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My Beloved
Mother*

WHOSE BLESSINGS, LOVE AND SACRIFICE BROUGHT ME HERE UP TO.....

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*ॐ कृष्णाय वासुदेवाय हरये परमात्मने!
प्रणतः क्लेशनाशाय गोविंदाय नमो नमः!!*

The burden of all complex tasks of the world becomes light with your kind grace.

-Jai Shri Sankat Mochan Hanuman Ji & Kashi Vishwanath Ji

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
AWS	Amazon Web Services
BGL	Blood Glucose Level
CC-IGSS	Cloud Connected Intelligent Gas Sensor System
CLI	Command Line Interface
CSS	Chirp Spread Spectrum
CKNN	Covariance k-nearest neighbour
DM	Diabetes Mellitus
DT	Decision Tree
E-nose	Electronic noses
FCC	Federal Communications Commission
GC-MS	Gas Chromatography-Mass Spectrometry
HP-IGSS	High-Performance Intelligent Gas Sensor System
IAM	Identity and Access Management
ICA	Independent component analysis
IDC	International Data Corporation
IFSTA	International Fire Service Training Association
IGSS	Intelligent Gas Sensor System
IMS	Ion Mobility Spectroscopy
IoT	Internet of things
ISM	Industrial, Scientific, and Medical
KNN	K-nearest neighbor
KPCA	Kernel Principal Component Analysis
LoRa	Long Range
LPG	Liquefied petroleum gas
LPWAN	Low Power Wide Area Networks
LR	Logistic Regression
MAE	Mean absolute error
MCU	Microcontroller
MLP	Multi Linear Perceptron
MOX	Metal-oxide Semiconductor
MQTT	Message Queuing Telemetry Transport
MSE	Mean squared error
NB	Naïve Bayes

NFPA	National Fire Protection Association
PCs	Principal Components
PCA	Principal component analysis
PM	Particulate Matter
QPCA	Quadratic Principal Component Analysis
PPG	Photoplethysmography
PTR-MS	Proton Transfer Reaction Mass Spectrometry
RDA	Regularized Discriminant Analysis
RDPC	Remote Data Processing Centre
RF	Radio Frequency
RF	Random Forest
RMSE	Root mean squared error
RSSI	Received Signal Strength Indicator
SGD	Stochastic Gradient Descent
SLDA	Standardized Linear Discriminant Analysis
SNR	Signal-to-noise Ratio
SPCA	Standardised Principal Component Analysis
SPI	Serial Peripheral Interface
SVM	Support Vector Machine
T1DM	Type-1Diabetes Mellitus
T1DM	Type-2Diabetes Mellitus
VOCs	Volatile Organic Compounds

PREFACE

Real-time air-borne pollution detection and monitoring is a crucial area of research with significant implications for health and monitoring protection. Traditional methods of air-borne monitoring are stationary, expensive, large-size machinery, limited area deployment and delayed processing. In comparison to traditional methods, electronic noses (e-noses) are portable, cost-effective solutions for continuous real-time monitoring of airborne pollutants.

The need for real-time detection comes because air pollution varies dynamically, changing because of factors like industrial/household activities, traffic congestion, and weather conditions, which can also adversely affect human health. By deploying e-noses in multiple areas, such as urban areas, industrial zones, and other pollutants sources, including smart homes, by creating Cyber-physical Systems (CPS). By using CPS, variations in pollution concentration can be tracked. This timely information enables rapid response and mitigation to avoid the adverse effects of air pollution. E-noses measure chemical interaction between pollutants and sensing material producing unique response patterns of fingerprints for various pollutants.

Advanced data-processing techniques, for example, Machine learning and Artificial Intelligence algorithms, can be applied to analyse collected data, identify pollutants and estimate their classes in real-time, which becomes equally critical from the mitigation aspects as well.

By promptly identifying the pollutant resources and analysing through advanced data processing techniques, e-noses offer promising solutions for air-quality monitoring in real-time, identifying pollutant sources and enabling timely intervention to protect health and the environment. Continuation of research and innovation in this field will play a crucial role in addressing the global requirement of air pollution monitoring, detection and mitigation for sustainable development.

Further, in our literature survey, we have observed that there is a significant gap in research which has been carried out in the area of smoke detection and mitigation using e-noses, especially during fire hazard situations, and pollution

detection. Normally, researchers have used gas sensor array and pattern recognition techniques such as dataset consisting of responses captured from e-noses or exposing the array of sensors with respective analytes.

Efficient detection and monitoring of VOCs in smart homes is essential for the good health of its residents. VOCs originate from various sources, including building materials, cleaning products, and household chores. All such things can pose risks even when they are odourless. Prolonged exposure to these high levels of VOCs leads to health issues, ranging from irritation to long-term respiratory disease, cancer, etc.

Smart homes offer the opportunity to integrate sensors and IoT devices for real-time monitoring, providing immediate feedback on indoor air quality and enabling prompt actions for its use as a CPS. Vulnerable populations like children or people with respiratory disease, they are particularly at risk because such exposure to identifying such VOCs and their sources will allow us to carry out preventive measures, including ‘sick-building syndrome’.

In this thesis, we have proposed a High-Performance Gas Sensor System (HP-GSS) by applying artificial intelligence-based computational models to primarily enhance the performance of gas sensor systems (GSS) during fire hazard situations. We have designed and tested the prototype using the smoke of wide varieties that are normally generated during fire hazard situations in smart homes, industrial warehouses and normal situations at homes during routine daily chores (e.g., worship, safety and security, hygiene and disinfectants, LPG leakage, cooking and smoking etc.) leading to pollution hazards as well. We have also tested our prototype to predict possible health hazards by sampling the Volatile Organic Compounds (VOCs) in human breath for use in real-time situations.

In the published literature, several works are on gas sensor arrays and applying soft computational techniques for developing electronic-nose (e-nose). Their performance is further optimized by mimicking the olfactory system of humans, as they can identify many different types of smells and odors found in VOCs and gases. Using the olfactory system, mammals in mammalian systems develop expertise and acquire the ability to identify a variety of VOCs/gases/odors. The human olfactory

system employs several non-selective sensory cells that form electrochemical patterns for different VOCs/gases/odors. The neuronal network of the human brain analyses these complex patterns using almost 10^{11} neurons configured in different segments and architectures, allowing humans to distinguish almost 10,000 types of VOCs/gases/odors.

The performance enhancement of electronic noses (e-noses) has always been a challenging task for researchers to detect and monitor different types of VOCs/gases/odors, especially for their use in real-time situations. Most VOCs/gases/odors have very complicated chemical compositions and characteristics, making it difficult and time-consuming to identify them by analysing their molecular structures. By the time we identify VOCs/gases/odors through such traditional procedures, the findings often become irrelevant and obsolete due to the delayed results. Consequently, it becomes imperative for the researchers to provide accurate results, without much delay, preferably in real time, to detect VOCs/gases/odors being released during fire hazard situations in smart homes, industrial warehouses and also during normal situations at homes during various daily chores (e.g., worship, safety and security, hygiene and disinfectants, LPG leakage, cooking and smoking etc.) detection leading to pollution hazards and for its use in health diagnostics.

In this thesis, we have made five contributions:

- In our first contribution, we have detected seventeen different types of VOCs/gases/odors as generated during daily chores and activities (e.g., worship, safety and security, hygiene and disinfectants, LPG leakage, cooking and smoking etc.) for detection of various activities carried out by the residents.
- In our second contribution, we have proposed a novel framework for creating a real-time map of ‘classes of fire’ for all the six types of fire classes by burning 16 different materials belonging to the aforesaid classes that may be present in a storage and distribution centres such as supermarkets, warehouses, shopping malls etc.
- In the third experiment, we developed a CPS-based intelligent gas sensor system, hereafter called as networked intelligent gas sensor systems (N-IGSS), using Long Range (LoRa) networking protocol-based platform. We captured six types of

VOCs/gases/odors from sensor nodes at the remote data processing station (RDPS) for low-cost real-time IoT-enabled detection and monitoring systems for airborne smoke-based pollution hazards.

- In our fourth contribution, we have proposed another CPS, which consists of an IoT-enabled High-Performance Intelligent Gas Sensor System (IoT-IGSS) for detecting and monitoring Volatile-Organic Compounds (VOCs)/gases/odors released from different disinfectants used in household environments.
- In our concluding work, we have also proposed a novel Cloud Connected IGSS as an IoT-enabled CPS which has been used for real-time qualitative estimation of Blood Glucose levels (BGLs), viz. high, low and normal, using the VOCs exhaled in the human breath.

In this thesis, we used various popular data pre-processing techniques and trained various classifiers to achieve major performance enhancements. We have used advanced data preprocessing and machine learning approaches, i.e. Analysis Space Transformation Methods. In this approach, the raw sensor responses are transformed into other domains, called pre-processing of the data, where the transformed data contains larger covariance and shows better visibility and the possibility of accurate analytics and detection. In such analysis domains, a better-performing classifier can be designed with a much simpler architecture to achieve higher performance.

Further performance enhancement has been derived by using notable pre-processing techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), Kernel Principal Component Analysis (KPCA), Standardised Principal Component Analysis (SPCA) based transformations. To achieve accurate classifications in the analysis space domains, we have used a variety of classifiers such as K-nearest neighbors (KNN), Logistic Regression (LR), Stochastic Gradient Descent (SGD), Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM), Recursive Discriminant Analysis (RDA), Random Forest (RF), Adaboost, XGBoost and Multi-Layer Perceptron (MLP) classifiers.

To the best of the author's information, our proposed intelligent decision support system (IDSS) has been introduced for the first time for the detection of

VOCs/gases/odors released during real-time situations such as activity detection and monitoring of residents in a smart home. The IDSS can also be used to generate a real-time map of ‘classes of fire’ during a fire hazard/outbreak in large storage and distribution centres (SDCs). We have also tested our device prototype for its use in the detection and estimation of pollution and health hazard.

This thesis has been presented in EIGHT chapters:

Chapter-1 Introduces the subject of mammalian and artificial olfaction systems, in general, and the use of artificial intelligence and analysis space transformation-based approaches as used in e-nose, in particular. It briefly describes the human olfactory system and discusses the need for artificial olfaction. It is followed by a brief introduction to the principles of tin-oxide metal oxide semiconductor (MOX) sensors and their array formation. We have also briefly introduced the other sensors, devices, processors and platforms, as used in this doctoral work, viz. particulate matter (PM) sensor, temperature and humidity sensor, ESP 32 and Arduino UNO microcontrollers, Long Range (LoRa) modules and cloud computing platform (AWS). This is followed by a review of relevant research which has been carried out in the recent past in the specific context of the smoke and fire-based pollution hazards, apart from possible application areas of e-noses for the estimation of health hazards. We have then presented the research gaps and proposed the identified problems which have been researched in this doctoral work.

Chapter II consists of three parts; in the first part, we present the way our proposed sensor array has been designed and fabricated for sensor array response data collection in real-time using the steady-state responses of tin-oxide MOX-based 6-element sensor array, PM sensor and Temperature and Humidity sensor.

In the second part, we briefly describe analysis space transformation models used at the pre-processing stage to achieve better class separability than the raw sensor response-based processing.

In the third part of this chapter, we introduce different classification and regression methods, including MLP and other classifiers, their training, validation and testing processes.

Chapter III describes our first contribution to this doctoral work, entitled “Analysis Space Transformation Based Electronic Nose for Efficient Detection and Monitoring of Volatile Organic Compounds, Gases/Odors in Smart Homes”. The proposed system is helpful for real-time classification of VOCs/gases/odors as generated during daily chores and activities (e.g., worship, safety and security, hygiene and disinfectants, LPG leakage, cooking and smoking etc.). This system can be used for the detection of various activities carried out by the house residents. This approach is based on the two-stage modular processing architecture for real-time detection of various VOCs/gases/odors for the purpose described. The proposed approach has been demonstrated by considering the responses of a six-element tin-oxide MOX-based gas sensor array and one temperature and humidity sensor to detect seventeen different types of VOCs/gases/odors released during various activities of the residents in a house. Various space transformation techniques transform the captured sensor responses into suitable analysis space domains. The sensor responses are then processed using different classifiers trained in respective transformation domains. Our proposed e-noses can be operated for real-time air ambient analytics of various VOCs/gases/odors as discussed. We have captured 2465 training samples belonging to 17 diverse VOCs (odors and smokes) commonly found in household ambience. Another 85 samples were also captured for testing purposes, which were not used during the training of the ANN classifier. The accuracy in correct classification has been 96.47% for the 17-class test samples while the precision, recall and F1-score were 96%, 95% and 95%, respectively. The mean squared error (MSE) in this experiment was between 1.35×10^{-6} and 2.15×10^{-2} with an average MSE of 1.42×10^{-3} .

Chapter IV describes a novel approach for “ID2S4FH: A Novel Framework of Intelligent Decision Support System for Fire Hazard”. In this work, we have proposed an Intelligent Decision Support System (IDSS) to generate a real-time ‘fire map’ of storage and distribution centres (SDCs) during a fire hazard using a six-element tin-oxide MOX based gas sensor along with a temperature and humidity sensor and a particulate matter (PM) sensor duly interfaced with microcontrollers to capture real-time signature patterns of the ambient air during a fire hazard situation. We have burnt sixteen different types of materials belonging to six classes of fire and classified

all classes of fire, and generated a real-time map of ‘classes of fire’ which may be used by the firefighters to mitigate the fire more efficiently by using the right kind of fire extinguisher. We have burnt sixteen different types of materials belonging to six classes of fires and created a dataset consisting of 2400 samples. The sensor array responses are then pre-processed and analyzed using various classifiers trained in different analysis space domains. Among these classifiers, four classifiers achieved ‘all correct’ identification of fire classes of 80 unknown test samples, and the lowest MSE achieved is 2.81×10^{-3} .

Chapter V presents another experiment for the “An IoT-Enabled E-Nose for Remote Detection and Monitoring of Airborne Pollution Hazards Using LoRa Network Protocol”. In this work, we have developed a CPS-based low-cost IoT-enabled Intelligent Gas Sensor System (IGSS) Network for centralised data collection and analytics across large buildings and houses for pollution hazard detection on a real-time basis. Using an array of seven tin-oxide MOX-based gas sensor elements interfaced with a microcontroller, we transmitted the real-time sensor array data using a LoRa transmitter. A LoRa gateway was also created using another LoRa module interfaced with a microcontroller to receive real-time transmitted sensor array responses. To verify the performance of the proposed system, we have used five different types of VOCs/gases/odors that are usually present in household environments and considered pollution hazards. Four different classifiers viz. AdaBoost, XGBoost, Random Forest (RF) and Multi-Layer Perceptron (MLP) were trained and tested in the SLDA transformation space. The proposed N-IGSS achieves ‘all correct’ identification of 30 unknown test samples with a low MSE of 1.42×10^{-4} . We have successfully identified the considered gases accurately at the remote LoRa gateway.

Chapter VI describes the “IoT-IGSS: Real-Time Detection of VOCs in Household Disinfectants using IoT-enabled Intelligent Gas Sensor System”. In this work, we proposed a CPS suitable for IoT-enabled High-Performance Intelligent Gas Sensor System (IoT-IGSS) for detecting and monitoring Volatile-Organic Compounds (VOCs)/gases/odors released from different disinfectants used in household

environments. We interface six tin-oxide-based metal-oxide semiconductor (MOX) gas sensor elements with a microcontroller to capture real-time signature patterns of VOCs/gases/odors released by the considered disinfectant materials when they are put in use. The microcontroller sends the gas sensor responses to the cloud, from where data is ported to a Remote Data Processing Centre (RDPC) for further analysis for its use in the real-time scenario. These sensor array responses are pre-processed using the two-stage analysis space transformation method, i.e., Quantile Principal Component Analysis (QPCA) is used in the first stage. Subsequently, Naïve Bayes (NB), Random Forest (RF) and Support Vector Machine (SVM) classifiers are used at the second stage of processing. The proposed HP-IGSS test uses 30 unknown VOCs/gases/odors samples not used during the training and validation. Experimentally, the SVM classifier trained in the QPCA transformed dataset could classify all 30 test samples with 100% accuracy. The lowest MSE achieve 2.46×10^{-6} .

Chapter VII describes the “Cloud-Connected Intelligent Gas Sensor System for Qualitative Estimation of Blood Glucose Level Through Analysis of Exhaled Breath VOCs”. In this work, we created a CPS-suitable cloud-based network of Intelligent Gas Sensor Systems (IGSS) to estimate blood glucose levels (BGLs) through the VOCs in the exhaled human breath in real time. We have interfaced seven tin-oxide MOX-based gas sensors with a microcontroller to capture and transmit the signature patterns from the VOCs present in the exhaled human breath on the Amazon Web Services (AWS) cloud platform. Using ensemble techniques, we have categorised the BGLs into three categories, i.e., low/normal/high blood sugar levels in three subjects. The best-performing system was an MLP trained in the SPCA transformed dataset, associating each test sample correctly with the BGL of the respective volunteer and achieving an MSE of 4.42×10^{-5} .

Finally, Chapter VIII summarises the work carried out in this thesis, followed by the conclusions we have drawn from our contributions to this doctoral work. The scope of future work has also been proposed for the realisation of the deliverables and further research in this area.

(Kanak Kumar)