Advancements in Gas Recognition Techniques for Electronic Nose Systems: A Comparative Review of Classical Methods and Spiking Neural Networks

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Abstract- *An electronic nose (E-nose) system's ability to recognize multivariate responses from gas sensors in a variety of applications necessitates gas recognition. Principal component analysis (PCA) and other traditional gas recognition methods have been widely used in E-nose systems for decades. ANNs have transformed the field of E-nose, particularly spiking neural networks (SNNs), significantly in recent years. In this paper, we compare and contrast recent E-nose gas recognition techniques in terms of algorithms and hardware implementations. Each classical gas recognition method has a relatively fixed framework and few parameters, making it easy to design. It works well with few gas samples but poorly with multiple gas recognition when noise is present.*

Keywords: Gas detection, electronic nose, artificial neural network, and spiking neural network.

1. INTRODUCTION

The human nose is a helpful scientific device for deciding the nature of food before utilization and distinguishing possibly unsafe gases in the climate in regular day-to-day existence. Tactile boards, which are gatherings of prepared or undeveloped people who finish assessment polls in view of the scents of the items, are utilized in numerous enterprises to survey the nature of beverages, food, aromas, beauty care products, and unstable synthetic items. As indicated by Bush did et al., the human nose has roughly 400 aroma receptors and can recognize no less than one trillion scents. The human nose is able to rate smells, but it cannot detect toxic gases, and individual judgments may be biased. Additionally, the human nose has limits for distinguishing gases. The human nose cannot be used for any kind of smell-related classification or discrimination because of these limitations. A gas sensor array known as an electronic nose (e-nose) responds in a fingerprint fashion to particular volatiles. Pattern recognition algorithms, such as artificial neural networks (ANN), to differentiate between objects, can then use this fingerprint response. An electronic nose's detecting, deciphering, and segregating process is a reenactment of human olfaction.

More often than not, unpredictable atoms respond with the gas sensor's detecting materials to change electrical properties like conductivity for eternity. Design acknowledgment calculations then, at that point, recognize and describe these progressions with the end goal of segregation or arrangement. Compared to conventional gas analytical equipment like GC–MS, HPLC, and FT-IR spectrometry, e-nose requires less time and is less expensive. E-noses are less one-sided than tangible boards and give more reliable estimations between gadgets. As a result, e-noses can be used to monitor a variety of smell-related handling processes, such as the maturation of tea and cocoa beans, the cooking of espresso and cocoa beans, and the duration of chocolate conching. E-noses can also be used to identify smells associated with food, such as the freshness of meat, vinegar varieties, and meat spoilage.

2. RELATED WORK

K et al. The biological olfaction-based E-nose system, which was first proposed in 1982, has been in development for nearly 40 years. According to reports in [3–5], E-nose has achieved remarkable success in a variety of applications, including public health [6–8], food safety [9–15], environment monitoring [16–17], agriculture [18], industry [19], air quality testing [20–22], the military [23], and so on.

Gardner, J.W. et al. is an important historical milestone for his 1994 E-Nose. [24], which he believes modularized the E-Nose system into two separate models for him: the signal conditioning circuit and the sensor. Rated. Tan KT and Goodman R. Seven years later, M. presented a fine-grained E-nose with a gas identification circuit, readout interface circuit, and sensor array [25]. His E-Nose method in [25] was more powerful than the work in [24] and was widely adopted shortly thereafter.

Despite the fact that the unrivaled E-nose structure has been proposed, fulfilling the market's prerequisites for convenience and ongoing detection is yet unfit. As reviewed in [24], E-Nose has evolved from being large, prohibitively costly, and power supply dependent to being small, minimally costly, and power dependent. Did. Analysts normally focus on the three fundamental parts of these E-nose frameworks while planning them: gas acknowledgment circuits, readout interface circuits, and sensor clusters. The sensor array combines a number of distinct gas sensors with a microfabrication process (MEMS). Each sensor in the array responds to various odors in a different way as a receptor. The sensor signal is converted into an electrical signal by the interface readout circuit [26].As discussed in [28]–[30], an E-nose chip typically contains both a CMOS (complementary metal oxide semiconductor) readout interface circuit and a MEMS sensor array [27]. The gas detection circuit processes the signal received from the interface readout circuit and then uses various gas detection methods to produce the final detection result.
In the 2000s, KNN, SVM, DT, NBM, PCA, and LDA were the main areas of research. Albeit every traditional gas acknowledgment technique has a moderately fixed system and few boundaries, simplifying it to plan and broadly utilized, it is trying for them to distinguish numerous scents within the sight of clamor precisely. In addition, they are frequently carried out by large microchips (such as MPU [30]-[33]), which require a significant amount of power to function appropriately in a compact E-nose framework.

It has been exhibited that gas acknowledgment circuits in view of counterfeit brain organizations (ANNs) are more successful thanks to their versatile designs [34, 36]. However, a significant amount of data from gas sensors is needed to train an ANN. In addition, the versatile E-nose framework cannot carry out an ANNs because of their intricacy. When designing ANN-based gas confirmation calculations that differ from standard gas confirmation calculations, Application Explicit Adjustment Circuits (ASICs) or Field Programmable Gate Exhibits (FPGAs) ([38]-[41]) are often used.

Gardner, J.W. et al. [24] As far as we know, the first instrumental version of the E-Nose framework was provided in 1994. It consisted of direct sensor readings, signal preprocessing circuitry, and gas detection circuitry utilizing back propagated brain tissue. Five years later, B.C. Muoz et al. [78] proposed a revised e-nose model framework. This system, similar to [24], consisted of a PC acting as a gas detection circuit, a backup board with a 22-bit ADC and chip, and a 32-channel touch panel display. Unfortunately, pre-2000 chip manufacturing was a bit outdated, so the E-Nose was a bulky device.

K.-T. Tang et al. presented an electronic olfaction framework on a chip in 2001[25]. With Euclidean distances, the framework joined gas acknowledgment and point of interaction readout circuits. With recording sensor information highlights, distinguishing eight unique odors was capable. Poor data connections between circuits and the lack of an energy-efficient architecture resulted in slow response times and too high power consumption for the chips. Several studies have focused on gas concentration estimation in addition to gas identification circuits. C. Hagleitner et al. developed his three sensors and chips for micro chemical sensor systems to measure his two unique concentrations of ethanol and toluene. This chip was created by combining complex and basic circuits.

Unfortunately, these efforts failed to produce a gas sensing circuit. Yes. Covington et al. presented a new chip for gas sensor systems in his 2003 [80]. In contrast to previous work in [79], this study produced an array with his 70 sensors and integrated circuits for driving, amplification, and baseline rejection. It was delicate to ethanol at 0.00012 percent/ppm and to toluene at 0.00644 percent/ppm, separately.

Before 2006, there were no reports of fully integrated E-nose chips with gas recognition, readout interface, and sensor arrays. Starting around 2006, specialists have been searching for a high-uprightness, energy-proficient arrangement with less power misfortune and longer battery duration. In 2006 Tang, K.- T et al. [81] created a polymer sensor chip with a diameter of 1.5 millimeters that could differentiate between eight distinct odors. Instead of the advanced partner, a simple memory introduced on the chip was picked. Thusly, simple to computerized (A/D) and advanced to simple (D/A) converters, which consume the most power, were tried not to by store information analogy. In reserve and full burden modes, the chip utilized 7.6 mW and 1.3 mW of force, separately. In 2011, they developed a chip with eight sensors and lower power consumption to completely classify three smells [31]. With a stockpile voltage of 1.8V, the gas acknowledgment circuit created in a 0.18 m cycle used 2.81 mW of power. When compared to their previous work in [81], this one made significant progress in terms of power savings.

The study of Tang, K.-T. et al. Described a fully integrated E-nose system-on-chip (SoC). [32], 2014. In contrast to [82] shown in Fig. 2, this fully integrated device had eight on-chip sensors, a gas identification circuit and a readout interface circuit. Two cores were used in the gas detection circuit. 1) CRBM focus with stacked probabilistic thinking networks to reduce data perspective. (2) RISC's status as an ANN classifier to provide confirmation results. At 0.5V, the chip utilized 1.27 mW and gave a fast method for diagnosing ventilator-related pneumonia with 95.73 percent precision utilizing a 0.18 mm process.

The device required 0.22 mW more power than its predecessor, which consumed 1.05 mW, but the overall system is integrated and higher thanks to two processor cores and a series of buses for high-speed data transfer. It has computing power. In addition, the E-nose chip's on-chip learning function and standard interface protocol make it easy to connect additional devices. In 2016 [33], the developer released another of his E-Nose SoCs with 92° curacy to continue screening for obstructive pulmonary disease. It used a structure similar to [32].

K.-T. Tan et al. In 2018, we published a follow-up paper [30] on an e-nose SoC with on-chip learning. In contrast to a previous study that used eight sensors [32], the device features his 36 on-chip sensors, including temperature and humidity sensors that collect natural data. The device was made using 180nm CMOS technology and 2.6mW at 1V. Additionally, a partial revision of the modified PCA was used as temperature and humidity compensation calculations around CRBM+KNN for grouping. They collected data from 70 gas sensors, including methanol and ethanol, to evaluate the chip's performance. In the end, we achieved an order accuracy of 93%.

Our research revealed that the classical gas recognition algorithms in E-nose achieve high accuracy for small samples with limited gas sensors [62, 67, 69, 71, 72]. This is due, in part, to their general nature. The majority of traditional approaches are based on SVM and other non-linear techniques. When the example size is small, it is not hard to find the non-straight connection between elements and information using SVM. Nevertheless, the customary calculations are not generally the most incredible in certain circumstances. On the same dataset, studies in [34, 35] demonstrate that ANNs-based gas recognition approaches are more accurate than traditional methods like SVM.

Our examination uncovers that two primary algorithmic constraints forestalled the vast majority of the proposed gas acknowledgment calculations from being carried out on chips: equipment agreeableness and the capacity to diminish commotion. The implicit elements of numerous customary gas acknowledgment calculations require lattice duplications and a lot of sensor information, making their execution in low-power chips testing. KNN is used in many e-noses because it is more reliable than other calculations and compatible with devices. Another drawback is the lack of noise protection. Sensor data may contain errors due to the general environmental tolerance of gas sensors [27]. The E-Nose system and its sensors work effectively in a stable laboratory. However, in practice, the representation of equivalent E-Nose frameworks with equivalent sensors varies significantly. Therefore, E-Nose systems require low-noise, hardware-friendly gas detection algorithms that can detect a wider variety of gases.

A back propagation neural network (BPNN), a fundamental ANN with a forward structure, transforms a set of input vectors into output vectors. An initiation capability influences the result of the information vector and the underlying load to be shipped off the neurons of the ensuing layer until it arrives at the result neurons. From that point forward, the genuine worth and the result esteem are handled by the misfortune capability, and the outcome is utilized by the chain rule backward to refresh the heaviness of every neuron in each layer. Iterations are used to discover this network's local optimal solution for classification or regression [83]. YH et al. [34] in 2009, he created his PCA + BPNN classifier that could predict green tea quality grades with an accuracy rate of 88%. Other applications of BPNN for gas detection have been published in recent years, such as 96.4°Curacy for identifying Aspergillus species and abundance in 2019 and 94°Curacy for identifying freshness in chicken [35].
Convolutional cerebrum association (CNN) is a prominent significant getting the hang of designing pushed by the typical visual wisdom instrument of the living creatures [94]. As indicated by our insight, Pai Peng et al.'s work was the first to use CNN to recognize gases. [84] in 2018. They acquainted a CNN with up with 38 layers to test 4 unmistakable scents with 95.2% precision in an extent of core interests. Xiao Fang Holder et al. introduced another work [85] in 2019 about a novel hybrid method that used convolutional and recurrent neural networks (RNNs) to accurately identify four distinct gases. In the year 2020, Wang and coworkers. In the convolutional and pooling layers of the proposed optimized CNN, a unique striped 1D kernel was utilized [86]. With an accuracy of 87.56 percent, the work classified a variety of Chinese herbal medicines. D. Mama et al. A deep conventional neural network with 15 layers that could recognize 10 distinct volatile organic compounds (VOCs) using a sensor array response map was proposed in 2021 [87].

T.J. Koickal et al., The mixed-signal SNN neuromorphic olfaction chip, which includes a gas recognition circuit, an interface circuit, and an on-chip sensor array, was first proposed in 2006, [123]. A two-layer SNN with 12 neurons and 81 synapses was created using analog circuits. The global STDP and local lateral inhibition learning rules of the output layer were used to train the spike weights of synapses. Beyeler et al. [44] proposed another gear prototype in 2010. In contrast to [123], the neuromorphic VLSI chip had 2048 neurons and 6144 synapses digitally constructed. The works in [44] and [123] laid a solid foundation for subsequent research as early SNN olfaction chips. The accuracy and power consumption of these two works were not, however reported, and no additional system design was published.

In 2010, H.S. Abdel-Aty-Zohdy and colleagues created an olfactory neuromorphic SNN chip for gas detection with 255 neurons and 32,000 synapses [124]. This allows on-chip learning to detect gases in noise. However, the sensor cluster and SRAM memory are not integrated into the device and neither test results nor power consumption are considered.

According to Tan, studies by K.T. et al. have shown that since 2011, wearable e-nose devices with spike sparsity have been suitable for energy-efficient SNN chips. 49]. This work produced his SNN chip for gas identification. He detects gases by comparing them to reference gases in a 2D spatiotemporal feature library and converting the sensor array data into a 2D peak sequence. The device was divided into four independent groups of SnO2 gas sensors and two sections of his SNN circuit to demonstrate odor detection. The sample I ordered was tested with three gases, the process was 0.35 mm, 6.6 mW, the voltage range was 0.15 V to 2.7 V, and the accurate detection rate was 94.9 percent.

Hsieh proposed better exploration on SNN olfaction circuits in 2012. Additionally, Tang K.T. described an energy-efficient SNN chip based on the OB model in [125]. In comparison to [49], sub-threshold oscillation and onset-latency representation further optimized chip area and power consumption. With no sensors cluster, this chip was made with interaction of 0.18 nm and consumed 3.6 watts.

Commercial e-nose sensors (Cyranose329) sampled three different kinds of gas data, with a correct detection rate of 87.59 percent.

Hsieh, H.Y., et al. in 2017 [126] proposed a probabilistic spike brain organization (PSNN) on-chip learning simple circuit with a gas acknowledgment precision of 92.3% for three fruity scents. Under the condition that every semiconductor was working in the subthreshold locale, this chip, which was developed utilizing a 0.18-m CMOS process, required under 10W to work at a stockpile voltage of 1V. Despite the fact that there were no on-chip sensors or SRAM, this low-power approach looks encouraging for planning wearable, implantable, and versatile E-nose gadgets.

3. CONCLUSION

In this work, we validate gas detection methods in E-nose in parallel with classical ANN- and SNN-based computations and their device implementations. Our findings show that classical gas confirmation calculations are easy to implement and perform well for limited gas tests with some boundaries and reasonably fixed structures, but under turbulence Not sufficient for checking multiple gases. They are commonly used to detect 5 different gases. On the other hand, ANN-based gas confirmation calculations can achieve satisfactory accuracy for various gas information. ANNs are often designed as ASICs rather than MPUs using standard methods.

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