Chapter-1

Introduction and Literature Survey

1.1. Introduction

In many fields and applications, it's essential to accurately detect and estimate gases and odors. Historically, gas sensor arrays have been employed for this, with highly selective sensors needed for accurate detection. Cross-selective gas sensors, however, can achieve high-performance classification of gases and odors when paired with artificial intelligence (AI) algorithms, according to recent studies [1]. Electronic noses (e-Noses), which employ arrays of broadly selective gas sensor elements, have been created as a result [2].

By converting physical sensor responses into additional virtual sensor responses, we describe a novel method in this thesis for improving the performance of gas sensor arrays [3]. Our suggested method, known as the three-input and three-output (TITO) technique, enables effective virtual sensor responses (VSRs) to be efficiently derived from the actual gas sensor array (GSA) responses in real-time. Using a GSA with four elements, we exhibit the efficiency of our method and show that it greatly improves the VSRs in comparison to its peer method.

We also discuss the requirement for real-time estimation of dangerous substances in ambient air [4]. We describe a unique method that uses convolutional neural networks (CNNs) to analyse multi-element gas sensor arrays in order to increase accuracy in this situation [5]. Lightweight CNNs are used to spatially upscale and analyse the raw sensor outputs locally. Using a thick-film gas sensor array made by our research team that is based on a four-element metal-oxide semiconductor (MOS) array, we test our hypothesis.

1.2. Background

Due to the significance of gases and odors in several sectors and applications, the detection and quantification of these substances has long been a subject of study. For this, gas sensors have typically been utilised, and highly selective sensors are needed for exact detection. These sensors can, however, be costly and challenging to produce [6].

Cross-selective gas sensors can provide high-performance categorization of gases and odors when paired with artificial intelligence (AI) algorithms, according to recent studies [7]. Electronic noses (e-Noses), which employ arrays of broadly selective gas sensor elements, have been created as a result [8]. These e-Noses have demonstrated potential in a number of applications, including food safety, environmental monitoring, and medical diagnostics [9].

Despite e-Noses' potential, there are still issues that need to be resolved if they are to work better. Deriving virtual sensor responses (VSRs) from the real-time physical gas sensor array (GSA) responses is one of these difficulties. The performance of e-Noses can be improved by VSRs by offering more details about the target gas or odor [10].

1.3. Objectives

The primary goals of the research work that is the subject of this thesis are to:

1. Develop a unique method for generating effective virtual sensor responses (VSRs) from the real-time physical responses of a gas sensor array (GSA).
2. Use a GSA with four elements to demonstrate the viability of the suggested method.

3. Outline a unique method that uses convolutional neural networks (CNNs) to detect and estimate hazardous gases in ambient air in real time.
4. Test the suggested method using a four-element thick-film gas sensor array made by our research team utilising metal-oxide semiconductors (MOS).

These goals are driven by the requirement to enhance the functionality of electronic noses (e-Noses) and solve the difficulties in real-time gas detection and estimate [11].

1.4. Gas Sensing

In many fields and applications, it's essential to accurately detect and estimate gases and odors. The literature on gas sensor arrays, electronic noses (e-Noses), virtual sensor responses (VSRs), convolutional neural networks (CNNs), unmanned aerial vehicles (UAVs), search and rescue (SAR) operations, and intelligent edge computing is reviewed in this part.

The detection and quantification of gases and odors have historically been accomplished using gas sensor arrays. These arrays are made up of several gas sensors, each with a unique selectivity for various gases [12]. Cross-selective sensors can achieve high-performance classification when paired with artificial intelligence (AI) algorithms, according to new findings, which contradict the conventional wisdom that highly selective sensors are needed for exact detection [13].

According to a study done in 1953 by Brattain and Bardeen on the surface characteristics of the elemental semiconductor germanium, semiconductor materials experience changes in their electrical resistance when exposed to a gaseous environment. This finding showed how semiconductor materials might be used for gas detection [14]. The development of gas sensors was started based on this phenomena, and gas detection utilising a sensing layer consisting of zinc oxide was successfully implemented. The first metal-oxide-semiconductor gas sensor that used tin oxide as the detecting medium was notabley patented in 1971. Due to its high sensitivity, low operating temperature need, and thermal stability, tin oxide was preferred to other metal oxides [15].

The ability to detect chemical signals and transform them into quantifiable information makes gas sensors chemical detectors with transducing capabilities. Based on the sensing techniques they employ, these sensors can be grouped. Catalytic gas sensors are used to identify flammable gases since their operation relies on catalytic combustion. The catalytic characteristics of metal oxides and their derivatives lower the ignition temperature of combustible gases. Before they approach the lower explosive limit (LEL) or concentrations that fall inside the explosive range, these sensors pick up on flammable gases and vapours [16].

Based on chemical reactions between gas molecules and oxygen inside the sensing material , electrochemical gas sensors work. On the two electrodes where the chemical reaction occurs, the ensuing reaction causes a current proportionate to the gas concentration, which is transduced and recorded. Gas sensing is made possible by this technique [17].

The materials used in optical gas sensors experience changes in their optical characteristics when exposed to gases. Gas detection is based on this alteration. For instance, some sensors use optodes/optrodes, which are optical fibres partially coated with palladium. The optical fibre is stretched in both directions as the gas and palladium interact, changing the effective optical path length. This change is measured using interferometry, which also makes it possible to detect gases [18].

Surface Acoustic Wave (SAW) and Quartz Crystal Microbalance (QCM) gas sensors are examples of a different family of gas sensors that use materials sensitive to mass. These sensors don't use chemical or physical processes to detect gases; instead, they use vibration frequency. A thin layer of gas-absorbing material is applied to the frequency-sensitive materials. By examining the frequency of the material and researching the properties of the adsorbed material, gas can be detected [19].

Additionally, many metal oxides have semiconductor properties and can be used to detect combustible, oxidising, and reducing gases. When in contact with gases, some materials exhibit variations in conductivity. These materials' viability for gas sensor design is determined by their inherent electrical structure. As a result, changes in conductivity (resistance) are used by metal-oxide-semiconductor gas sensors to detect gas [20].

1.5. Gas Chromatography: The Gold Standard

A sophisticated analytical method for examining the components of gases and volatile organic compounds (VOCs) is gas chromatography mass spectrometry (GC-MS). It combines gas chromatography (GC) and mass spectrometry (MS), two complimentary techniques, to provide comprehensive details regarding the composition and structure of complicated mixtures.

Based on their volatility and affinity for the stationary phase, specific components that are present in a mixture can be separated using the GC separation technique. The components are separated as they interact with the stationary phase in a chromatographic column after the mixture has been vaporised and injected there. The distinct identification and measurement of the separated components is made possible by the fact that they elute from the column at various intervals.

Instead, MS is a method for determining the mass-to-charge ratio (m/z) of ions formed from sample molecules. It involves ionising the molecules of the analyte, then separating and detecting the ions according to their m/z values. The analyte molecules' molecular weight and structural details are shown in the ensuing mass spectrum.

The volatile components separated by the GC are successively delivered into the MS for ionisation and detection when GC and MS are combined to form GC-MS. Based on their GC retention periods and MS mass spectra, this coupling enables the identification and measurement of individual chemicals within complicated mixtures.

Numerous sectors, including forensic science, the food and beverage industry, metabolomics, pharmaceutical analysis, and environmental analysis, have found considerable use for GC-MS. In environmental analysis, GC-MS is used to identify and quantify contaminants in air, water, and soil samples, including volatile organic compounds (VOCs) and air toxins [21]. The analysis of flavour components, aroma profiling, and the detection of pollutants are all done in the food and beverage business using GC-MS [22]. GC-MS is used in forensic science to identify drugs, explosives, and other trace evidence. For the characterisation of drug molecules, impurity profiling, and stability testing in pharmaceutical analysis, GC-MS is used [23]. In metabolomics, GC-MS is used for the analysis of small molecules in biological samples, providing insights into metabolic pathways and disease biomarkers [24].

Improvements in instrument technology, such as increased resolution, sensitivity, and analysis speed, have made it easier to use GC-MS in these applications. Additionally, the identification and interpretation of challenging GC-MS data has improved with the introduction of extensive mass spectral libraries and advanced data analysis software.

Analysing the components of gases and volatile organic compounds (VOCs) uses the sophisticated analytical technology known as gas chromatography mass spectrometry (GC-MS), which combines gas chromatography and mass spectrometry. It has numerous uses in forensic research, pharmaceutical analysis, environmental analysis, food and beverage industries, and metabolomics. The capabilities and applicability of GC-MS in numerous sectors have been significantly improved by developments in instrument technology and data analysis tools.

1.6. Gas Sensor Arrays

The typical purpose of gas sensors is to identify particular gases or odors. However, because gases are frequently present in mixes in real environments, gas sensors are often also sensitive to other gases. As a result, each gas sensor performs as a non-selective sensor for all other gases in addition to the target gases for which it is intended. Recognising this, a model nose concept using a variety of general-purpose gas sensors was introduced in the early 1980s. The results of this study demonstrated that non-selective sensors were more capable of high-performance gas discrimination than individual gas sensors. The development of artificial olfaction systems or electronic noses (e-Noses) was made possible because to the introduction of gas sensor arrays in this groundbreaking work [25].Figure 1.1 shows the Schematic of a sensor array based on oxide, organic, metallic, and two-dimensional materials [28].

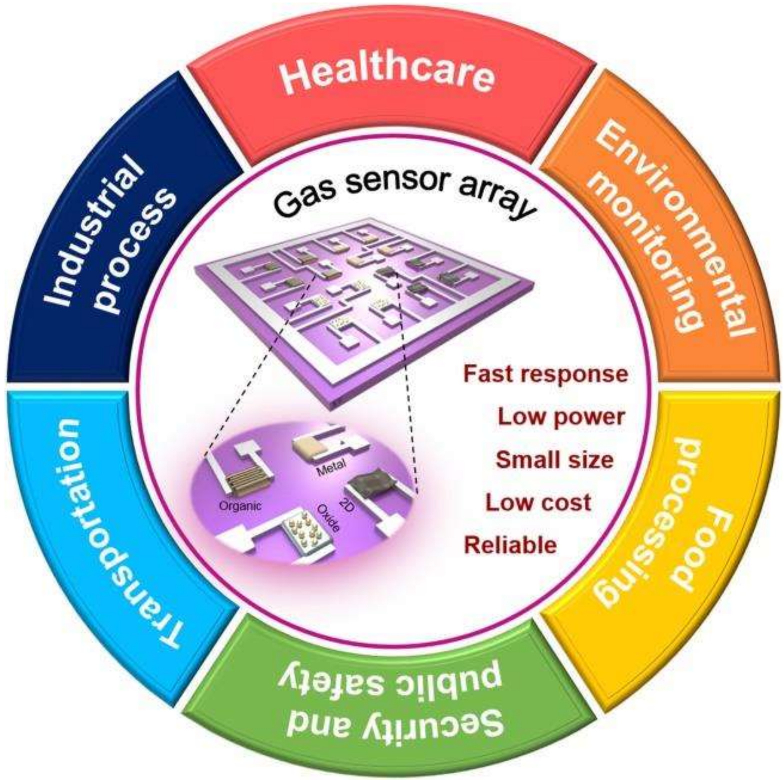

Figure 1.1 : Schematic of a sensor array based on oxide, organic, metallic, and two-dimensional materials.[28]

1.7. Electronic Noses (e-Noses)

Electronic noses (e-Noses) are machines that simulate the human sense of smell by using arrays of broadly selective gas sensor elements [26]. These tools have demonstrated potential in a number of applications, including food safety, environmental monitoring, and medical diagnostics [27].

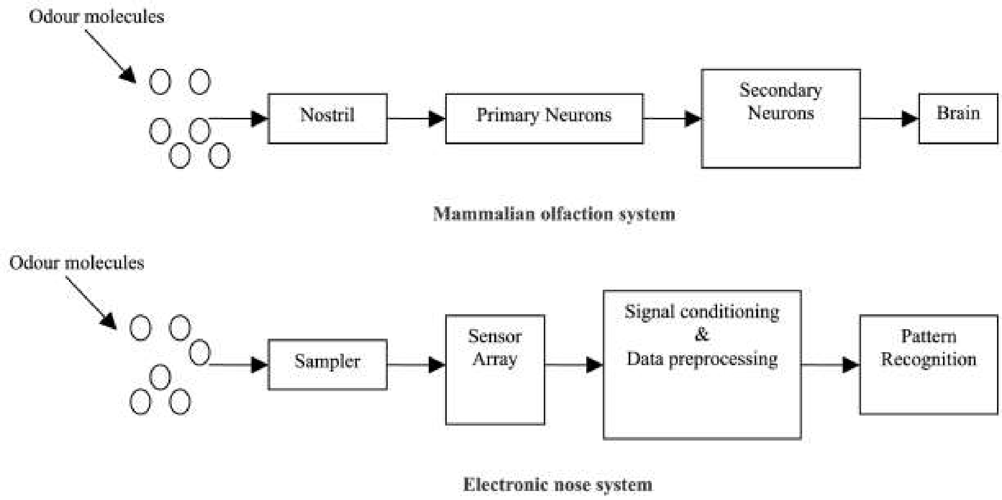

Figure 1.2 Comparison of the mammalian olfactory system and the e-nose system [19]

The typical purpose of gas sensors is to identify particular gases or odors. However, because gases are frequently present in mixes in real environments, gas sensors are often also sensitive to other gases. As a result, each gas sensor performs as a non-selective sensor for all other gases in addition to the target gases for which it is intended. Recognising this, a model nose concept using a variety of general-purpose gas sensors was introduced in the early 1980s. The results of this study demonstrated that non-selective sensors were more capable of high-performance gas discrimination than individual gas sensors. This groundbreaking work set the groundwork for the creation of electronic noses (e-Noses) or artificial olfaction systems by introducing gas sensor arrays [26].Figure1.2 shows the Comparison of the mammalian olfactory system and the e-nose system [19].

The selectivity and sensitivity of the gas sensor elements, as well as the data processing methods employed, affect how well e-Noses perform [28]. It has been demonstrated that cross-selective gas sensors and artificial intelligence (AI) algorithms work together to produce high-performance classification [29]. Principal component analysis (PCA) and artificial neural networks (ANNs) are two examples of data processing methods that can be utilised to improve the classification performance of e-Noses [30].

Metal-oxide semiconductor (MOS), conductive polymer, and quartz crystal microbalance (QCM) sensors among others have all been employed in e-Noses as gas sensors [31]. Due to their great sensitivity and quick response times, MOS sensors are frequently used [32]. High selectivity towards particular gases is a well-known characteristic of conductive polymer sensors [33]. QCM sensors are extremely sensitive to changes in mass and are capable of detecting gases at incredibly low concentrations [34].

By optimising the operating parameters, such as temperature and humidity, the performance of e-Noses can be increased [35]. Virtual sensor responses (VSRs), which can provide additional details about the target gas or odor, can also be obtained from the physical gas sensor array (GSA) responses [36].

1.8. Virtual Sensor Responses (VSRs)

To offer more details on the target gas or odor, virtual sensor responses (VSRs) are created from the physical gas sensor array (GSA) responses. By increasing the dimensionality of the data and enhancing classification accuracy, VSRs can improve the performance of electronic noses (e-Noses) [36].

There are several methods that have been suggested for obtaining VSRs from GSA responses. The three-input and three-output (TITO) technique is one such method that enables effective real-time VSR derivation [36]. When compared to peer techniques, this strategy has been proven to dramatically increase the VSRs [37].

The calibre of the physical GSA reactions affects how well VSRs work. By optimising the operating parameters, such as the temperature and humidity, the performance of GSAs can be increased . The classification performance of GSAs can also be improved by using data processing techniques like principal component analysis (PCA) and artificial neural networks (ANNs) .

1.9. Pattern Recognition Techniques used in e-Nose Systems

In gas sensing applications, a wide range of pattern recognition approaches have been investigated for the categorization and quantification of gases and odors. However, since the introduction of gas sensor array responses, neural networks have continually maintained their dominance in this industry. Due to their outstanding performance in gas and odor classification/quantification tasks, neural networks, in particular convolutional neural networks (CNNs), have drawn a lot of interest. This thesis is concerned with the efficient classification and quantification of gases and odors using CNNs, one of the most well-known neural network designs.

Reviewing different pattern recognition methods used in gas sensing is crucial for a thorough understanding of the subject. Principal component analysis (PCA), fuzzy logic, support vector machines (SVM), and statistical methods are only a few of the methodologies that are included in these strategies [38],[39],[40],[41]. Before diving into neural network applications, it is critical to weigh each method's advantages and disadvantages when used for gas sensing.

For instance, gas classification based on the statistical characteristics of sensor responses has been done using statistical techniques like linear discriminant analysis (LDA) and k-nearest neighbours (KNN) [38]. To deal with uncertainty and ambiguity in gas sensing data, fuzzy logic techniques, on the other hand, include linguistic factors and expert knowledge [39]. By mapping sensor responses to a high-dimensional feature space, SVM, a potent machine learning algorithm, has been used to accomplish accurate gas classification [40]. To extract key features from gas sensor data and increase classification accuracy, PCA, a dimensionality reduction technique, has been frequently applied [41].

The use of neural networks, particularly CNNs, has revolutionised the field of gas sensing research even though these pattern recognition approaches have made a substantial contribution. Effective gas and odor classification/quantification is made possible by CNNs, which take use of the hierarchical nature of the data and use convolutional filters to extract local characteristics [42]. In a number of areas, including computer vision, speech recognition, and natural language processing, these networks have displayed astounding performance.

In order to learn and distinguish between various gases and odors based on their distinctive patterns, CNNs can be used to feed the responses from gas sensor arrays into the network. CNNs are ideally suited for gas sensing applications because they can automatically learn discriminative features and capture complicated correlations within the data.

In conclusion, CNNs have emerged as the most effective strategy for gas and odor classification/quantification, despite the fact that several other pattern recognition approaches have also been investigated. This thesis focuses on the efficient classification and quantification of gases and odors using CNNs. To give a thorough understanding of the topic, a thorough analysis of alternative pattern recognition methods in gas sensing will be done before going into the specifics of neural network applications.

1.9.1. Principal Component Analysis

Unsupervised pattern recognition techniques like Principal Component Analysis (PCA) are widely employed in a variety of industries. The main goal of this technique is to convert high-dimensional data into a lower-dimensional space while preserving crucial information. Through PCA, subsequent analysis is made easier and the computing complexity is reduced by lowering the number of dimensions in the data.

Researchers have used PCA for a variety of purposes, including the classification of alcoholic beverages based on odors. For instance, one study [43] used a gas sensor array along with PCA to determine the vintage years of wines belonging to the same category. This demonstrated the efficacy of the method. The researchers successfully distinguished between various vintage years by applying PCA to extract the important features from the data from the gas sensor array.

PCA has also been used in conjunction with pattern recognition methods to categorise and quantify explosive gases and odors including methane, propane, and butane. Nine sensor elements made up a gas sensor array that was used in one investigation [44] . The researchers' achievement of a recognition accuracy of 76.8% using PCA and discriminant analysis (PCA-DA) highlights the potential of this method for classifying and quantifying gases.

Nanomaterial-based gas sensor arrays have also been investigated for fragrance analysis in addition to conventional gas sensor arrays. A gas sensor array made of nanomaterials was utilised in a study that aimed to identify five Chinese liqueurs [45]. The effectiveness of the method was demonstrated by the researchers' achievement of a recognition accuracy of 76.8% using the synergistic combination of PCA and discriminant analysis (PCA-DA).

Additionally, nitrogen dioxide, hydrogen cyanide, hydrogen chloride, chlorine, acetone, and benzene have been distinguished between using carbon nanotube-based gas sensor arrays recorded at various concentration levels (parts per million, PPM) [46]. The researchers successfully identified and separated these gases depending on concentration exposure by using PCA.

In conclusion, PCA is a useful tool for pattern detection since it can reduce data dimensionality and make further analysis easier. Researchers have used PCA for a variety of purposes, including gas classification, quantification, and liquor discrimination. These studies show how PCA can effectively extract important data from gas sensor arrays and help with accurate categorization and identification of different gases and odors.

1.9.2. Probability Based Techniques

Techniques for recognising patterns frequently estimate posterior probability or take a Bayesian approach. Gaussian Mixture Models (GMM) are a frequently used technique for identifying and analysing gases, odors, and their mixtures. In one particular work, GMM was used to analyse the responses of an integrated gas sensor array that was created to identify flammable gases [47]. The authors demonstrated the efficacy of this method by achieving an amazing recognition accuracy of 96 percent using GMM on the sensor array data.

GMM is a potent statistical model that combines numerous Gaussian components to reflect the data distribution. When working with complex datasets with numerous sources or classes, it is especially helpful. In the context of gas sensing, GMM can accurately distinguish between various gases and their mixtures and capture the underlying properties of the gas responses.

Identification and categorization of flammable gases are made possible by the use of GMM to an integrated gas sensor array. The scientists were able to identify significant features and patterns related to several gases by modelling the sensor array's responses with GMM. Because of this, they were able to attain a high recognition accuracy of 96%, demonstrating the usefulness of GMM for gas identification.

In general, using GMM as a pattern recognition technique provides a stable foundation for analysing data from gas sensor arrays and differentiating between gases and their combinations. The aforementioned work serves as an excellent example of how GMM may be successfully applied to an integrated gas sensor array and shows its potential for precise gas recognition and categorization.

1.9.3. Cluster Analysis – Based Techniques

When attempting to find innate patterns and relationships within a dataset in unsupervised settings, cluster analysis-based pattern recognition algorithms are frequently used. A researcher has used hierarchical cluster analysis (HCA), one of these methods, to distinguish between several alcoholic odors [48]. By creating a hierarchical structure based on distances or similarities, HCA offers a technique for classifying and organising relationships.

HCA creates a dendrogram, which resembles a tree, by repeatedly merging or dividing groups in a hierarchical fashion. In a dendrogram, each node stands for a cluster, and the branches show how similar or dissimilar the clusters are to one another. The linkages and groups within the dataset can be deduced by looking at the dendrogram.

The researcher used HCA to examine the sensory properties of several alcoholic beverages in the specific study on liqueur fragrances. HCA assisted the differentiation and clustering of spirits samples based on their aromatic qualities by taking into account the distances or similarities between various aroma profiles. This method helped with the comprehension and categorization of the scents of the various alcoholic beverages by revealing important insights into the similarities and differences between them.

HCA's use in the context of alcohol aroma analysis serves as an illustration of how well it recognises patterns without supervision. HCA enables researchers to better comprehend the underlying structures in the dataset by investigating the relationships between samples and visualising them in a dendrogram.

The identification of linkages and groups within a dataset is made possible by the unsupervised pattern recognition technique known as hierarchical cluster analysis (HCA). The aforementioned study was successful in differentiating between several liquor samples based on their sensory properties by using HCA to the analysis of liquor scents.

1.9.4. Discriminant Analysis-Based Techniques

An method to parametric pattern recognition known as discriminant analysis-based techniques seeks to categorise patterns by combining linearly discriminating characteristics. These methods aim to produce clusters of discriminating parameters that are statistically distinguishable to the maximum extent. These methods maximise the ratio of inter-cluster to intra-cluster variances to estimate the weights of the linear discriminant functions. The discriminant functions will be able to successfully distinguish between various classes thanks to this optimisation process.

Multiple discriminant analysis (MDA) is a frequently used method in discriminant analysis. MDA has been used to separate or group wines according to their qualities and attributes. It enables the discovery of the essential discriminating factors that aid in differentiating between various wine samples. Researchers can successfully divide wines into various groups based on their unique characteristics by using MDA [49].

A researcher has also used linear discriminant analysis (LDA) to distinguish between different alcoholic beverages based on their scents [50]. Finding linear combinations of variables that maximise the separation between various classes is the main goal of LDA, a variation of discriminant analysis. LDA permits the identification of discriminating characteristics that contribute to the differentiation between spirits samples by examining the scent profiles of various alcoholic beverages.

The categorization of wines and discriminating of alcoholic beverages based on scents using discriminant analysis-based techniques, such as MDA and LDA, shows their efficacy in parametric pattern recognition. These methods enable the distinction and categorization of samples according to their unique properties and traits, as well as the discovery of important discriminating criteria.

In conclusion, discriminant analysis-based approaches to pattern recognition use linearly discriminating characteristics to categorise patterns. Wines have been successfully classified using multiple discriminant analysis (MDA), and liquors have been distinguished based on their scents using linear discriminant analysis (LDA).

1.9.5. Nearest Neighbor-Based Techniques

The closest neighbor-based techniques, which depend on the idea of nearest neighbour distance, are regarded as non-parametric pattern recognition methods. Based on the dimensionality of the data, these strategies compute the Euclidean Distance in a multidimensional analysis space. The results of these techniques' categorization or recognition depend on the "k" number of nearest neighbours that are taken into account.

Researchers have used the closest neighbour pattern recognition technique to categorise wines according to their features in the context of wine, utilising varying values of k, such as 1, 3, and 5 [51]. This method establishes the class membership of a given sample based on the dominant class of its neighbours by taking into account the k nearest neighbours.

Another study used the k-nearest neighbour (kNN) algorithm to recognise a variety of odorants, including alcohols and ketones [52]. The number of nearest neighbours taken into account during the categorization process depends on the value of k. The researchers were able to categorise various odorants according to how closely they resembled their nearest neighbours by using the kNN approach.

Additionally, different concentrations of n-butanol, a volatile substance frequently used in odor perception experiments, have been classified using the kNN algorithm [53]. The kNN technique was used by the researchers to classify the various concentrations of n-butanol, and they were successful in doing so with a high classification accuracy of 93%.

Nearest neighbor-based algorithms provide flexible pattern detection without making assumptions about the underlying data distribution due to its non-parametric character. These methods use the local characteristics of the data to classify the data by taking into account the k nearest neighbours.

In conclusion, nearest neighbor-based approaches to pattern recognition, such k-nearest neighbour (kNN), establish class membership based on the distances to the k nearest neighbours. These methods have been used to classify wines, identify odorants, and determine the concentration of volatile substances like n-butanol.

1.9.6. Genetic Algorithms

Finding the best solutions to challenging issues is the goal of genetic algorithms (GA), which are optimisation techniques inspired by the evolutionary process seen in living things. A genetic algorithm was used by a researcher to process the signals obtained by gas sensor arrays [54]. The goal was to use the data to extract the best feature parameters that would allow two different kinds of vinegar to be recognised. The researchers were able to find the most important features and increase the classification process' accuracy by using the genetic algorithm.

In order to categorise target odors, other researchers in the field of odor classification integrated fuzzy support vector machines (SVM) with genetic algorithms [55]. To improve classification performance, the researchers combined the genetic algorithm's ability to optimise with fuzzy SVM's capacity to handle ambiguous or imprecise input. The fuzzy SVM model's parameters were optimised using the evolutionary method, which increased the classification accuracy of odors.

It is possible to explore broad solution spaces and find the best solutions by using evolutionary algorithms in signal processing and pattern recognition. Genetic algorithms offer an effective method for identifying the best feature subsets, optimising model parameters, and improving classification performance by imitating the process of natural evolution.

Genetic algorithms (GA) are essentially optimisation methods that get their inspiration from the processes of evolution in biological things. GA has been used to extract the best feature parameters for distinguishing between distinct kinds of vinegar in the setting of gas sensor arrays. Additionally, to enhance the classification of target odors, a hybrid of evolutionary algorithms and fuzzy SVM has been used. These examples demonstrate how evolutionary algorithms can be used to improve feature selection and model parameters to improve pattern recognition performance.

1.9.7. Decision Tree-Based Techniques

The decision tree is a popular classifier in gas sensing applications because it uses a hierarchical approach and a succession of binary decision-making phases. Researchers have used an advanced decision tree structure to categorise the odors that were recorded by an electronic nose (e-Nose) in the context of odor classification

[56]. The decision tree represents knowledge about chemical components and can classify various odors because of its hierarchical structure. The decision tree approach was used by the authors of the study to classify 11 different odors with an amazing accuracy of 97.18 percent.

Additionally, decision trees have been used to reduce the number of dimensions in e-Nose data in addition to classifying odors. To minimise the complexity and dimensionality of the data while keeping crucial discriminatory information, researchers used a decision tree approach [57]. The data can be effectively compressed without suffering significantly from information loss by building a decision tree based on the pertinent attributes. This dimensionality reduction technology makes it possible to analyse and categorise gases and odors more effectively.

Additionally, low-power hardware implementation in gas sensing devices has been facilitated by the use of decision tree classifiers. Researchers were able to create hardware-friendly solutions for gas sensing applications by using a binary decision tree classifier [58]. This method makes it possible to use decision tree-based classifiers in contexts with limited resources where power usage is a key factor.

A common method for making binary hierarchical decisions in gas sensing applications is the decision tree. It has proven successful at classifying odors, achieving high accuracy in identifying various smells detected by an e-Nose. In order to reduce the number of dimensions in e-Nose data, decision trees have also been used. Decision tree classifiers have also been enhanced for hardware implementations in gas sensing devices that require less power.

1.9.8. Support Vector Machine (SVM)

The mathematical formulation of SVM involves identifying support vectors, which represent the closest data points from various target classes [59]. Since their introduction, Support Vector Machines (SVM) have grown in popularity as a supervised pattern recognition technique. SVM can be applied to both classification and regression problems, utilising the idea of geometric separation among different classes.

Researchers have used SVM as a pattern recognition method in conjunction with a gas sensor array in the context of gas sensing applications to find sour skin disease in onions. The volatile compounds released by the onions are detected by the gas sensor array, and SVM is used to divide the samples into healthy onions and onions with sour skin disease [60]. The identification and grouping of onions according to their state of health is made possible by this binary classification method.

SVM has been used for multiclass classification tasks in addition to binary classification. For instance, utilising the responses of a gas sensor array made up of 12 gas sensor components, researchers have used multiclass SVM to categorise different concentrations of n-butanol [61]. The answers from the gas sensor array may be precisely categorised into their corresponding concentration levels by training the SVM model on various concentrations of n-butanol.

Popular supervised pattern recognition methods for classification and regression tasks include SVM. It works well in a variety of fields, including gas sensing applications, due to its capacity to generate geometric separation between diverse classes. SVM has been used in gas sensor arrays to identify different n-butanol concentrations and detect sour skin illness in onions.

1.9.9. Ensemble Techniques

The ensemble learning algorithm requires iteratively running a classifier to provide various results that are then merged to produce the final conclusion. Using the results of Support Vector Machines (SVM) trained at various points in time and combining them using a weighted mixture of results is one method of ensemble learning. This enhances the classification of gases and odors and compensates for drift [62]. The ensemble approach improves the resilience and accuracy of the classification process by taking advantage of the diversity of the results.

To recognise ginseng using e-Nose technology, researchers have proven the usage of several classifiers ensemble employing SVM, K-Nearest Neighbours (KNN), and Linear Discriminant Analysis (LDA) as base learners. Based on their odor profiles, ginseng samples may now be classified in a more thorough and trustworthy manner thanks to the combination of various classifiers [63]. The ensemble approach can successfully handle the complexity and variability of ginseng odor data by utilising the strengths of various classifiers, such as SVM, KNN, and LDA, which leads to enhanced recognition accuracy.

By pooling the results of various models, ensemble learning approaches provide a potent method for enhancing classifier performance. The categorization of gases and odors can be improved using the weighted combination of SVM results by addressing drift. Additionally, the combination of several classifiers, such as SVM, KNN, and LDA, allows for accurate identification of ginseng utilising e-Nose technology.

1.9.10. Artificial Neural Networks (ANNs)

With the advent of model noses using gas sensor arrays made up of generic gas sensor elements, the area of gas sensing has made considerable strides. The development of novel methods based on the mammalian olfactory system has been facilitated by these model noses, allowing for the detection of intricate odorant mixtures [64]. Model noses have revolutionised the study of gas perception and opened up new avenues for odor categorization and identification.

Researchers have used gas sensor arrays made up of six quartz resonators to successfully execute discrimination between the scents of liquors. Neural networks were used in their investigations to recognise patterns and accurately classify various alcoholic scents [65]. There are now potential for robust and trustworthy odor classification thanks to the integration of neural networks with gas sensor arrays.

Artificial neural networks (ANNs) have been used to improve electronic olfactory systems further. When it comes to odor classification tasks like detecting alcohol in varied situations, ANNs have proven their adaptability for hardware implementation [66]. Gas sensor arrays and ANNs work together to create a potent tool for quantifying and categorising various odorous chemicals.

Kohonen feature maps and multilayer perceptrons (MLPs) are examples of neural networks that have been investigated for use in recognising and measuring gases like hydrogen sulphide and nitrogen dioxide that are present in the air [67],[68].

These neural network-based methods produce precise and trustworthy findings, demonstrating the value of coupling ANN methods with gas sensor arrays.

In a number of odor classification problems, the combination of Genetic Algorithms (GAs) with ANNs has also demonstrated promise. This hybrid technique has proved successful in classifying fragrances, detecting odors in hog farm air, and classifying soft drinks [69], [70], [71]. The accuracy and effectiveness of odor identification systems are increased by the integration of GAs and ANNs, which offers a strong technique for feature selection and classification.

The development of portable e-Nose systems [72], explosive gas/odor recognition [73], wine vintage classification [74], vinegar classification [75], and hydrogen detection [76] are a few other uses of ANNs in gas sensing that have been investigated. These studies demonstrate the adaptability and efficiency of ANNs when used in various gas sensing applications employing gas sensor arrays.

1.10. Convolutional Neural Networks (CNNs)

In image and signal processing tasks, convolutional neural networks (CNNs) have become a popular type of artificial neural network [77]. By using local filters to extract pertinent features, these networks are especially created to take use of the spatial structure of input data [78]. CNNs perform exceptionally well in applications like image classification, object detection, and speech recognition thanks to this property [79].

Convolutional, pooling, and fully linked layers are among the layers that make up a standard CNN's architecture. In order to extract local features from the input data and identify significant patterns like edges, corners, and textures, convolutional layers use a collection of learnt filters [77]. In order to improve computational efficiency and robustness to tiny translations in the input, pooling layers then use downsampling techniques like max or average pooling to minimise the dimensionality of the data [77]. The collected features are then combined by the fully connected layers to produce predictions [78].

Due to their capacity to extract hierarchical representations of input data, CNNs have displayed astounding performance across a wide range of applications [**79**]. According to benchmark datasets like ImageNet and COCO, CNNs in computer vision have produced state-of-the-art results in tasks including image classification, object recognition, and semantic segmentation [**80**]. By identifying local dependencies in text input, CNNs have demonstrated promise in tasks like sentiment analysis and machine translation in natural language processing [81].

Optimisation of the network architecture and hyperparameters is essential to further improve CNN performance. Grid search, random search, and Bayesian optimisation are only a few of the methods that have been suggested for this purpose [82],[**83]**. These methods allow for the systematic study of the hyperparameter space to locate the best setups for particular tasks.

Another strategy that uses pre-trained CNNs to boost performance on new tasks is transfer learning. The model can be adjusted to the unique requirements of the task at hand by fine-tuning a pre-trained network using a fresh dataset [84].

In conclusion, CNNs are effective tools for signal and image processing applications because they can recognise hierarchical patterns in incoming data. Several applications in the fields of computer vision and natural language processing have effectively used these networks. Careful network construction and hyperparameter optimisation, as well as the application of transfer learning techniques, can improve CNN performance even more.

1.11. Unmanned Aerial Vehicles (UAVs)

Drones, sometimes referred to as unmanned aerial vehicles (UAVs), are currently essential aircraft that can be flown remotely or automatically [87] Their ability to enter dangerous or inaccessible locations, gather high-resolution data, and complete tasks quickly and efficiently has been the driving force behind their use in a variety of applications **[85]**. Due to advancing technology and falling costs, the usage of UAVs has significantly increased over time [**86]**. UAVs are currently offered in a variety of sizes and functions to meet both consumer and military needs [**87]**.

UAVs have proven their usefulness in a number of sectors thanks to their ability to carry a variety of sensors and payloads, including cameras, lidar, and gas sensors [**86**]. The high-resolution data gathered by UAVs has helped environmental monitoring, enabling thorough evaluations of air and water quality, wildlife populations, and land use [**88**]. UAVs have shown to be helpful in agriculture for monitoring crop health, applying pesticides, and using precision farming techniques [**89]**. UAVs provide crucial assistance in disaster response situations by evaluating damage, carrying out search and rescue operations, and easing the delivery of necessary supplies [90].

The design and control algorithms of UAVs must be optimised if they are to perform better. Genetic algorithms, particle swarm optimisation, and reinforcement learning are a few of the methods that have been suggested to accomplish this goal

[**91**], [**92**], [**93**]. Through rigorous design space exploration made possible by these approaches, the best configurations for certain tasks can be found.

In conclusion, because they can enter dangerous or inaccessible locations and gather high-resolution data, UAVs are effective instruments for a variety of applications. Agriculture, disaster relief, and environmental monitoring have all benefited from their effective application. Additionally, by improving the design and control algorithms for UAVs, using methods like genetic algorithms, particle swarm optimisation, and reinforcement learning, the performance of these aircraft can be further improved.

1.12. Search and Rescue (SAR) Operations

In order to find and save people in need, search and rescue (SAR) activities are essential to disaster and emergency response [94]. SAR operations necessitate the cooperation of numerous authorities and organisations. SAR operations face many difficulties because of the dynamic and complex character of disasters as well as the requirement for quick action [95]. Unmanned aerial vehicles (UAVs), satellite imaging, and geographic information systems (GIS) have all been used to support these activities [**86**].

UAVs have the ability to collect high-resolution data in disaster zones, search for survivors, and provide supplies, all of which increase the effectiveness of SAR operations [96]. In order to identify crucial locations, satellite photography offers a thorough overview of the impacted area [97] GIS makes it possible to combine and analyse data from many sources, which facilitates making wise decisions during SAR operations [**98**].

The efficiency of SAR operations can be greatly increased by enhancing coordination and communication among the participating agencies and organisations. For this objective, methods such incident command systems (ICS), common operational pictures (COP), and interoperability standards have been suggested [94]. These methods facilitate effective information and resource sharing, which enhances response and results .

Figure 1.3 shows the search and rescue operation (SAR).

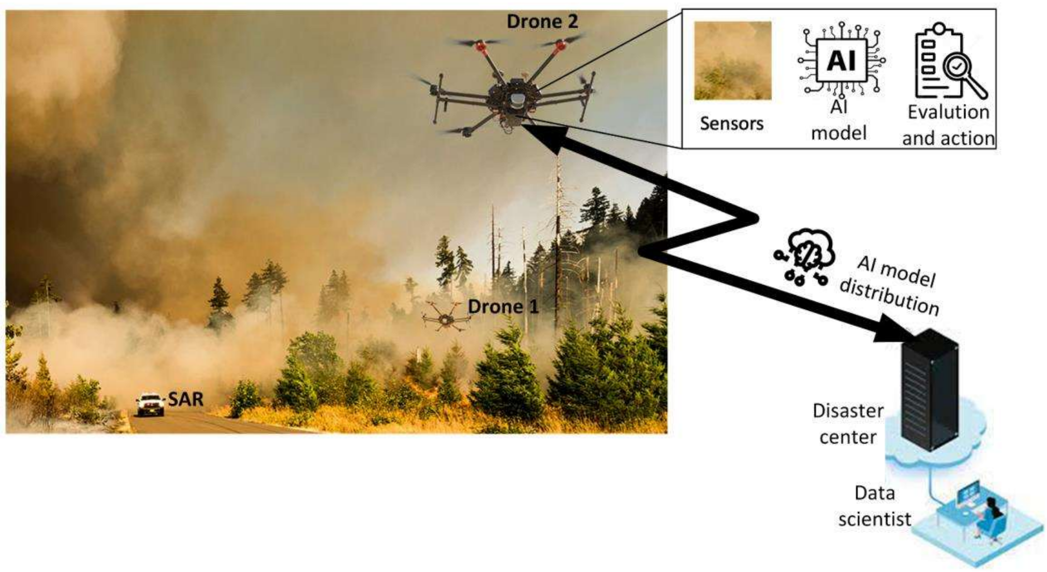

Figure 1.3 : Search and Rescue (SAR) Operation [99]

In conclusion, SAR operations are crucial to disaster and emergency response, requiring the coordinated efforts of numerous organisations to find and save people in need. The efficiency of SAR operations can be increased by utilising technology like UAVs, satellite images, and GIS. The total response can also be improved by maximising coordination and communication using strategies such as ICS, COP, and interoperability standards.

1.13. Intelligent Edge Computing

By reducing the need for data transmission and central processing, intelligent edge computing, which combines artificial intelligence (AI) and edge computing, makes it possible to process and analyse data in real-time at the network edge, potentially improving performance and efficiency for a variety of applications [100]. Edge computing is the practise of placing computational resources near data sources at the network's edge, allowing for immediate data processing and analysis while lowering latency and bandwidth requirements [101]. In the areas of industrial automation, smart cities, and healthcare, it has been widely used [102].

The creation of intelligent edge devices that can learn from data and make decisions in real time is made possible by integrating AI with edge computing. Depending on the application and data characteristics, these devices can utilise a variety of AI techniques, including machine learning, deep learning, and reinforcement learning [103]. Object recognition, anomaly detection, and predictive maintenance are three areas where intelligent edge computing has found use.

In predictive maintenance, intelligent edge devices keep an eye on the health of the equipment and foresee potential breakdowns [104]. Operators can proactively address possible problems thanks to anomaly detection, which makes use of intelligent edge devices to spot unusual patterns in data [103]. To identify things in pictures or video streams in real-time, object recognition uses intelligent edge devices [105].

In order to provide real-time data processing and analysis at the network edge, intelligent edge computing combines AI and edge computing. By reducing the need for central processing and data transfer, this strategy may improve performance and efficiency across many applications. Applications for intelligent edge computing include item recognition, anomaly detection, and predictive maintenance.

1.14. Literature Review

When applying AI-based pattern recognition approaches, gas sensor systems—also known as electronic noses—can achieve great performance [106]. The growth of the IoT has enabled the creation of low-cost intelligent gas sensor systems [107]. Researchers who are trying to create high-performance systems have taken notice of these systems because they are essential for changing cities into intelligent and sustainable environments [108].

Gas sensor systems are able to identify and categorise a variety of gases and odors as well as calculate their concentrations [109]. The monitoring of harmful gases like carbon monoxide, nitrogen dioxide, sulphur dioxide, and particulate matter in the air is just one use for these systems in smart cities [110]. Advanced sensing and smart sensors, in addition to gas sensors, are used in various smart city scenarios[111].

The use of e-Noses has increased in a number of real-world scenarios in a variety of industries, including forensics, textiles, agriculture, automotive, agriculture, food and beverage, beauty and cosmetics, robotics, safety and security, and coal mines [112], [113], [114],[115] ,[116],[117] ,[118].

By adsorbing gas molecules to their surface, gas sensors work. The sensing elements' resistance is decreased as a result. The variation in resistance is inversely correlated with the affinity of various compounds for various sensing components.

This is commonly referred to as the sensing element's sensor response to a specific gas or odor[119].

The creation of electronic noses (also known as "e-Noses") that mimic mammals' olfactory systems has significantly increased during the past three decades [120]. [120]initial notion of a gas sensor array was to resemble the human olfactory system. In order to recognise patterns, they used a variety of general-purpose gas sensors and a neural model. Several pattern recognition methods, including as PCA and its variants, LDA, stepwise discriminant analysis, hierarchical cluster analysis, average slope multiplication, SVM, and others, have been applied to the detection of gases[121]. Intelligent gas sensor systems can be created by combining a variety of unique sensor components with pattern recognition methods. These devices are useful instruments for tracking air quality in smart cities since they can precisely detect and categorise different gases and odors [122].

For pattern detection in gas sensor array responses, neural network-based techniques including ANNs, back-propagation neural networks, MLP classifiers, neural-genetic classification algorithms, and FPGA-based MLP classifiers have also been used [123]. A modular ANN with two connected modules was proposed by Mishra et al., with a classifier module that includes pre-processing and detection blocks and a quantifier module that includes parallel blocks for quantifying gases and odors[124].

Peng et al. introduced a deep convolutional neural network dubbed GasNet with a success rate of 95.2% for gas classification in addition to conventional neural network-based methods. In terms of classification accuracy, GasNet performed better than other classifiers like SVM and MLP [125].

A gas sensor must be both sensitive and selective to detect gas or odor accurately. The choice of an adequate detecting material is crucial for the successful construction of such a gas sensor, frequently sending researchers on an endless search for the best material. These gas sensors have a short lifespan and quickly get poisoned [126].

Conversely, widely-tuned non-selective gas sensor elements react to a variety of gases/odors with varying sensitivity. A significant obstacle to the creation of effective gas sensors is the lack of selectivity for the target gas or odor or cross-selectivity for several gases or odors. This flaw is utilised, however, by developing a variety of diverse sensor elements that produce distinctive signature patterns for various gases and VOCs and by employing AI-based algorithms [127]. The fundamental idea behind virtual gas sensors (VGSs) and virtual gas sensor responses (VGSRs) may be useful in this situation [36].

Gas sensor array (GSA) was an important step in the development of e-noses and prompted a rise in the use of this technology [128]. However, based on the information currently accessible [129], there is currently no defined guideline defining the ideal number of gas sensors to be employed in a GSA. Hardware redundancy occurs within the system as a result of the unrestricted use of gas sensors in a GSA [130]. The gas sensor system (GSS) has a higher risk of system failure as a result of the complexity of the circuitry, higher power consumption, and increased chip or mounting platform space requirements that come with using more gas sensors [131].

Virtual gas sensors (VGSs) were proposed as a solution to these problems, with the intention of reducing the dependency on actual gas sensors [132]. There are two widely used methods for determining virtual sensors (VSs) or virtual sensor responses (VSRs) in contemporary research. A single gas sensor is used in one method, but the dynamic responses are captured by adjusting physical factors including affinity, temperature, resonance frequency, and more [133]. The alternative method relies on a few physical gas sensors' responses to extract the VGSRs utilising a variety of transformation techniques [134].

By modifying the characteristics of a single sensor, which was built using the electrochemical chemo-transistor approach, a virtual sensor array was created. Through changes in the redox states, which were managed by electrical processes, this manipulation involved changing the affinity of the chemosensitive material in the sensor [136]. The analysis of fish freshness using the virtual sensor array approach [135]. Researchers made use of temperature modulation to increase the number of sensors that were actually useful. They developed a biological olfactory system (BOS) employing a metal oxide (MOX)-based gas sensor and accomplished temperature modulation using a micro-hotplate. They were able to improve the system's performance with this strategy, scoring an astonishing 96 percent accuracy [137].

In addition, by varying the frequency of various resonant modes, a virtual sensor array was created for the detection of volatile organic compounds (VOCs). In order to analyse the experimental results, the researchers used machine learning algorithms, and they were successful in correctly identifying 95.8% of VOCs and 87.5 percent of mixes [138].

In the context of e-Noses, the use of data-driven virtual sensors (VRs) or virtual sensor responses (VSRs) has become more common. As previously indicated, this strategy entails applying several transformation algorithms to derive VSRs from the responses of a physical gas sensor array [36].

The Normalised Difference Sensor Response Transformation (NDSRT) is a method used to derive VSRs. The number of VSRs was effectively increased by a factor of (n -1)/2! using this method on a particular dataset, where n is the number of gas sensors in the related gas sensor array (GSA). They also conducted a qualitative evaluation of their method, exhibiting unique reactions that permitted the classification of gases and odors. The results of the experimental classification of gases and odors were not, however, compared quantitatively [134]. Principal component analysis (PCA)-based VSRs and the usage of zero padding have also been described [3].

There have been numerous methods for creating high-performance gas sensor systems, but one important application for these clever gas sensor systems is in search and rescue efforts in disaster-affected areas [138]. Additionally, it has recently been demonstrated that unmanned aerial vehicles (UAVs) are particularly beneficial in a number of applications, including smart agriculture, security, power line inspection, surveying and mapping, surveillance, search and rescue (SAR), delivery, and disaster area coverage [139]. In example, by enabling operations that were previously only possible for on-site farmers, UAVs with gas sensor systems as payloads can play a significant role in crop monitoring [140].

In SAR operations using UAVs, an auction-based technique can be used to assign the best UAV to a survivor based on the distance between the UAV and the survivor[141]. During natural disasters, the majority of survivors are typically concentrated in one area. SAR activities should therefore give priority to this core position and become less important the farther they are from it[142]. In a catastrophe emergency communications system, UAVs may be immediately deployed, and their coverage can be dynamically changed. They offer quick and efficient network assistance for SAR at disaster sites and are able to relay real-time information from the catastrophe scene back to the SAR crew to help with rescue efforts[143]. Since disasters sometimes impair business networks in the afflicted area, communication between the disaster relief command centre and SAR is essential during the disaster relief process. In order to monitor the region and help SAR find and track people or animals in danger, a UAV network fitted with gas sensor systems can be deployed at the catastrophe site[144].

In several applications, AI plays a significant role in enhancing the performance of robotics, including UAVs fitted with gas sensor systems. Air Learning is a Deep Reinforcement Learning (DRL)-based open-source simulator environment for UAVs that has been developed by several researchers [145]. Without exchanging private raw data, federated learning (FL) has been utilised to enhance UAV swarm computing scheduling and power allocation[146]. In Internet-of-Vehicles applications like parking and traffic prediction, FL has also been utilised to protect privacy[147]. Decentralised FL architecture over UAV networks has been discussed by researchers [148]. Edge servers in base stations are used as intermediary aggregators with widely shared data in a novel and highly effective FL technique for edge-aided UAV networks that has been reported by certain researchers [149]. Blockchains have been introduced by certain researchers to secure data exchange in B5G for UAV computer networks for privacy and high levels of security [150]. Blockchain-enabled FL in UAV edge computing networks has been noted by one researcher [151]. Additionally, a different researcher has talked about the use of FL and blockchain for UAV edge intelligence in smart environments [152].

1.15. Problem Statement

There are several factors that might be utilised in light of the aforementioned literature review and by gaining knowledge of the patterns of present and potential future advances with enhanced gas sensing systems. For the detection and estimation of various gases and odors, gas sensors are frequently utilised. However, it might be challenging to evaluate and comprehend the raw sensor outputs. In addition, CNNs are demonstrating to be particularly effective tools for automatically extracting features from datasets. However, due to the small number of gas sensing elements in a gas sensor array—for example, an array of three gas sensor elements, six sensor elements, or even if it is a 16 element gas sensor array—we need a larger set of input data vectors for better feature extraction in CNNs, which is typically not possible in gas sensor systems. As a result, one extremely practical approach is to scale up the gas sensor answers that were physically collected by adding virtual sensor responses. We can also use mirror mosaicking to provide the same data to CNN in a different way while boosting the elements of the gas sensor response vector. Through mirror mosaicking in the North, North-East, North-West, South, South-West, and East and West directions, a simpler 3-element gas sensor array can be upscaled to a 2x2 gas sensor array, which can then be upscaled to a 6x6 (i.e. 16-element) vector. We can make the resulting metrix larger by mirror mosaicking it, making it 18x18 and so on. By including virtual sensor responses that are perfectly square and upscaling them further, CNNs can extract a significant quantity of relevant characteristics that would otherwise be impossible to use. In order to enable the use of CNNs on significant data points, one of the studies we have selected for exploration adopts the spatial upscaling strategy to convert steady-state gas sensor responses into a two-dimensional template. The suggested transformation has been demonstrated to accurately identify and estimate a variety of gases and odors while retaining the information included in the raw sensor response.

Additionally, we can create as many virtual sensor replies as necessary to complete the ideal square shape, even if we can add the necessary zero-value vector elements to transform the real sensor array response into a perfect 2-D $n \times n$ vector. As a result, we have also thought about proposing a novel method for creating data-driven virtual sensor responses (VSRs) that uses a three-input, three-output (TITO) mechanism. This method results in upscaled and downscaled VSRs that scale-up the dynamic range of responses and increases the number of VSRs by 6(n -1)(n -2)/3!. The improved dynamic range makes it easier to improve response patterns later on, introducing saliency for more accurate classification of gases and odors. Nine machine learning algorithms were used to test the effectiveness of this method, and it was found to be more effective than the well-known data-driven VSRs methodology "NDSRT."

Additionally, search and rescue (SAR) efforts may be time-sensitive during catastrophic events. This study discusses a variety of UAV computing paradigms that can help with SAR by offering targeted missions, clever techniques, and functions.

High-resolution photos can be captured by UAV computer intelligence, which enables data scientists to identify urgent circumstances immediately. Smart devices and UAVs can be used to speed up SAR and cut down on valuable search time. The proposed network framework has been tested for delay, throughput, load, traffic delivered and received, and path loss from UAVs to SAR at various ranges. It also incorporates SAR and crisis centres.

In conclusion, this research project discusses the difficulties in analysing gas sensor results and suggests a creative method for converting them. It also introduces UAV computing to speed up SAR operations in emergency situations.

1.16. Outline of the Thesis

In many different applications, such as environmental monitoring, workplace safety, and healthcare, gas sensing is essential. However, there are substantial difficulties in analysing and interpreting the raw gas sensor data. Contrarily, Convolutional Neural Networks (CNNs) have demonstrated tremendous promise for automating the feature extraction process from datasets. However, due to the lower input data vectors, the constrained number of gas sensing components in gas sensor arrays makes it difficult to use CNNs effectively. Therefore, it is necessary to investigate methods that enable better feature extraction in CNNs using responses from gas sensors.

The suggested method of upscaling gas sensor answers by incorporating virtual sensor responses and using mirror mosaicking enables the extraction of more beneficial characteristics from gas sensor arrays, boosting CNNs' capacities for precise detection and estimation of various gases and odors. The ability to use spatial upscaling to convert gas sensor data into a two-dimensional template, permitting more effective use of CNNs, and overcoming the shortcomings of conventional gas sensing systems is the driving force behind this research.

This study work combines the use of UAV computing in search and rescue (SAR) missions during disaster events in addition to the transformation of gas sensor response. The utilisation of UAVs with intelligent computing skills can speed up difficult problem-solving and provide essential functionality in SAR missions, which are time-sensitive. We can record the ground-zero signature patterns of the gases and VOCs being emitted from the disaster-affected area using UAVs fitted with clever gas sensor systems, enabling data scientists to analyse and make decisions in real time. A network structure is provided to improve the effectiveness and efficiency of SAR operations where our proposed improved e-noses can be deployed as payloads by integrating UAV computing with SAR and crisis centres. In order to improve communication and coordination between UAVs and SAR teams at various distances, the framework is assessed based on a variety of performance criteria, including delay, throughput, load, traffic, and path loss. The goal of this study area is to use UAV computing to increase the efficiency and precision of SAR operations, thereby saving lives and lessening the effects of disasters.

The necessity to overcome the difficulties in analysing gas sensor responses and the potential advantages provided by cutting-edge approaches serve as the driving forces behind this research. This project intends to increase the capabilities of gas sensing systems and boost the effectiveness of disaster response by spatially upscaling gas sensor responses and applying UAV computing paradigms in SAR missions. Through improved feature extraction and real-time assistance for crucial decisions in

SAR operations, the suggested methodologies have the potential to revolutionise gas sensing analysis.

The outcomes of this research work have been presented in the following chapters:

We give a thorough overview of the history and current condition of gas sensing system development in Chapter 1. To better comprehend the research environment, we examine the hardware component of these systems. We create the groundwork for investigating creative solutions to current problems by looking at the parts and technologies used in gas sensing. We also cover the software side of gas sensing systems in great detail, with an emphasis on the use of Artificial Intelligence (AI) methods. Gas sensing systems' intelligence and adaptability can now be improved with the help of AI. In order to unlock new possibilities and enhance the precision and effectiveness of gas detection and estimate, we investigate several AI approaches and their possible applications in the field of gas sensing. Gas sensing systems can learn, adapt, and make wise judgements based on the gathered data if we can harness the power of AI algorithms. To identify and characterise the precise issue statements in the area of gas sensing, we have incorporated a thorough literature review. Reviewing earlier research helps us understand the flaws and restrictions in the methods used now. Based on this knowledge, we suggest fresh approaches to fill in these knowledge gaps and progress the field of gas sensing. We have presented a thorough review of gas sensing systems in this chapter, discussing the hardware, software, and AI techniques in the context of more sophisticated and optimised gas sensing systems.

In Chapter 2 of our thesis, we give a thorough summary of the resources and procedures we used, illuminating the scientific foundation of our investigation. We want to clarify the benefits and potential of advanced neural networks in improving gas sensing performance and accuracy by providing our research and analysis. This chapter presents the materials, methodologies, and technical background required to comprehend our approach, serving as a fundamental building block for our research. We draw attention to the advantages of advanced neural networks over traditional ANNs and explain how MOX gas sensors function. The datasets utilised in this research are also included.

The critical requirement for real-time detection and assessment of dangerous gases and odors in the air is addressed in Chapter 3 of this thesis. We have developed a novel method for examining the signature responses of multi-element gas sensor arrays using a convolutional neural network (CNN). The goal is to increase detection and estimation accuracy for hazardous gases by geographically upscaling and processing real-time responses on the edge using lightweight CNNs. We have shown that the raw sensor answers, initially consisting of a four-element (22) array, when upscaled to 66 responses, can be generated utilising 42 samples of 66 input vectors and a lightweight CNN, and 16 unknown test samples could be accurately recognised. The system's adaptability enables its generic design, which enables it to be tailored to other gases and interesting odors. This study work delivers a substantial contribution to the field of real-time monitoring and air pollution reduction with AI-based gas sensing devices.

The use of partially selective gas sensors for high-performance classification is the main emphasis of Chapter 4 of this thesis, which explores the subject of gas and odor detection. Since the 1980s, electronic noses (e-Noses), which employ arrays of broadly tuned gas sensors in a variety of scientific and technical applications, have grown in popularity. In order to achieve high selectivity in gas sensing systems (GSS), e-Noses combine comparable or dissimilar sensors in an array. Virtual sensor responses, or VSRs, are the prominent qualities obtained from the initial responses of the gas sensor array (GSA) that determine how well an e-Nose performs. In this study, a brand-new method known as the three-input, three-output (TITO) strategy is put forth to generate effective VSRs that outperform previously reported methods. The four-element GSA used to demonstrate the suggested technique shows that it improves the VSRs four times more than the peer technique. Nine fundamental classifiers are used to assess the effectiveness of the suggested method, and ten-fold cross-validation is used to reduce bias. Interestingly, four classifiers attain a phenomenal accuracy of 100 percent. This chapter introduces and validates an effective method that makes a substantial contribution to the field of gas and odor detection while also promisingly advancing the design of electronic noses.

The employment of UAVs with improved gas sensor systems as payloads to boost the effectiveness of Search and Rescue (SAR) missions is the main topic of Chapter 5 of this thesis. Disasters pose serious risks to human life and frequently lead to a breakdown in the public communication infrastructure, which hinders SAR attempts and slows down emergency response. In difficult conditions and during disasters, SAR is essential for risk mitigation. Rapid communication networks must be set up immediately in order to enable the exchange of emergency data during SAR operations. A potential answer to these issues is provided by unmanned aerial vehicles (UAVs). UAVs may be immediately deployed and act as flexible and dependable emergency communication backbones, assisting with the prompt rescue of people in disaster-affected areas. In this study, we assess the network performance of intelligent edge computing supported by UAVs, which can greatly speed up SAR missions and improve functionality. Our evaluation takes into account important network factors such path loss, throughput, traffic sent and received, and delay. Furthermore, we show that optimising these parameters enhances network performance significantly, allowing for more effective SAR operations in disasters and difficult situations. We seek to improve the efficiency of SAR operations by merging cutting-edge gas sensor systems with UAVs, enabling swift and precise rescue operations to save lives in emergency situations.

The study conducted in the earlier chapters is concluded in Chapter 6, which also offers a summary and future prospects based on these research activities. In order to illustrate the dissertation's contributions, it also shows the key discoveries.

1.17. Conclusion

In summary, this thesis offers a thorough investigation of gas sensing systems, examining the hardware, software, and AI methodologies utilised in their creation. The usage of MOX gas sensors and cutting-edge neural networks has been emphasised, highlighting its benefits in improving gas sensing performance. Through spatial upscaling and quick CNN processing, the unique method of using convolutional neural networks for real-time identification of dangerous gases has shown improved accuracy. Additionally, the performance of partially selective gas sensors has been enhanced thanks to the proposed three-input and three-output technique, making a contribution to the field of gas and odor detection. Advanced gas sensor systems have been researched for integration with UAVs, with a focus on their potential to improve Search and Rescue (SAR) operations by building quick communication networks and maximising network performance. This study makes significant contributions to the area and opens the door for hopeful future developments in gas sensing and SAR missions.