Rapid Detection of Toxic Emissions Using DNN Based Sensing

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***Abstract*— Smoking remains one of the top 3 causes of illness in the US; it is one of top 5 causes of fire hazards in a home and is the single most preventable cause of illness and premature death in the US. The use of Deep Neural Networks (DNN) is demonstrated to detect cigarette smoke much sooner and with much higher accuracy than conventional smoke/carbon monoxide detectors used today. The hardware demonstration and prototype engages machine learning to not only discriminate cigarettes from other sources of smoke and carbon monoxide such as burning coal, wood or food – typically not possible with conventional smoke detectors, but also to accurately detect cigarette smoke produced in a room from a single cigarette when concentrations of component gases of cigarette smoke are extremely low. Our prototype also demonstrates the opportunity to classify and discriminate different levels of toxicity and flammability for spaces used by different people.**

Keywords- DNN; IoT; Cigarette; Toxic; Detection; Sensors

I. INTRODUCTION

Secondhand smoke is a serious health hazard causing more than 41,000 deaths per year [1]. Secondhand smoke is not risk-free and even short-term exposure can potentially increase the risk of heart attacks. Secondhand smoke contains chemicals known to be harmful. These include formaldehyde, benzene, vinyl chloride, arsenic ammonia and hydrogen cyanide [2]. Smoking is not just a health hazard but also a significant fire hazard. The National Fire Protection Association (NFPA) reports [3] During 2012-2016, an estimated annual average of 18,100 (5%) or, one in 20 home (5%) structure fires were started by smoking materials. These fires caused almost one in four (23%) home fire deaths, and one in 10 (10%) home fire injuries.

Conventional smoke detectors are mostly responsive to carbon monoxide and generally trigger an alarm when the concentration of carbon monoxide exceeds a given threshold. These detectors are also generally agnostic to the source of carbon monoxide and cannot discriminate cigarettes from burning coal, wood or food. The urgency to detect cigarette smoke – especially for people vulnerable to secondhand smoke or other toxic gases is much higher and warrants a trigger at a much earlier time. The trigger should also not require the concentration of cigarette smoke in the air to be as high as conventional detectors since early warning can potentially remove the source of cigarette smoke in areas especially sensitive to second hand smoke such as Hospitals. The detection of cigarette smoke should also be consistently accurate even at low concentrations of the components of cigarette smoke such as hydrogen cyanide, formaldehyde, benzene and carbon monoxide.

The rest of the paper is structured as follows: Sections II & III describe conventional gas detector technology, methods and their weakness. Sections IV and V describe our prototype hardware used with AI algorithms instead and measurements. Section VI discusses the Training accuracy and loss of our DNN algorithms.

II. CONVENTIONAL DETECTOR TECHNOLOGY AND USE

Conventional gas detectors have evolved in their technology and how they are used as the need to detect CO and fires is emphasized by NFPA regulations.

A. Technology

Conventional gas detectors use a metal oxide sensor to measure the concentration of specific gases. Typically employed to prevent toxic exposure and fire, these cover a range of gases in the flammable and toxic range but most detectors include CO sensors. The metal oxide sensor technologies [4] work by engaging the relationship between electrical conductivity and oxygen partial pressure of a metal oxide sensor. The resistance of the sensor correlates to the concentration of the reducing gas. MQ Sensor modules include op-amp comparators and digital output pins to provide an indication of the presence of gases. Where a quantified measure of the amount of gas (in ppm) is needed, the bare sensor is used in conjunction with a microcontroller.

B. Methods and Limitations

The sensors used in Google Nest (2nd gen) [5] include the Smoke Split-spectrum sensor that detects the presence of smoke in the air using two wavelengths of light to look for smoke. An infrared light is used to detect larger particles generated by slow, smoldering fires, while a blue light detects smaller particles created by fast fires. All of commercially available sensors rely on the sensor itself to identify smoke, fires, flammable or toxic gases. Their common weakness is that detection of smoke, fire occurs too late when the premises are already on fire or when the concentrations of toxic/flammable gases are already dangerously high to be able to trigger the sensor. The primary cause for home structure fires – unextinguished and undetected cigarette butts cannot be detected by conventional detectors simply because the concentrations of emissions produced by a single cigarette are too low to trigger conventional detectors.

III. SENSORS AND METHODS USED

We used industry standard MQ sensors but our methods to detect toxic and flammable gases relied on measurements of changes in patterns of component gas concentrations and their recognition instead of direct measurements of gas concentrations.

A. *Pattern Recognition*

Pattern recognition works well for toxic gases that have signature patterns of component gases – as typically found in cigarette smoke or vape. Gases found in hospitals (Anesthetic's, aerosolized medications and chemicals used as a fixative such as formaldehyde, toulene etc.), Waste water treatment plants, Restaurants (CO, CO2, N2, CH4), Mechanical/boiler rooms (refrigerants), Pharmaceutical Labs (HCN), Oil refineries (BTEX), Cold storage (NH3) and Industrial manufacturing. These classifications help Hospitals, Workplaces and Schools to monitor toxicity and flammability according to the tolerance people have in designated areas to cigarette smoke or other toxic gas emissions

B. *Detection Thresholds*

Our prototype enables accurate detection of a toxic emission at much lower concentrations of component gases of the emission by using Classifiers trained to detect signature patterns of small changes in these component gas concentrations as measured by MQ sensors using neural networks..

IV. MICROCONTROLLER HARDWARE USED

The easiest way to be able to control and automate the measurement tasks and sequence of data acquisition from an array of sensors is the use of an inexpensive 8b Microcontroller – the primary component of an IoT system.

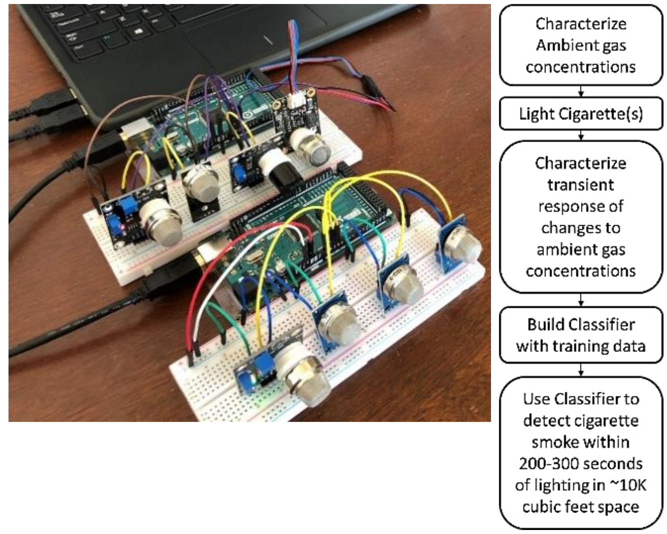


Figure 1. Microcontrollers with an arrays of Gas sensors are used to build a Classifier (top). Measurement flowchart (at right)

A. *IoT System Hardware*

The IoT type hardware we assembled uses three 8-b RISC Microcontrollers (ATmega2560 in the Arduino mega Dev Board) that can concurrently support 16 sensor IO to collect training data (Figure 1). Conventional sensors used consume significant current (150 mA/sensor at 5V) to heat sensors before they can function. Since the Dev Board sources insufficient current to support all 12 sensors used (Table 1) to capture training datasets, three 'off-the-shelf' Dev Boards were engaged to build this prototype. Air was sampled once every 2 seconds by the sensor array to balance size of dataset Vs accuracy delivered. A NodeMCU WiFi module is used to drive sensed data wirelessly for training and/or inference. C-code was developed to read and print the values the sensors sampled every second.

TABLE I: SENSITIVITIES OF AN ARRAY OF GAS SENSORS TO EACH COMPONENT GAS MEASURED BY A SENSOR [7]

Sensor/Gas	MQ2	MQ3	MQ4	MQ5	MQ6	MQ7	MQ8	MQ9	MQ135	MQ136	MQ137	MQ138	MG811
H2	-0.431		-0.275	-0.391	-0.387	-0.936	-0.295				-0.292		
LPG	-0.45	-0.222	-0.379	-0.447	-0.431	-0.122		-0.431					
CH4	-0.324	-0.046	-0.386	-4.278	-0.368	-0.1	-0.085	-0.324				-3.035	
CO	-0.244	-0.162	-0.074	0.13	-0.085	-0.737	-0.06	-0.579	-0.292	-0.292		- 0.2866	
CO2									-0.073				-0.104
Alcohol	-0.406	-1.154	-1	-0.205	-0.146	-0.087	-0.06					-0.314	
Propane	-0.528											-0.5	
Benzene		-0.344										-0.301	
Hexane		-0.397											
Smoke			-0.092										
NH3											-0.292		
Toulene													
NH4										-0.431			
H2S										-0.292			
C2H6O											-0.415		
N-Hexane												-0.483	

Data from the sensor array was normalized. By scaling data between 0 and 1, the classifier can read the data more effectively and converge faster [6]

B. Building a Classifier using a DNN

The algorithm used to build this classifier was a Deep Neural Network (DNN). A Deep Neural Network is a certain kind of ML algorithm that is represented as a hierarchical (layered) organization of neurons (similar to the neurons in the brain) with connections to other neurons [6]. Input data is passed through the first layer of the DNN and the hidden layers until it reaches the output layer, which is where the DNN makes a prediction on how to classify the input data [6]. The DNN recognizes patterns in the data and learns how to classify accurately through a learning process which is updating the weights of the neural network through a mechanism called Backpropagation.

The sensor dataset is a quantitative measure of the concentrations of a unique combination of different gases corresponding to a given source (See Table 1). The DNN is used to classify the source of the gases emitted using this data from multiple sensors. The combination of component gases in the corresponding sources measured across several sensors are compiled into 'training data' and passed through the DNN. The DNN then learns how to detect the source given the pattern detected by the gas sensor array of the component gas combinations. Prior to the classifier learning the data, the data was split into two parts: the training set and the testing set. The testing set was not used in training and was only used to measure the accuracy of the DNN classifier. The testing set accuracy tells us how well or badly the classifier performed, which gives insight into how to fine-tune the hyperparameters of the DNN.

For the DNN to be able to perform on the data with high accuracy the parameters had to be fine-tuned. After multiple trials the most optimal parameters for the DNN were having 4 layers-14 nodes in the first layer, 13 in the second, 5 in the third, and 1 in the fourth. Also, a dropout chance of 20% was added after every layer before the output. Furthermore, the activation function used for every layer except the output layer was ReLU (Rectified Linear Unit); the activation method for the output layer was a Sigmoid function

C. Measurement Setup

We used a large space (garage) that measures 32' x 20.3' with a 10.5' ceiling. The area and volume of this space is 650 sq ft and 7K ft^3. We flushed the air in garage with multiple exhaust fans, and then closed doors giving sensor array enough time to reach a stable unchanging reading as representative of environment (Figure 1). Smoke rises upwards due to it being at a higher temperature when emitted. However, it settles as it cools in the air with sensors placed in our test space a few feet off the ground demonstrating sufficient sensitivity within 300 seconds of lighting the cigarette

V. MEASUREMENTS

Our measurements had a primary goal of characterizing the patterns in component gas concentrations from toxic, flammable and similar but non-toxic emissions such as burning food or incense while also providing enough 'training' to the neural network to discriminate gas detection at different levels of toxicity, flammability and also be able to recognize post priori the presence of toxic emissions at a previous time.

A. Speed of Source Detection

We lighted a cigarette and used a bulb syringe to 'puff' at the lighted cigarette/vape (neither of us smoke) to emulate emissions typically seen from a cigarette/Vape for 9 minutes. We observed the first response of the sensor to gas emissions from any source was *proportional to the distance the source was from the sensor*. We conclude that the *response time of the sensor is limited by the time it takes for component gases of the source to diffuse through the air to the sensor*. The minimum time it takes for the sensor array to correctly identify the emission source is characterized as the speed of gas detection.

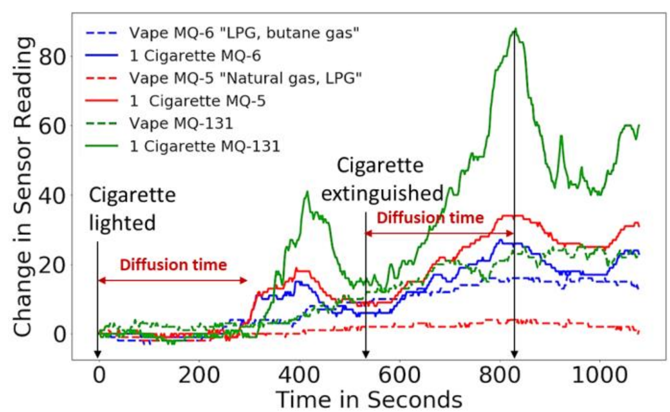


Figure 2. Changes registered in sensor array are different – Cigarette Vs Vape patterns can be discriminated by Classifier (MQ5 responsive to CO as well.

Two peaks were observed at very small changes in concentrations (from a single cigarette/vape) (Fig 2). *The first peak* registers initial contact at sensors of cigarette/vape emissions followed by diffusion away from sensor. *The second peak* registers extinguishing cigarette/vape, diffusion time after extinguishing at the Sensor

B. Residual Gas Component Patterns

Initial data is captured by the sensors and processed as a training set given the sensitivities of each sensor to component gases of the toxic emission (Table 1). We then extinguished the cigarette/vape, continued measuring sensor data for another 10–500 minutes to characterize cigarette smoke 'residue' post cigarette extinguishing (Figure 3). Classifiers using this data can detect cigarette smoke that lingers from the previous 24 hours after the cigarette was extinguished – useful in hospitals, hotels, schools to classify toxicity of spaces to be used by different people.

C. *Cigarettes Vs Burning Food*

Emissions from Burning Food (Figure 4) are *relatively* harmless but trip conventional smoke/CO detectors anyways. Measurement data sets from burning food train the neural network to learn these patterns from burning food and discriminate it from Cigarette/Vape emissions

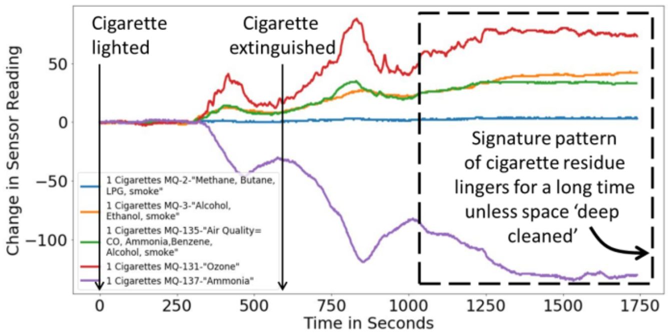


Figure 3. Cigarette emission residual component gases in room characterized for its signature pattern that persists long after cigarette extinguished.

Use of Pattern Recognition thus eliminates '*False Alarms*' from CO detection in the ambient when conventional detectors are calibrated to trigger at low CO concentrations

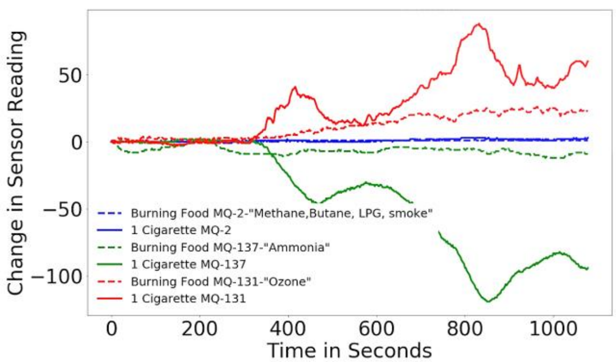


Figure 4: Classifier to discriminate Burning Food emissions from Cigarette emissions sensed by sensor array

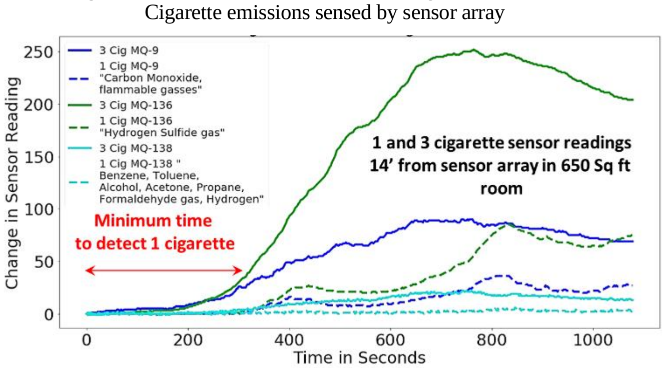


Figure 5. Speed of Source detection, reproducibility and consistency of Cigarette emissions Classifier demonstrated with measurements of 2 different levels of toxicity using the same source (Cigarettes).

D. *Toxicity Level Classification*

The Sensor array response to 1 cigarette is similar to emission from 3 Cigarettes emissions. Classifiers built using these measurements can discriminate between different levels of. toxicity (Figure 5).

From the above observations, we demonstrate that cigarette smoke gas component density patterns at even small concentrations (from a single cigarette) that are detected by the sensors, are sufficient for the DNN to correctly classify the emission source as a cigarette – enabling a DNN based gas detection to be much faster than conventional smoke detectors that rely exclusively on CO gas concentration as the threshold for detection.

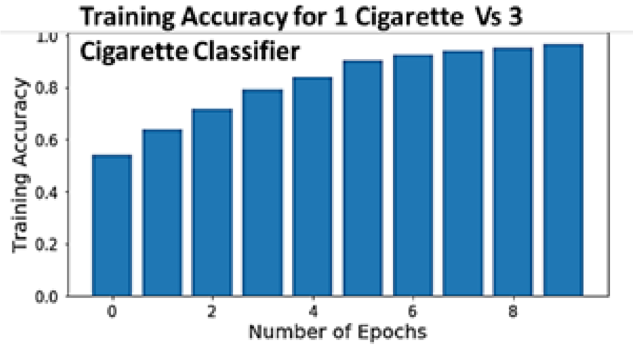
VI. ACCURACY OF CLASSIFIERS

The algorithm to train a DNN classifier is described in this section

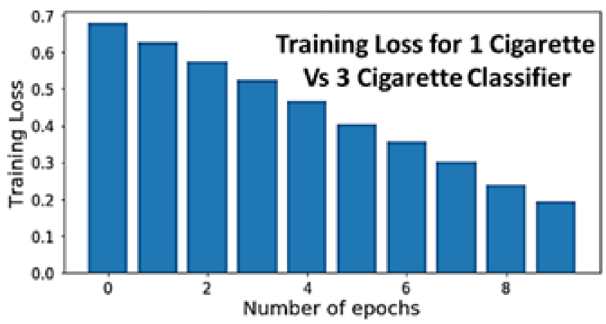
A. *Training Loss and Accuracy of Classifier*

To train a DNN classifier the training data has to be split into an "X_train" dataset and "Y_train" dataset. The "X_train" dataset consists of just the sensor readings as a function of time. The "Y_train" dataset consists only of the corresponding source name. While the DNN classifier was training on "X_train" and "Y_train" the classifier gave two different metrics: the training accuracy and the training loss, which were for each epoch. An epoch is one cycle through the full training data [9]. Three different classifiers were created. The first classifier was built to detect between 1 cigarette Vs 3 cigarette emissions (Fig 6a, 6b), the second was built to discriminate between 1 cigarette Vs 1 vape (Fig 7a, 7b), and the third was built to discriminate between a Cigarette or Vape Vs Burning food emissions (Fig 8a, 8b). The training accuracy reached >95% accuracy for all three classifiers (Figure 6b, 7b & 8b).

The training loss, which was calculated using binary cross-entropy, reached ~19% [Fig 7a] and ~10%[Fig 8a] after ten epochs for the first and second classifiers respectively. And for the third classifier, the training loss reached around ~8% (Figure 8a) after only 5 epochs. The training loss could have decreased to below 5% - however, to prevent the classifier from overfitting, the epochs were shortened up until the training loss for the third classifier reached a minimum of at least 10%. To test how well the classifier will perform on data it has never seen, the testing set was broken into the X_test and Y_test sets



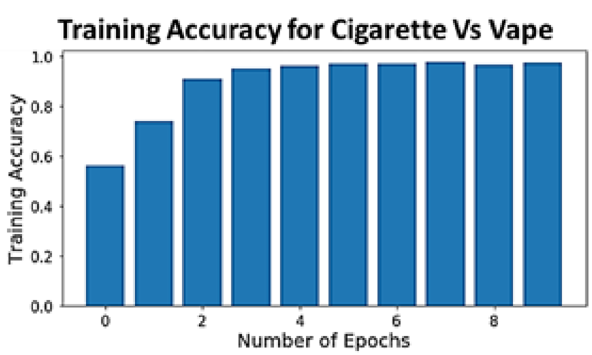
(a)



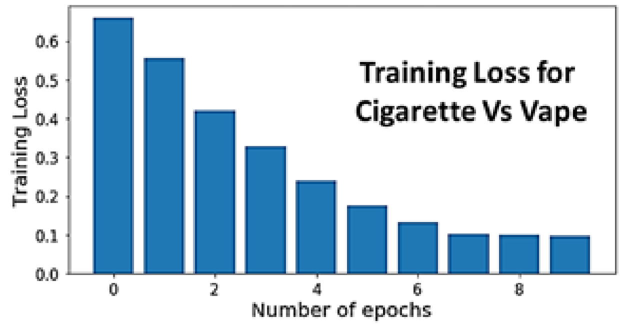
(b)

Figure 6. Training Vs Number of epochs in Classifier for 1 Vs 3 Cigarette emissions to discriminate Cigarette emissions at different levels of toxicity for (a) Accuracy and (b) Loss

The training loss, which was calculated using binary cross-entropy, reached ~19% [Fig 7a] and ~10%[Fig 8a] after ten epochs for the first and second classifiers respectively. And for the third classifier, the training loss reached around ~8% (Figure 8a) after only 5 epochs. The training loss could have decreased to below 5% - however, to prevent the classifier from overfitting, the epochs were shortened up until the training loss for the third classifier reached a minimum of at least 10%. To test how well the classifier will perform on data it has never seen, the testing set was broken into the X_test and Y_test sets.



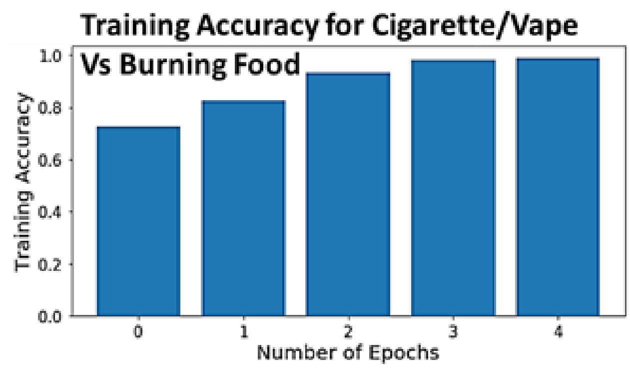
(a)



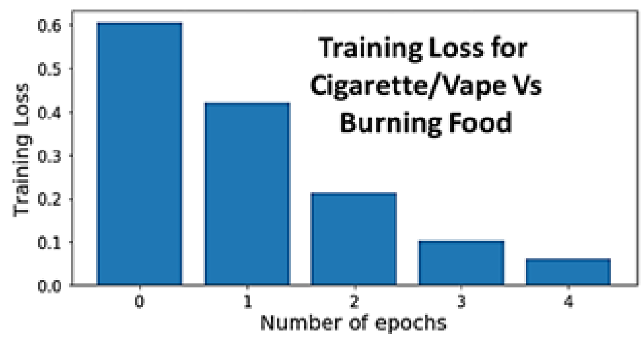
(b)

Figure 7: Training Vs Number of epochs in Classifier for Cigarette Vs Vape emissions to discriminate Cigarette emissions with similarly toxic emissions from Vape for (a) Accuracy and (b) Loss

The X_test only consists of never before seen data (by the classifiers) that only contains the sensor readings of the gases. The "Y_test" dataset only contains the corresponding sources of the "X_test".



(a)



(b)

Figure 8: Training Vs Number of epochs in Classifier for Cigarette Vs Vape emissions to discriminate Cigarette emissions with similarly toxic emissions from Vape for (a) Accuracy and (b) Loss

The "X_test" was passed through the classifier and the resulting predictions are named "Y_predictions". The "Y_predictions" and "Y_test" matched 100% accurately to each other. This is plausible given that the training accuracy reached >95% as shown in Figure 6b,7b & 8b

VII. Conclusions and Future Work

We demonstrate, using a simple inexpensive IoT system, equipped with an array of gas sensors and WiFi connectivity, the ability of a DNN to quickly identify a toxic gas by recognizing patterns in the concentrations of its component gases. These patterns are recognized at very low component gas concentrations *enabling a DNN based gas array sensor to provide early and accurate detection while toxic emissions still have low concentrations*. The DNN based detection is also limited only by the speed of toxic gas diffusion to the sensor arrays enabling the toxic gas detection to take place much sooner than conventional smoke/CO/gas sensor-based detectors

We see the need to extend these intelligent sensors to function as a distributed network of a few hundred IoT devices in a hospital or school for example, driving data wirelessly to a common AI hardware platform that could also support other AI workloads in the building as the use of AI proliferates.

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