Smart and Selective Gas Sensor System Empowered with Machine Learning over IoT Platform

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***Abstract*—Simple, accurate, portable, and selective gas sensors with autonomous, remote, and real-time access have become a requisite in various fields of applications. In this paper, we report the development of a stand-alone and selective gas sensor system incorporating a single resistive sensor with wireless monitoring and internet connectivity. The sensor is fabricated in-house with platinum decorated tin-oxide hollow-spheres as the sensing material, which exhibits a prominent response towards the tested volatile organic compounds (VOCs) at different concentrations. The intelligence in terms of accurate identification of VOCs and their concentration is attained by employing a machine learning tool based on deep neural network. The applied model displays an average accuracy of 96.43% with a fast prediction speed of 310µs, allowing a real-time recognition capability. The wireless connectivity is established utilizing a low-power microcontroller board and a Bluetooth module. The real-time data is made available for the users over an Android-based mobile application and a webpage while utilizing cloud services through the internet. The implemented system is successfully experimented with and validated under different test conditions that verify the whole platform. Further, the sensor system can be potentially applied to a remote application without needing any manual involvement. The demonstrated work with an internet-of-things (IoT) paradigm strengthens the next-generation gas sensing technology for developing smart, selective, and real-time gas sensor systems.**

***Index Terms*— gas sensor, selectivity, metal-oxide, machine learning, IoT, volatile organic compounds.**

I. INTRODUCTION

OVER the last decade, automated and real-time detection in the field of gas sensors has been the motivation throughout the research community and very much essential for domestic and industrial applications [1-5]. Smart gas sensors have been key for several areas such as indoor and outdoor air quality, freshness/spoilage control in food and agricultural industry, leakage alarm/warnings, explosive detection, preliminary clinical diagnosis using breath biomarkers and thereby increasing interest of ambient assisted living. Hence, an accurate, remote, end-to-end, real-time, and wireless gas sensor system and connectivity to other internet components are necessary for modern and future upgradation. In this regard, integration of gas sensors with wireless modules (near field connection devices), internet connectivity, and cloud storage along with real time monitoring is a paradigm of the internet of things (IoT). Recently, IoT became very popular, providing simple, easy to understand, plug and play access to the end-user application [4-10]. However, particular areas of concern like selectivity, small size, and durability of the sensor remain with this technology's deployment for seamless and ubiquitous sensing. Another desirable aspect lies with the IOT environment is incorporating intelligence within the system while using minimum computing resources.

Among different types and species of analytes, volatile organic compounds (VOCs) have been a few prime targets that require accurate sensing, monitoring, and control depending on the areas of applications [2, 3, 11-15].

II. LITERATURE REVIEW

The gas sensing methods based on chromatography and spectroscopy have excelled in the employment of gas sensors due to their high accuracy; however, those are bulky, expensive, require continuous manual intervention, and are not capable of real-time detection [16]. Thus, not suitable for IoT applications. In contrast, resistive sensors have been very prevalent in gas sensing domain and can be an upright candidate for IoT applications due to their high sensitivity, compact size, portability, low cost, ease of production, and many more, but they suffer with poor selectivity [17-20]. Though many efforts have been laid towards mitigating the selectivity issue through different functionalization of sensing material, additives in crystal structure, composite formation, array of sensors, etc., but they were limited depending on applicability [21-24]. Now, recent reports clearly establish that the selectivity aspect can be dealt with incorporation of proper pattern recognition techniques [25-30].

The employment of machine learning (ML) tools has been

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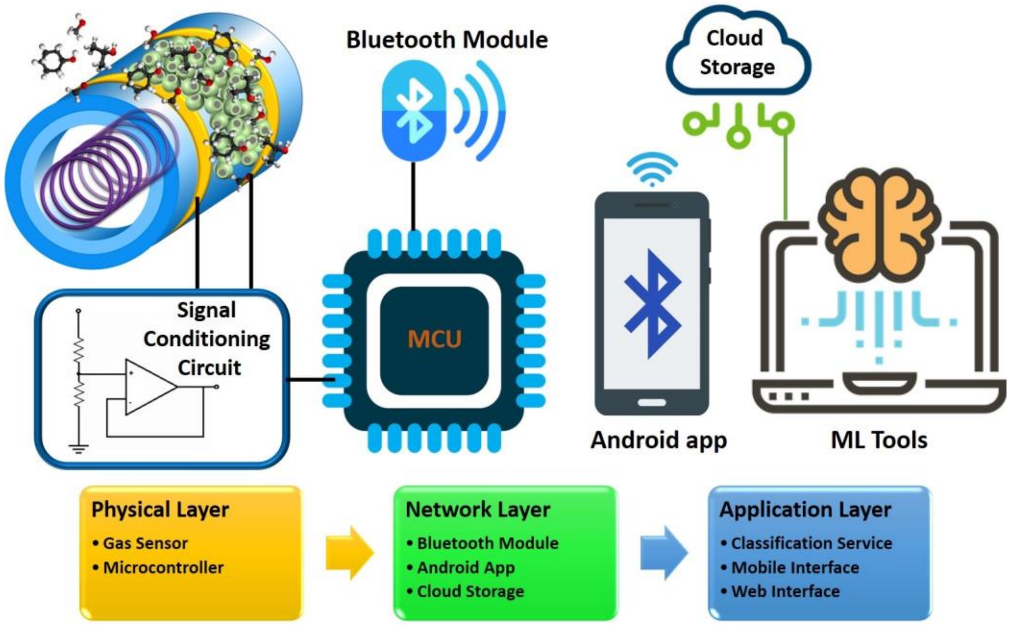

Fig. 1: Schematic overview of the gas sensor system over IoT platform.

proven to be beneficial in classifying among different classes. Specifically, neural network-based models have shown better overall performance due to their efficient learning ability and adaptability to the variance in the data [31, 32].

In this context, an amalgamation of metal-oxide-based chemiresistive sensor and ML algorithm is an admirable strategy to solve the bottlenecks of present gas sensing technologies. Previously, few works have addressed the selectivity issue while adopting ML tools; however, those were complex, computationally exhaustive, slow, and did not account for real-time analysis [32-36].

Previously reported works on gas sensors with IoT vision have shown that the measured data was transmitted through a wireless network gateway using Wi-Fi or Bluetooth modules [5, 6, 8]. Some of the reports also presented the involvement of cloud storage and a web-based interface for monitoring [7, 37]. However, most of these reports employ commercial and multiple sensors, which are comparably costly, wear considerably over time, and increase hardware complexity for fetching data and transmission. Moreover, these systems do not account for the selectivity among the target gases/VOCs. Although some reports involve neural network-based classification, they do not support IoT-based platforms [32-36]. Few works have been reported in the past, incorporating gas sensors over IoT along with machine learning [8, 37], but those were focused on activity recognition that leads to the emission of gas/VOC rather than classifying the type of gas/VOC emitted and detected.

A recent work reported by S. Dhingra et al. [5], presents an air pollution monitoring system over IoT using commercial gas sensors to measure the air quality (CO, CO_2, CH_4). However, the system does not categorically recognize the type of pollutant and its concentration. A similar work by E. Gambi et al. [8], focused on air quality while classifying activities of daily living through the employment of ML tools.

Another study [6] demonstrates low power and wireless gravimetric sensor system while providing real-time sensor readings over graphical user interface, where the results were restricted to only one type of VOC, without multi-gas detection capability. In contrast, J.B.A. Gomes et al. [7] proposed IoT based multi-gas sensor system providing real-time data with plug and play access. But the system does not have the capability to recognize the type of VOC selectively. Later, an improved work reported by J-H Suh et al. [4], presents gas sensor module which attains the selectivity among CO and H_2S, using PCA tool and displays the sensor data utilizing Bluetooth and Wi-Fi communication.

The work reported by G. Wei [33] and X. Zhao [35], presents employment of convolutional neural network (CNN) to classify gases with high accuracy using multiple commercial gas sensors. A similar work by P. Peng, et al. [36], demonstrates selective detection of tested gases using CNN having six hidden layers, which also increases the model complexity. However, none of the above works include IoT based platforms.

In another study, an interesting work was reported by S.M. Saad et al. [37], which employs artificial neural network (ANN) to classify the indoor air quality environment based on influencing sources with high accuracy. The system employs different types of commercial sensors with a Web interface for data monitoring. However, the system does not provide any information about the type of pollutant (source) and its concentration affecting the air quality.

Moreover, none of the above-reported works account for the concentration estimation. In contrast, this presented work envisions an autonomous and selective sensing system over an IoT platform capable of continuously monitoring and facilitating accurate readouts of detected target gases/VOCs qualitatively and quantitatively using machine learning while improving the state of the art.

III. Overview of the Work

The sensor system consists of an in-house synthesized and fabricated single resistive gas sensor device based on platinum (Pt) decorated tin oxide (SnO_2) hollow-spheres to detect target VOCs (acetone, benzene, ethanol, formaldehyde, methanol, propanol, and toluene). The incorporation of Pt nanoparticles over the SnO_2 surface facilitates the lowering of required activation energies for the interaction of analyte molecules [38]. This allows the sensor to operate at comparatively lower operating temperature. The sensor signals were acquired by a low-power microcontroller and transmitted over a wireless communication gateway which was established using a Bluetooth module. The sensor readout was obtained over an Android application connected via Bluetooth while simultaneously storing the data in the cloud via internet connectivity for further data analysis. At the same time, the gas sensor data can also be observed over a webpage with a real-time graphical viewpoint. Finally, the stored sensor data was engaged with a deep learning model to learn inherent features corresponding to the tested VOCs and accurately classify and quantify them with provision to future real-time prediction. Fig. 1 demonstrates the applied approach.

To the best of our knowledge, for the first time, this work present machine learning-enabled accurate detection and quantification of VOCs in real-time with remote access over mobile/web Interface and shows high metrics of accuracy while employing only single chemiresistive sensor device. The main highlight and contribution of our developed sensor system can be realized by taking the features altogether, stated as follows: (i) Most crucial aspect is the selective identification of VOCs with fast prediction speed and minimum computational calculations; (ii) Plug and play access to the users; (iii) Compatible to include other sensing materials over the gas sensor platform; (iv) The real-time data can be monitored remotely using simple mobile/web interface.

The rest of the paper is organized as follows: Section IV explains the proposed system/approach and architecture; Section V presents the applied methodology and experimental details for the development of the sensor system; Section VI highlights and discusses the obtained results; and Section VII portrays the summary of the presented work.

IV. System Architecture

The system comprises three major layers namely, (i) physical layer having hardware components such as gas sensor, circuit boards, microcontroller board; (ii) networking layer having Bluetooth Module, Android application, cloud storage; (iii) processing and application layer having machine learning model, Mobile and Web interface for real-time visualization. The system was developed to provide simple and plug-and-play access to any user without prior technical training.

The target VOCs were sensed using a single resistive sensor having metal-oxide as sensing material which was synthesized and fabricated in our lab. The sensor was hardwired with a signal conditioning unit that was further connected to the microcontroller board. A low-power 16-bit microcontroller

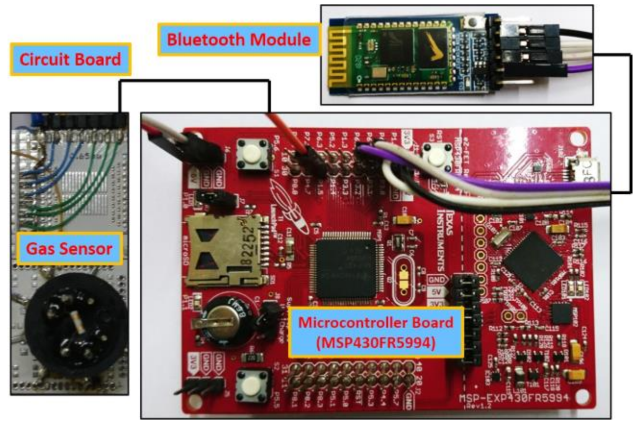

Fig. 2: Picture of hardware components having gas sensor, circuit board, microcontroller board and Bluetooth module.

launchpad MSP430FR5994 (Texas Instruments Inc., USA) was adopted, having a 16 MHz clock frequency, 256KB RAM, with an inbuilt 12-bit analog-to-digital converter (ADC) and enhanced serial communication (universal asynchronous receiver transmitter or UART with an automatic baud-rate detection). The microcontroller board can be powered by a 5V USB power source or lithium-ion battery with a minimum voltage rating of 3.7V. The collected sensor data (analog voltage) gets converted into digital form and transmitted using serial communication by a Bluetooth module connected to the microcontroller's transmission port. Here, a Bluetooth module (Model: HC-05) working on 3.3V while following IEEE 802.15.1 standardized protocol and having a range up to 100 m was programmed to transmit at an interval of 3 seconds which was wirelessly connected to a Mobile phone. Fig. 2 shows the applied hardware arrangement of the sensor system. The microcontroller was programmed using codes developed over *Energia* integrated development environment, an open-source platform with a minimal program memory size of 3.41 KB.

The mobile user interface was designed using the freely available *MIT app inventor* software platform, where an Android-based mobile application was developed that also serves as a communication gateway. The measured sensor output gets continuously displayed over the mobile application and instantaneously uploaded to the cloud storage through internet connectivity for further visualization and analysis. Here, *Firebase* (Google Inc., USA) was utilized as the cloud storage. In addition, a Web interface was also developed using the *Visual Studio* (Microsoft Inc., USA) platform, which fetches the data from the cloud and shows the historical and real-time tabulated sensor readings along with the graphical representation of the data updates acquired by the sensor.

Next, the collected sensor data was obtained from the cloud and applied to train a machine learning model which predicts the type of VOC and its concentration detected by the sensor. For the classification service, a deep neural network was implemented using *scikit-learn* and *Keras* library with *Tensorflow* backend in the *Python* programming environment (version 3.6). An external computer with internet connectivity was utilized for the execution of a machine learning task, which

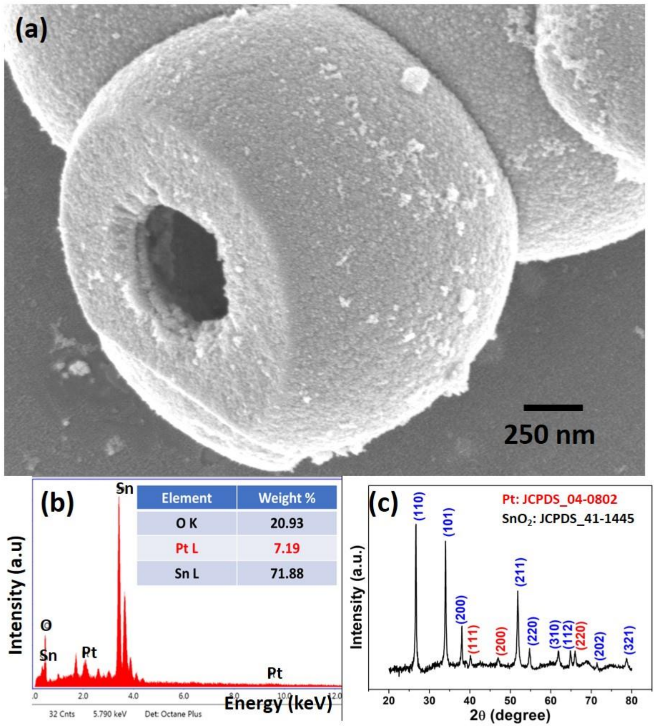

Fig. 3: (a) FESEM image, (b) EDS spectra and (c) XRD pattern of Pt decorated SnO_2 hollow-sphere (sensing material).

downloads the sensor data from the cloud database and uploads the classification and quantification results. Prior to prediction using test data, the model was trained empirically for seven tested VOCs with various concentrations to obtain the best possible training and validation accuracy while utilizing minimum computational time and resources.

V. Experimental Details

A. Gas Sensor Device

The gas sensor was fabricated using platinum (Pt) nanoparticles decorated SnO_2 hollow-spheres as the sensing layer, which was synthesized by a facile chemical process involving hydrothermal technique as adopted in our earlier report [25]. The field-emission scanning electron microscope (FESEM, Model: MERLIN) image, energy dispersive X-Ray spectra (EDS, Model: Oxford EDS detector), and X-Ray diffraction (XRD, Model: Rigaku SmartLab) pattern of the synthesized material as shown in Fig. 3 clearly elucidate the formation of a well-defined hollow structure with metal (Pt) nanoparticles over the surface with good crystallinity. The bright spots over the surface depict the decorated platinum nanoparticles. The average diameter of the spheres is 850 nm with 200 nm average circular opening. The large specific surface area allows increased analyte molecule exposure, resulting in better sensing. The XRD peaks in Fig. 3(c) corresponding to SnO_2 crystal planes (blue color) clearly indicate the formation of tetragonal SnO_2 structure with rutile phase (JCPDS 41-1445). And the peaks ascribed to (111), (200) and (220) crystal planes positioned at 40.12˚, 46.32˚ and 66.05˚, respectively, exhibit the existence of Pt in the sample (JCPDS 04-0802).

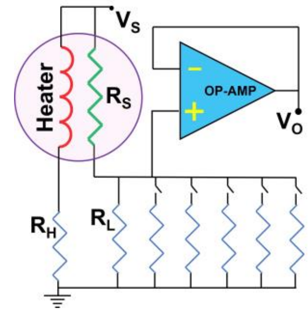

Fig. 4: Illustration of signal conditioning circuit connected to the gas sensor.

The powdered sensing material was mixed with deionized water to make a thick paste. The gas sensor device was made by coating the sensing material (paste) over a ceramic tube, followed by drying and calcination to maintain adequate adherence to the material. The tube contains gold electrodes for electrical contacts and has nichrome wire as a heater coil passing through the tube (Taguchi type). As shown in Fig. 4, the sensor (R_S) was connected with a load resistance (R_L) and a constant voltage (V_S) was applied, where the voltage change was measured across R_L. The sensing layer resistance (R_S) changes when it comes in contact with target VOC analytes. The heater coil was connected with a series resistance (R_H) for controlled heating to enable the required sensitization of the sensor. The gas sensor was positioned over the circuit board, which consists of signal handling circuitry in a voltage divider fashion. The operational amplifier is connected in a voltage follower fashion which acts as a buffer to handle any impedance issues and provide stability. A resistor bank with a combination of different resistor values ranging from 1kΩ to 10MΩ was reserved to allow compatibility with a wide range of sensor resistance to withstand sensitivity swing and provide quantifiable voltage change. The whole signal conditioning circuit was made with the provision to accommodate and adapt to any other gas sensor for future improvisations. The microcontroller board was utilized to supply the voltage (V_S) to sensor and heater as well as to measure and collect the voltage change across R_L continuously through different defined ports.

B. Gas Sensing Measurement

The gas sensing measurements were performed dynamically, keeping the sensor in a custom-made leak-proof chamber. The tested VOCs were passed through the chamber while the desired concentration was achieved by dilution with dry air using a combination of digital mass flow controllers (ALICAT Scientific). More details can be found in our previously reported work [28]. Initially, the sensor was allowed to stabilize in the presence of dry air, meanwhile, the sensing material also attains sufficient activation energy from the temperature provided by the heater. The tested VOCs were exposed over the sensor until the response reached saturation, thereafter, the recovery was attained where the response attained the baseline with minor drifts.

The voltage output from the sensor board varies from 50mV to 750mV, which was converted to digital values using 12-bit ADC having 2.5V as the reference voltage. The voltage swing

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immensely depends upon the load resistance (R_L) value connected in parallel with the sensor resistance. This has been chosen wisely to accommodate maximum swing without compromising the sensitivity of the sensor.

C. Data Transmission and Visualization

The received analog signal from the gas sensor device gets converted into digital values by the ADC. Then the microcontroller encapsulates them into digital data packets that are transferred to the Bluetooth module using a serial communication port. The mobile application scans the nearby Bluetooth signals at a 2.4 GHz carrier band and connects to it over the user's command after validating its MAC address. Once the connection was established, the mobile application was programmed to upload the received data in real-time to the cloud storage through *Firebase* (database) extension call with internet availability. The previously generated database storage account was validated, and storing the data from an external source was allowed only after a proper authentication check.

Furthermore, a web user interface can be accessed globally using an internet connection after a successful and secure login check. After authentication, the web page continuously downloads the data from the cloud storage using *Firebase* web extension. The user dashboard was configured to provide a comprehensive understanding of the detected VOC in terms of its characteristics through a graphical display and cumulative sensor readings in tabular format with timestamps.

D. Data Handling and Classification Technique

A neural network model was implemented for the classification of tested VOCs, which was effectively trained to predict future test values. In order to train the neural network model, a gas sensing study was conducted where the measurements were recorded for seven tested VOCs with four different concentrations. The measurements were repeated twice to acquire the variance and drift in the sensor response over time, making the count of 84 measurements. Additionally, the data augmentation was followed where the white gaussian noise was added to the original measurements making the whole dataset having 168 measurements (data item), so that the models learn the features in more adaptive manner. The time series sequence of 125 sensor response values (including response and recovery transients) was taken as input features which were fed to the model for training/testing purposes. The length of the sequence was selected judiciously such that all the inherent dynamic details corresponding to the tested VOC is intact within the series. Therefore, the complete dimension of the dataset matrix stands out as 168x125, which was engaged with the deep neural network model.

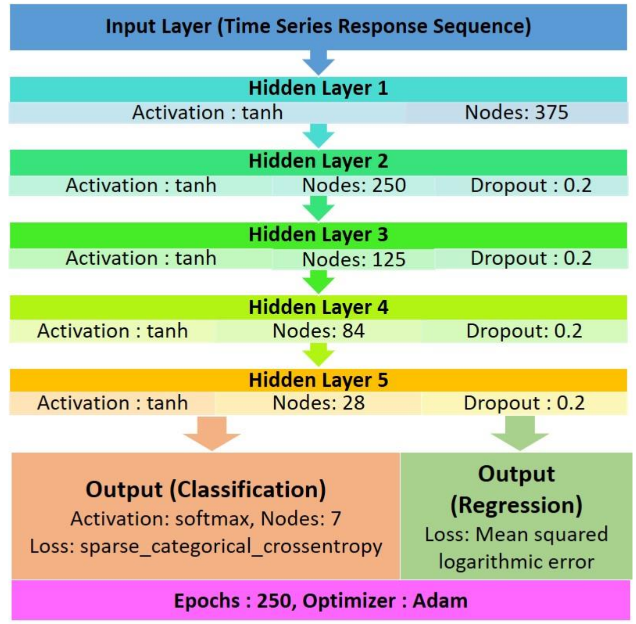

Fig. 5: Architecture of applied Deep Learning model.

The model architecture (illustrated in Fig. 5) was constructed with 5 hidden layers, each layer having 'tanh' as the activation function except the output layer which has 'Softmax' activation function. The model was compiled with 'sparse categorical entropy' as a loss function and optimized with 'Adam' optimizer, which reads the computed loss and updates the

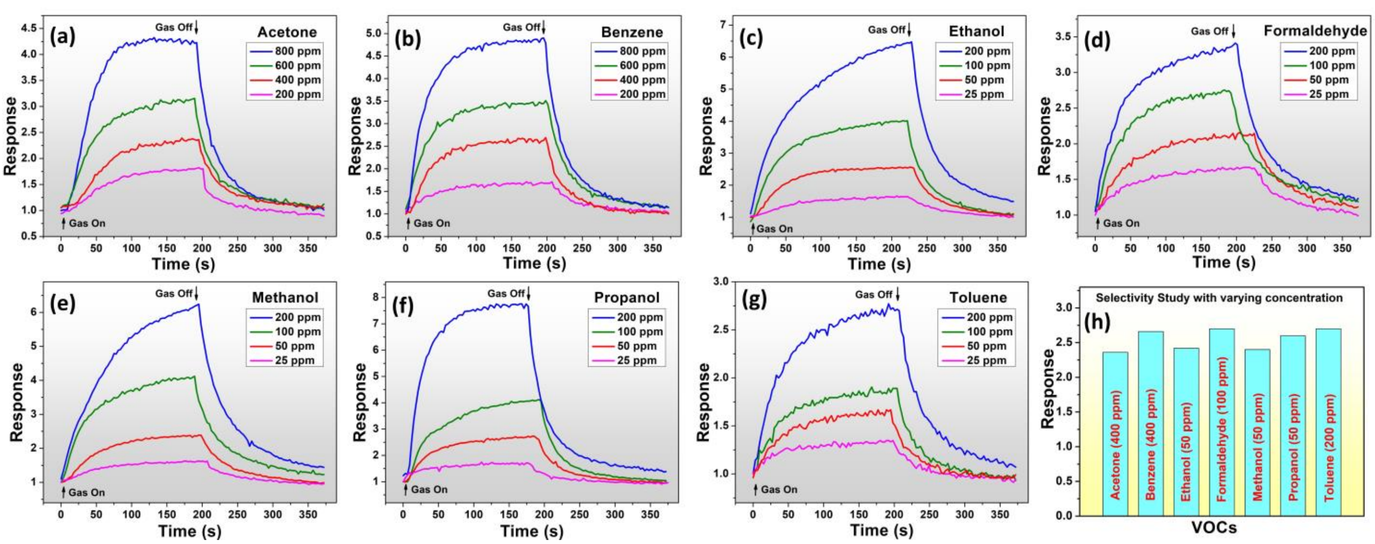

Fig. 6: (a-g) Transient response curves of tested VOCs at different concentration, (h) Selectivity study.

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weights accordingly to attain classification among the tested VOCs. Subsequently, the concentration of the classified VOCs was also predicted in a quantified manner using parallel regression analysis, with the linear activation function at the output layer having a single node while using 'mean squared logarithmic error' as the loss function. Moreover, each layer was connected to subsequent layer with a 20% dropout between the nodes to handle the chance of overfitting and to achieve better generalized performance. The training-testing process was carried out by random shuffle of entire dataset, followed by train-test split with 80-20% ratio while maintaining homogeneous stratification. The model was trained with 250 epochs. This was performed for 10 times to obtain and validate a consistent accuracy from the model over the dataset. The hyperparameters of the model and number of epochs were found and chosen through empirical observation to achieve the best and most stable accuracy over the complete dataset.

VI. Results and Discussion

A. Gas Sensing Performance

The gas sensor readings towards tested VOCs (acetone, benzene, ethanol, formaldehyde, methanol, propanol, and toluene) were recorded and stored in the cloud storage. For further analysis and convenient data handling, all the transient response curves were normalized with respect to the baseline value of the sensor reading. This strategy provides a clear distinction and understanding of the response characteristic associated with a particular VOC and its concentration variation. Fig. 6(a-g) depicts the normalized transient response corresponding to the tested VOCs at different concentrations. It is evident in Fig. 6(h) that the response values are nearly similar for various VOCs while considering different concentration values. This describes the lack of selectivity due to intrinsic cross-sensitivity of metal-oxide-based gas sensors. However, it can be envisaged that each VOC has a distinctive nature in its response transient due to characteristic adsorption/desorption phenomenon (gas sensing kinetics) dependent on the type of analyte. Therefore, this hidden dynamic information can help distinguish the analytes using the appropriate pattern recognition technique.

B. Deep Learning Model Performance

A deep learning model was implemented to identify and discriminate between the tested VOCs along with quantification. The applied architecture was meticulously trained with a collected gas sensor dataset for 250 epochs to reach 99.25% training accuracy. Subsequently, the model accuracy was tested and validated, where the average testing accuracy was attained as 93.57% for ten different datasets (iterations). The model was developed to exploit the minimum possible computational resources and time. For the dataset applied in this work, the model spends about 10.67s for training purpose (250 epochs with 126 samples) and clocks 12.5ms to predict 42 samples. Fig. 7(a) represents the variance of the accuracy for different datasets thereby showing the generalized performance of the trained model. The success of the classification task can be better inferred from the confusion matrix, as displayed in Table I. The average quantification error

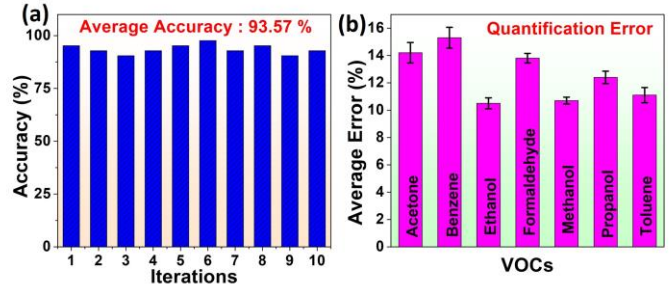

Fig. 7: Performance of Deep Learning model in terms of (a) Classification of tested VOCs, (b) Quantitative prediction of concentration of corresponding VOCs.

TABLE I
Confusion matrix for Deep Learning Model

Actual/ Predicted	*A*	*B*	*E*	*F*	*M*	*P*	*T*
A	6	0	0	0	0	0	0
B	0	6	0	0	0	0	0
E	0	0	6	0	0	0	0
F	0	0	0	6	0	0	0
M	0	0	1	0	5	0	0
P	0	0	0	0	0	6	0
T	0	0	0	0	0	0	6

***A**: Acetone, B: Benzene, E: Ethanol, F: Formaldehyde, M: Methanol, P: Propanol, and T: Toluene*

for the tested VOCs was obtained as 14.2%, 15.3%, 10.5%, 13.8%, 10.7%, 12.4%, and 11.1% for acetone, benzene, ethanol, formaldehyde, methanol, propanol, and toluene respectively, which is visualized in Fig. 7(b). To examine the tolerance to disturbances/drifts/variance (that may appear in the future sensor measurements), the deep learning model was tested with transient response containing 2-5% Gaussian noise, for which the model classifies with 94.1% accuracy (79 correct classifications out of 84 data entities) and average quantification error was obtained as 12.73%. These results confirm the ability of the model to handle noise with acceptable metrics. The classification service was made available to the user for real-time identification of the VOCs by simply downloading the instantaneous sensor readings, which were sequentially streamed from the cloud storage and treated as the test item by the model for prediction.

C. Sensor System Validation and Comparison

The deep learning enhanced selective VOC gas sensor system with the internet-based data acquisition was validated methodically while featuring a user interface over an Android-based smartphone and a website. The complete setup acts as a stand-alone system where the sensor detects any of the seven VOCs for a wide concentration range. To test and validate with all the possible measurements (7x4=28), the gas sensor setup was kept under test conditions with exposure to different concentrations of all the selected VOCs (acetone, benzene, ethanol, formaldehyde, methanol, propanol, and toluene), which were previously used to train the deep learning model.

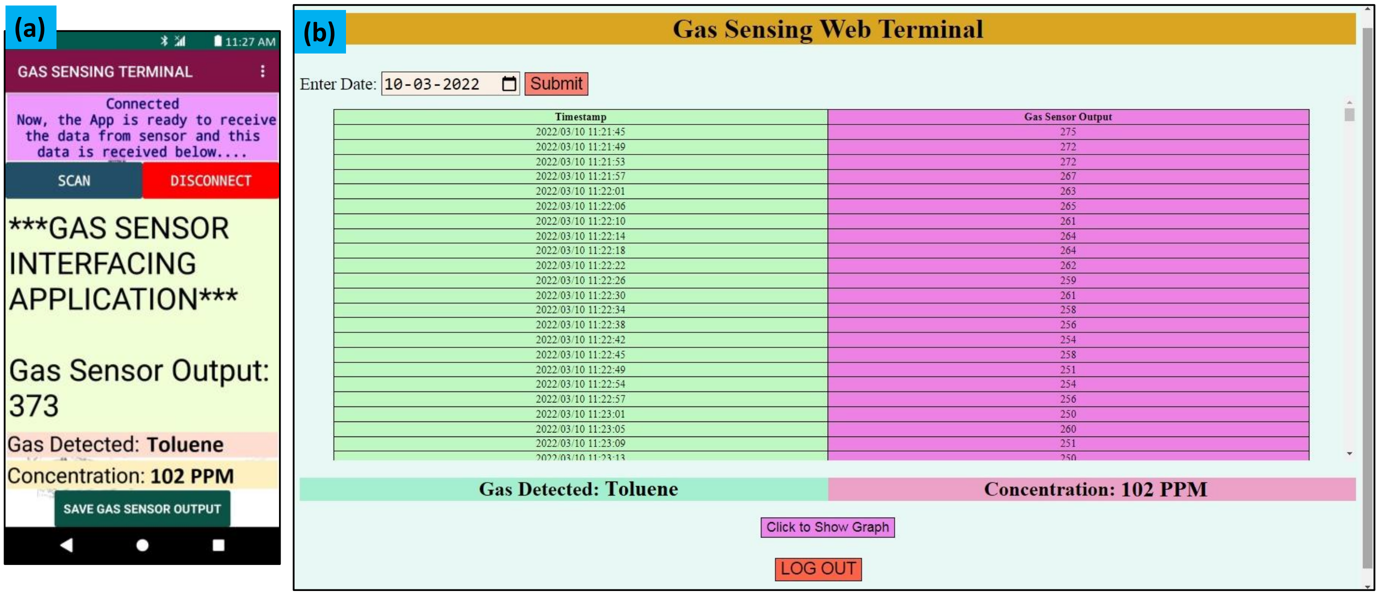

Fig. 8: Screenshot of (a) Android based mobile application and (b) Web user interface.

The classification service from the employed deep neural network exhibited excellent performance with accurate identification of VOCs (classification accuracy = 96.43%, 27 correct identifications out of 28 test conditions) and very close prediction of corresponding concentration values having a prediction speed of 310µs. The detected VOCs and the concentration value are near real-time displayed on the mobile phone application and also over the web interface dashboard. The screenshot presented in Fig. 8 demonstrates the overall interface.

The comparison in Table II, shows that our work outshines the listed earlier reported works in terms of use of in-house fabricated single sensor, selective detection of analytes using machine learning, concentration quantification, fast prediction,

TABLE II
Comparison with similar reported works on gas sensors.

Ref.	Number of Sensors	Target Gases/VOCs	Selective Detection	Machine Learning Model	Classification Accuracy	Computational Complexity (Typical)	IoT and Remote Access	Real-time Detection
[4]	4 (In-house)	2 (CO, H_2S)	Yes	PCA	100% (Unsupervised)	Low	Yes	Yes (Only sensor data)
[5]	3 (Commercial)	3 (CO, CO_2, CH_4)	No	Not Done	-	High	Yes	Yes
[6]	6 (In-house)	Ethanol	No	Not Done	-	-	Yes	Yes
[7]	10 (Commercial)	10 (O_2, H_2, CH_4, LPG, CO, NH_3, C_3H_8, C_6H_6, alcohol vapor, smoke)	No	Not Done	-	-	Yes	Yes
[8]	6 (Commercial)	Various Gases/VOCs for Indoor activities	No	k-NN	96% (Activity recognition)	Low	Yes	Yes
[33]	12 (Commercial)	2 (CO, CH_4)	Yes	CNN	99.67%	Very High	No	No
[35]	16 (Commercial)	3 (Ethylene, CO, CH_4)	Yes	1D-CNN	96.3%	High	No	No
[36]	8 (Commercial)	4 (CO, CH_4, H_2, Ethylene)	Yes	CNN	95.2%	Very High	No	No
[37]	8 (Commercial)	8 (CO, CO_2, O_3, NO_2, VOCs and PM-10)	No	ANN	99.1% (Activity recognition)	High	Yes	Yes
This work	**1 (In-house)**	**7 VOCs**	**Yes**	**DNN**	**96.43%***	**Low**	**Yes**	**Yes**

*NOTE: None of the above compared reports have carried out the quantification of detected gases/VOCs.

IoT platform and real time detection capability. Though, the works reporting activity recognition task demonstrates good results with excellent accuracies but they do not provide distinction among gas/VOC type and concentration [8, 37]. Thus, the compared reports carry few limitations and do not facilitate a complete all-around detection of target gases/VOCs.

VII. Conclusion and Future Work

The presented work portrays implementing a machine learning enhanced IoT system for an automated, selective, intelligent, and real-time gas sensor system with user plug-and-play access. The sensor system utilizes a custom-developed single resistive gas sensor that incorporates the nano-meter scale platinum decorated SnO_2 hollow spheres as the sensing material. Integrating a sensitive gas sensor, a low-power microcontroller, a Bluetooth module, an Android mobile application, a cloud service, a machine learning tool, and a simple user interface realizes an improved flavor of an IoT system with accurate real-time monitoring and visualization of tested VOCs. The practical and efficient association of the deep learning model with ultrafast prediction speed decorated the complete system for selective detection of VOCs and its concentration. The deep learning model was trained to be capable of predicting accurately while handling variance, disturbance, and noise in the test data. The developed gas sensor system can be modified and utilized to detect any target gas/VOC, with necessary prior training in the ML model.

The ML computations could be accommodated on-board using appropriate hardware and programming, but that will aggressively increase the complexity of the sensor system. Involvement of additional hardware components increases the complexity due to several factors like interfacing (hardware and software), additional power requirement, time management between the peripherals, overall programming, and memory requirements. Furthermore, all of these will make the system expensive. On the contrary, sending the data to cloud and using the services remotely allows to refrain from above mentioned issues. In addition, transmitting data to the cloud will continuously consume battery, but, as the employed microcontroller and associated modules have very low power ratings the power requirement would be less critical. However, with proper power management circuitry and appropriate sampling intervals, the life-time of the battery could be improved and this will be considered in our future work.

Besides, the system's functionality can be potentially extended and applied to remote applications. The future work also focuses on detecting mixture of VOCs at lower concentration levels and any possible improvement in the current hardware in the direction of minimum power consumption including integration of micro-heater-based sensing platforms. In coming years, IoT-based multi-sensor system deployment is our vision in field of agriculture, food-freshness, and indoor air quality monitoring.

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