Highlights that the dataset of measurements collected is limited, affecting the training and testing of models. Cross-validation necessity: Mentions that this limitation required the use of cross-validation to maintain dataset size. Quick pathogen detection: Emphasizes the need for quick pathogen detection, which may be hindered by the limited data. Impact on accuracy: Points out that limited data could impact the accuracy of the electronic nose in differentiating pathogens.	Dynamic improvements in e-nose technology: Discusses the expectation of ongoing advancements in electronic nose (e-nose) technology, contributing to the development of odour analysis and classification systems. This suggests a future trend towards enhancing e-nose capabilities in various fields like medical care and environmental monitoring. Integration of machine learning (SVM): Highlights the use of machine learning algorithms, particularly the Support Vector Machine (SVM), for classifying odours emitted by forest pathogens, indicating a trend towards advanced computational techniques in odour profile classification for more accurate species differentiation. Low-cost e-noses: Points to the exploration of low-cost electronic noses and their effectiveness in recognizing and differentiating odours, suggesting a future direction in making odour detection technology more accessible and practical for a range of applications.

[50]	Accuracy	Health medicine	Challenges in integration: The integration of e-nose systems faces challenges due to high costs and potential damage to the integrity of Chinese medicinal materials. Simple algorithms limitation: Simple algorithms in integrated e-nose designs limit performance, leading to low accuracy and slow recognition speeds. Impact of chip performance: Complex algorithms are hindered by the computational performance of simple chips, affecting odour recognition capabilities. Chip performance constraints: The design of integrated e-noses is constrained by chip performance, restricting the use of advanced algorithms. Limited DSP resources: Limited DSP resources in FPGA chips necessitate optimization techniques to enhance performance and reduce computational demands.	Optimizing machine learning algorithms: The implementation of a deep neural network for odour identification, specifically using the OI-DSCNN model for efficient FPGA hardware performance, suggests a trend towards optimizing algorithms for real-time odour classification applications. Enhancing accuracy and speed: Future research could focus on enhancing the accuracy and speed of e-nose systems by integrating more complex algorithm structures or exploring novel sensor technologies. Fluctuation enhanced sensing (FES): The use of FES in e-noses opens the possibility of using noise to improve sensitivity and selectivity in odour detection, which could be a promising area for further investigation. Future trends: The future of odour profile classification may focus on hardware optimization, algorithm complexity, and innovative sensing techniques to advance real-time applications in odour detection.
[51]	-Accuracy -Odour classification monitoring model (OCMM)	Environmental	Slow pattern-recognition performance: The complete response signals, though informative, hinder the efficiency of the pattern-recognition algorithm. Data distribution issues: Some variables do not follow normal data distribution, impacting the accuracy of results. Limitations of ANN: The ANN technique's dependence on noise handling may reduce its effectiveness in certain scenarios.	Optimizing machine learning algorithms: The implementation of a deep neural network for odour identification, specifically using the OI-DSCNN model for efficient FPGA hardware performance, suggests a trend towards optimizing algorithms for real-time odour classification applications. Enhancing accuracy and speed: Future research could focus on enhancing the accuracy and speed of e-nose systems by integrating more complex algorithm structures or exploring novel sensor technologies. Fluctuation enhanced sensing (FES): The use of FES in e-noses opens the possibility of using noise to

				improve sensitivity and selectivity in odour detection, which could be a promising area for further investigation. Future trends: The future of odour profile classification may focus on hardware optimization, algorithm complexity, and innovative sensing techniques to advance real-time applications in odour detection.
[52]	Accuracy	Health	Cost and time limitations: The applied techniques are costly and time-consuming, requiring educated experts for effective analysis, which may limit their widespread adoption and practical use in routine applications. Complicated conventional methods: Conventional methods for detecting <i>Alternaria spp.</i> fungi are often complicated and time-consuming, suggesting a need for more efficient and accessible techniques for fungal disease detection. Aroma exchange rate: The aroma exchange rate from the inner parts of pomegranate occurs at a low speed, which may affect the sensitivity and responsiveness of systems designed to detect aromas related to fungal infections. Ignored sample preparation time: Previous studies on fungal disease detection often ignored sample preparation time, which could lead to inefficiencies in real-world applications where timely results are critical.	Optimizing E-nose capabilities The research highlights the need for developing alternative methods to overcome the limitations of conventional techniques in detecting fungal diseases like <i>Alternaria spp.</i> in pomegranate fruit, suggesting a trend towards more efficient diagnostic tools such as the Electronic Nose (E-nose) system. Improving fungal disease detection Future research could focus on enhancing the E-nose system's capabilities, particularly in improving the detection of internal fungal diseases, which are challenging due to the thick-skinned nature of pomegranates. Advancing odour profile classification The study indicates that further exploration of the E-nose's application in various food products could lead to advancements in odour profile classification, as it has shown promising results in detecting quality and fungal infections with high accuracy. Incorporating advanced data analysis techniques Additionally, the integration of advanced data analysis methods like Linear Discriminant Analysis (LDA) and Back Propagation Neural Network (BPNN) could be a significant direction for future research in odour classification.

[53]	Accuracy -Latency	Environmental general	Inconsistent spiking order The approach is susceptible to inconsistent spiking order, affecting classification performance. High computational and power requirements High computational and power requirements are limitations of the current methodology. Limitations of traditional methods Traditional pattern-matching methods hinder the performance of rank-order-based olfactory systems.	Bioinspired artificial olfaction The research focuses on bioinspired artificial olfaction, particularly utilizing spike-based neuromorphic methods to enhance the detection and classification of odours. Limitations of traditional approaches It addresses the limitations of traditional approaches, such as difficulties in handling multivariate data and issues related to computational power and accuracy. Spiking neural network (SNN)-based solution The study presents a spiking neural network (SNN)-based solution for classifying rank-order spiking patterns, enabling real-time recognition of target gases. Offline learning and nearest neighbor classification The system employs offline learning to store reference patterns and applies nearest neighbor classification logic for effective recognition. High accuracy and low processing latency The results indicate a high accuracy of 96.5% in identifying target gases with a nominal processing latency of 16ms per spike, showcasing the system's robustness and efficiency in odour detection.
[54]	Accuracy	Environmental	Limitations of existing methods The research highlights that existing methods for detecting toxic gas levels have failed to accurately determine the tolerance levels of these gases in polluted air. Challenges in quick gas identification The quick identification of flammable and toxic gas substances within a short reaction time remains a challenging task for gas detection devices. Impact of real-world conditions Additionally, the complexity of real-world conditions can hinder the	Integration of e-noses in humanoid robots The research indicates a future trend towards the integration of electronic noses (e-noses) in humanoid robots for detecting various odours, including toxic gases and organic substances. This could enhance safety and environmental monitoring. Improvement in machine learning algorithms There is a focus on improving machine learning algorithms for better classification accuracy in gas detection, with methods like Random Forest and various supervised learning techniques being explored.

			effectiveness of the detection systems, as they may not perform optimally outside controlled environments. Reliance on specific sensors and algorithms The reliance on specific sensors and algorithms may also limit the adaptability and accuracy of the detection systems in diverse scenarios.	Development of portable e-nose devices The development of portable e-nose devices that can operate in real-time and under various environmental conditions is a significant direction for future research. Use of advanced neural network architectures The use of advanced neural network architectures, such as recurrent and convolutional networks, is suggested to improve gas detection capabilities and response times. Exploring the relationship with human health Future research may also explore the relationship between toxic gas levels and human respiratory health, aiming to create systems that can provide real-time health alerts. Implementation of IoT in gas detection systems The implementation of IoT technologies in gas detection systems is expected to enhance data collection and analysis, leading to more efficient monitoring of air quality.
[55]	-Accuracy -Mean squared error (MSE).	Environmental	Performance degradation with sensor removal The study acknowledges potential performance degradation when removing redundant sensor elements, which must be mitigated through advanced techniques. Redundant element identification assumption The optimization approach relies on the assumption that redundant elements can be identified without affecting overall performance. Limitations in gas generalization The research is limited to the specific gases tested, which may not generalize to all hazardous gases.	Low-power sensor nodes with edge intelligence The research highlights the potential of utilizing low-power sensor nodes with edge intelligence in 6G-IoT ecosystems, indicating a trend towards integrating advanced AI techniques for odour profile classification in resource-constrained environments. Optimizing gas sensor systems The study emphasizes the importance of optimizing gas sensor systems by removing redundant sensor elements, which not only reduces power consumption but also maintains high classification accuracy. This suggests a future direction for research focused on enhancing sensor efficiency while ensuring performance integrity. Application of Convolutional Neural Networks (CNNs) The application of Convolutional Neural

				Networks (CNNs) for real-time gas classification and quantification is identified as a promising trend, paving the way for further exploration of AI-based methodologies in odour detection and analysis. Data pre-processing techniques Future research could also explore the integration of specialized data pre-processing techniques, such as zero-padding and spatial augmentation, to improve the robustness of odour classification systems. AI-driven gas sensor systems Overall, the paper indicates a clear trend towards the development of more efficient, AI-driven gas sensor systems for odour profile classification in various applications.
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