fire

Article

ID2S4FH: A Novel Framework of Intelligent Decision Support System for Fire Hazards

Kanak Kumar [1], Navin Singh Rajput [1,*], Alexey V. Shvetsov [2,3], Abdu Saif [4], Radhya Sahal [5,6] and Saeed Hamood Alsamhi [7]

[1] Department of Electronics Engineering, Indian Institute of Technology (BHU), Varanasi 221005, India; kanakkumar.rs.ece18@iitbhu.ac.in
[2] Department of Smart Technologies, Moscow Polytechnic University, St. Bolshaya Semenovskaya, 38, 107023 Moscow, Russia; a.shvetsov@vvsu.ru
[3] Faculty of Transport, North-Eastern Federal University, St. Belinsky, 58, 677000 Yakutsk, Russia
[4] Department of Communication and Computer Engineering, Faculty of Engineering and IT, Taiz University, Taiz P.O. Box 6803, Yemen; abduh.saif2017@siswa.um.edu.my
[5] School of Computer Science and IT, University College Cork, T12 K8AF Cork, Ireland; rsahal@ucc.ie
[6] Faculty of Computer Science and Engineering, Hodeidah University, Al Hodeidah P.O. Box 3114, Yemen
[7] Faculty of Engineering, IBB University, Ibb P.O. Box 70270, Yemen; s.alsamhi.rs.ece@iitbhu.ac.in
* Correspondence: nsrajput.ece@iitbhu.ac.in

Abstract: Modern societies and industrial sectors are serviced through storage and distribution centres (SDCs) such as supermarkets, malls, warehouses, etc. Large quantities of supplies are stocked here, e.g., food grains, clothes, shoes, pharmaceuticals, electronics, plastics, edible oils, electrical wires/equipment, petroleum products, painting materials, etc. Fires due to the burning of these materials are categorized into six classes, viz., Class A, Class B, Class C, Class D, Class K, and Class F. A fire is extinguished better when the right type of fire retardant is used. A thumb rule on firefighting also says, "never fight a fire if you do not know what is burning". In this paper, we have proposed an Intelligent Decision Support System (ID2S4FH) to generate a real-time 'fire-map' of such SDCs during a fire hazard. We have interfaced six tin-oxide-based gas sensor elements, a temperature and humidity sensor, and a particulate matter (PM) sensor with microcontrollers to capture the real-time signature patterns of the ambient air. We burned sixteen different types of materials belonging to six classes of fire and created a dataset consisting of 2400 samples. The sensor array responses were then pre-processed and analysed using various classifiers trained in different analysis space domains. Among the classifiers, four classifiers achieved 'all correct' identification of the fire classes of 80 unknown test samples, and the lowest mean squared error (MSE) achieved was 2.81×10^{-3}. During a fire hazard, our proposed ID2S4FH can generate real-time fire maps of SDCs and help firefighters to extinguish the fire using the appropriate fire retardant.

Keywords: fire detection; PM 10; PM 2.5; particulate matter; Arduino UNO; Intelligent Gas Sensor System (IGSS); fire extinguisher

Citation: Kumar, K.; Rajput, N.S.; Shvetsov, A.V.; Saif, A.; Sahal, R.; Alsamhi, S.H. ID2S4FH: A Novel Framework of Intelligent Decision Support System for Fire Hazards. *Fire* **2023**, *6*, 248. https://doi.org/10.3390/fire6070248

Academic Editor: Grant Williamson

Received: 10 May 2023
Revised: 12 June 2023
Accepted: 21 June 2023
Published: 25 June 2023

1. Introduction

Fire hazards have been the most challenging event to handle. They affect the environment significantly and put human life at risk. Early-stage identification and diagnosis of the fire's high-risk factors can help us reduce the losses and save lives. It requires well-timed notifications to those near the fire, which may help people to vacate the burning area and help the appropriate care unit to efficiently extinguish the fire. The International Fire Service Training Association (IFSTA) characterizes fire events in four phases, viz., incipient (ignition), growth, fully developed, and decay, and each stage is influenced by the amount of heat, oxygen, and fuel sources [1]. Four primary fire-detecting effects exist: heat, gas, flame, and smoke. Fire generates smoke, a mixture of airborne gases, liquid particulates, and solid particles. In other words, smoke is an undesirable air contaminant. It arises from the burning of materials and degrades the air quality in the surroundings by the release of volatile organic compounds (VOCs), gases/odours, and particulate matter (PMs) [2]. Further, gas sensing for fire detection has been considered a promising technique. Fire detection based on chemical sensing provides faster alert signals when VOCs, gases, and odours are emitted before smoke particles. At the same time, PM can be sensed using laser-based PM-sensing phenomena when a fire gives rise to steep PM concentrations [3]. While the primary fire indicators are ambient heat, flame, air quality, smoke, and air track, sensors and actuator technology have seen a lot of activity recently and have become a key component of real-time assessment [4].

Four primary components, i.e., fuel, heat, oxygen, and a chemical chain reaction, are required to keep a fire burning. The flow of one or more of these elements is interrupted by fire extinguishers. The fire triangle must be maintained with proper lighting and fire maintenance. If one of these components is missing, the fire will diminish and finally go out independently. Similarly, the approach will fail if one of the components is missing while attempting to create a fire. The fire triangle tetrahedron is shown in Figure 1.

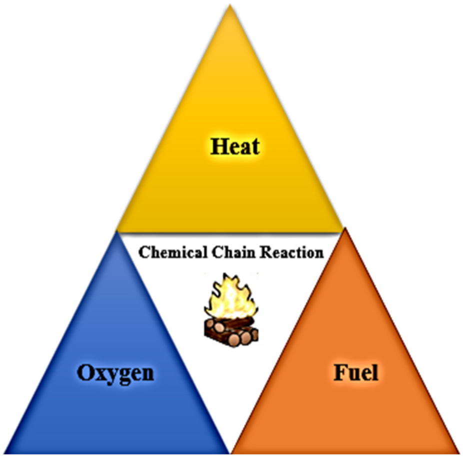


Figure 1. The fire triangle tetrahedron (fuel, oxygen, and heat).

Without flammable material, a fire cannot start. Oxygen is necessary for the combustion process to take place and for heat to be generated. Fire can quickly burn almost everything and depletes the oxygen in the air, which causes casualties from suffocation, shortage of oxygen, and smoke inhalation. Therefore, it is necessary to sense the fire at its early stages and then activate suitable extinguishers to extinguish it and minimise the loss of life and property [4].

Based on the kind of material being burned and as per the National Fire Protection Association (NFPA) standards, fire has been categorized into six classes, viz., Class A (combustible solids—paper, cloth, wood, etc.), Class B (flammable liquids—paints, kerosene, diesel, etc.), Class C (electrical components—PVC, rubber, electrical wires, etc.), Class D (fats and cooking oils—refined oil, mustard oil, coconut oil, etc.), Class K (combustible metals—magnesium), and Class F (flammable gases—LPG, CNG, etc.) [5]. Accordingly, various fire extinguishing agents have also been recommended for use over different classes of fires, as shown in Table 1.

Extinguishing agents the fire triangle tetrahedron; foam-based agents eliminate the oxygen component, while water-based agents cool the fire's heat component, and CO_2-based agents deprive the fire of the oxygen component and reduce the flames. The dry chemicals prevent a fire's chemical reaction. Wet chemicals provide a barrier between the fuel and oxygen during a fire and create a blanket-like cover over the fuel. Dry powder removes the fire's heat and deprives it of oxygen [5].

Table 1. Recommended extinguishing agents for various classes of fire.

Fire Class/Extinguishers	Water	Water Mist	Foam	ABC Dry Powder	CO_2	Wet Chemical	Specialist Powder
Class A	√	√	√	√			
Class B		√	√	√	√	√	
Class C		√		√			
Class D							√
Class K		√		√	√		
Class F							√

In addition to having massive fire suppression capabilities for various fire types, fire extinguishing systems must not generate excessive harmful gases during operation. We must determine the types of burning materials to choose the best extinguisher to put out the fire [5]. Accordingly, we need to identify a distinguishing "feature" that might enable us to recognize various fire sources in a real-world fire hazard situation. Moreover, each fire source belonging to a particular class of materials will have a consistent "fire smoke pattern", which may be used to identify the respective sources of fire and their subcategories.

As a response, an Intelligent Decision Support System (ID2S4FH) can detect the class of a fire from the smoke present in the ambient air and generate a real-time infographic map for the firefighters. An indicative illustration of the concept of real-time fire map generation is shown in Figure 2.

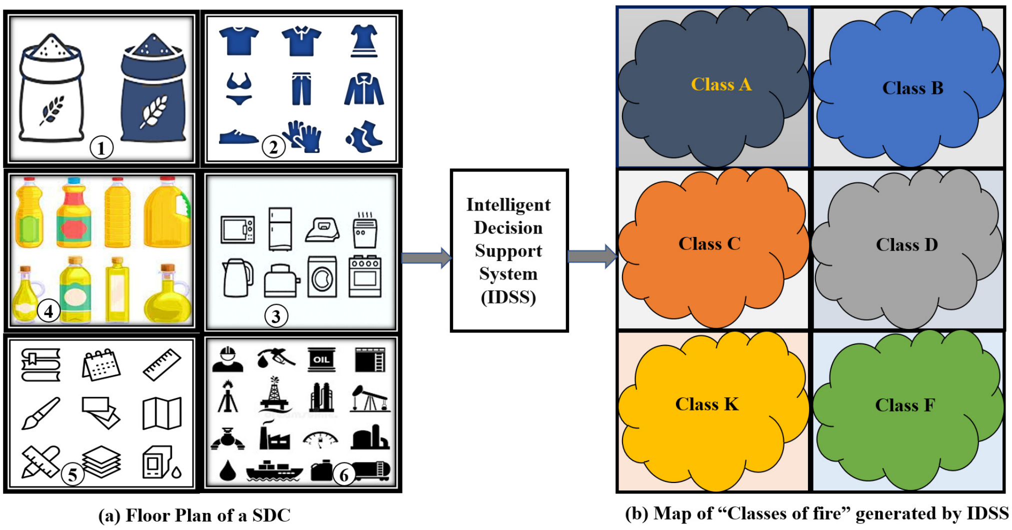


Figure 2. (**a**,**b**) Illustration of an ID2S4FH for real-time fire class map generation. (1: Grains store; 2: clothes store; 3: edible oil; 4: electronics appliances; 5: stationary; 6: oil and liquids).

The ID2S4FH consists of a pattern recognition (PR) system to detect various VOCs, gases, and odours released due to the burning of various materials during a fire. It consists of a gas sensor array with a PM sensor and a temperature and humidity sensor to detect and identify various classes of fire from the smoke using pattern recognition techniques. A basic block schematic of an ID2S4FH for fire class detection is presented in Figure 3.

In the ID2S4FH, multiple sensors are used to capture and analyse the fire-linked signature patterns using various pattern recognition methods, sometimes by mimicking the human olfactory system, which are essentially an extended version of popular electronic noses (e-noses) [6]. E-noses have been popularly used for detection of the presence and types of explosives, food and beverage quality assurance, process monitoring, cosmetics and fragrance testing, medical diagnostics and health monitoring, and automotive and aerospace applications.

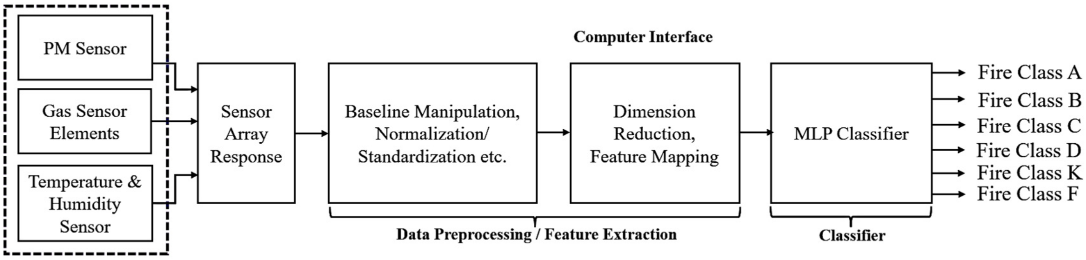


Figure 3. Basic block schematic of an Intelligent Decision Support System (ID2S4FH) for fire class detection.

In the recent literature, semiconductor, catalytic bead, photoionization, infrared, electrochemical, optical, acoustic, gas chromatograph, calorimetric sensors, etc., have been reported as some of the popular gas sensors [7]. Among these, semiconductor metal oxide gas sensors are high-sensitivity, low-cost, and have a longer operational lifetime [7–9]. Various researchers have used various commercially available instruments and processed the data using machine learning methods such as Bayesian classification, Convolutional Neural Networks (CNN), Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Networks (ANN)-based classifiers for the identification of VOCs, gases, and odours released during a fire. Wang et al. developed an ANN model to train their classification model. Three different ANN models, including backpropagation, RBF, and PNN, were used to train the fire classification model to detect the presence of a fire every time. The ANN models stated above can analyse multivariate data. However, they cannot categorise temporal patterns in sensor inputs [10]. D. Guttmacher et al. performed experiments on fires of burning wood, cotton, foam, and alcohol under standardized (EN54) test fire scenarios and found that MOS sensors have a faster response time [8]. Adib et al. proposed an electronic nose as a fire detector. Linear Discriminant Analysis (LDA) was employed on a 16-element sensor array for the detection of cotton, beech, and printed circuit boards (PCBs) from their burning smells [11]. Wu et al. created an e-nose for the qualitative and quantitative monitoring of five volatile, highly flammable liquids (ethanol, tetrahydrofuran, turpentine, lacquer thinner, and gasoline) using a 14-element Figaro metal-oxide sensor-based array with one digital temperature and humidity sensor interfaced with a microcontroller and used principal component analysis (PCA) and ANNs for identification of the fire materials [12]. Tam et al. developed a system for the prevention of cooktop ignition using 14 sensors and used SVM, RF, and Decision Tree (DT) for the fires obtained by burning oils from canola, maize, olive, sunflower, and soy, achieving 96.9% accuracy when using SVM to predict the pre-ignition situations [13].

Furthermore, Rajput et al. (2010) demonstrated high sensor array responses in more efficient analysis spaces. They used standardized PCA (SPCA) with simpler ANNs to achieve 100% accurate classification and quantify the considered hazardous gases/odours [9]. Jaffe et al. studied wildfires through the spread of PM 2.5 and PM 10.0, which show a steep rise in their concentrations during the spread of fire [14]. Findlay et al. used a single CO sensor and a PM sensor to identify wildfires before they started [15]. Sahal et al. presented a dynamic mechanism to recommend the optimal window size and type based on the dynamic context of the Internet of Forest Things (IoFT) application [16]. Kanak et al. developed a LoRa (long-range)-based airborne pollution hazard detection [17]. Saif et al. developed a disaster management system using multi-UAV and SAR collaboration [18]. Alsamhi et al. investigated the potential of a tethered balloon network architecture deployed as part of public safety networks and emergency communications [19]. Alsamhi et al. developed a system for using drones and the internet for public safety in smart cities [20]. A table highlighting the major contributions of our work with the previously published literature is shown in Table 2.

Table 2. Comparative study of the proposed contributions with respect to the published literature.

Ref.	Contributions and Limitations of the Reference	Contributions to Our Proposed Work
[8]	Used EN54 commercially available e-nose and classified four materials, wood, cotton, foam, and alcohol, without identifying the respective fire class.	We have developed our e-nose prototype with 06 gas sensor elements and have classified 16 different types of smoke belonging to six classes of fire.
[9]	Used SPCA transformation ANN for only four gases, classified them accurately, and developed suitable real-time applications.	We have used SPCA-transformed MLP for all six classes of fire and classified them accurately in real time.
[10]	Used commercially available smoke sensor devices and developed three ANN models for smoke detection during fire hazards. They did not attempt to classify various classes of fire.	We have developed our gas sensor array-based system, used three MLP models, and classified all six classes of fire for real-time applications.
[11]	Used e-nose to detect and classify cotton, beech, and printed circuit boards (PCBs) from their burning smells using the LDA method.	Our e-nose system detects all six types of fire classes using PCA and SPCA for pre-processing the dataset. In comparison, we designed and tested 08 different types of classifiers to achieve high-performance classification.
[12]	Used 14-MOX Figaro sensors and one temperature and humidity sensor to detect five volatile, highly flammable liquids (ethanol, tetrahydrofuran, turpentine, lacquer thinner, and gasoline).	We have used six low-cost tin-oxide-based MOX sensors, one PM Sensor, and one DHT-22 for temperature and humidity sensors to detect all VOCs, gases, odours, and other releases from fire smoke.
[13]	Observed cooktop igniting using 14 sensors and SVM, RF, and DT for the fire smokes obtained by burning oils from canola, maize, olive, sunflower, and soy, achieving 96.9% accuracy using SVM.	We have achieved 100% accuracy using SPCA-transformed MLP for identifying 16 types of smoke-releasing materials belonging to 06 fire classes.
[14]	Classified wildfires by using PM 2.5 and PM 10.0 sensor data.	We have detected all kinds of fires using a PM sensor (PM 2.5 and PM 10), a six-element gas sensor array, and a temperature and humidity sensor to achieve 100% accuracy over all the test samples.
[15]	Used a single CO sensor and a PM sensor to identify wildfires.	We have detected all kinds of fires using a PM sensor (PM 2.5 and PM 10), a six-element gas sensor array, and a temperature and humidity sensor to achieve 100% accuracy over all the test samples.

In this paper, we have developed an ID2S4FH by using six-element tin-oxide-based gas sensor elements, with one digital temperature and humidity sensor and one PM sensor for particulate matter (PM 2.5 and PM 10) for the detection of all the six types of fire classes, and by considering sixteen different types of burning materials belonging to each class of fire. The basic block schematic of the proposed ID2S4FH is presented in Figure 4.

We captured the gas sensor array and PM sensor responses in real-time in an interfaced computer while burning the 16 considered types of materials. Later, we transformed the data into various analysis space transformations, viz., kernel PCA (KPCA), LDA, PCA, and SPCA. In these transformation domains, the data are very well-segregated and show well-organized clusters [10–12,21]. Furthermore, K-Nearest Neighbour (KNN), Naïve Bayes (NB), Logistic Regression (LR), Stochastic Gradient Descent (SGD), Decision Tree (DT), and Support Vector Machine (SVM) analyses were used with different kernels and multilayer perceptron (MLP)-based classifiers for achieving superior classification performance over the considered dataset of sixteen types of fire smoke [13,22–24]. The MLP-based classifier, trained using 2320 training data samples in the SPCA transformed analysis space domain, outperformed all the other transformation spaces considered and achieved 'all correct' classification accuracy of the 80 test samples belonging to the six classes of fire. The proposed ID2S4FH aims at being portable, easy to use, and affordable.

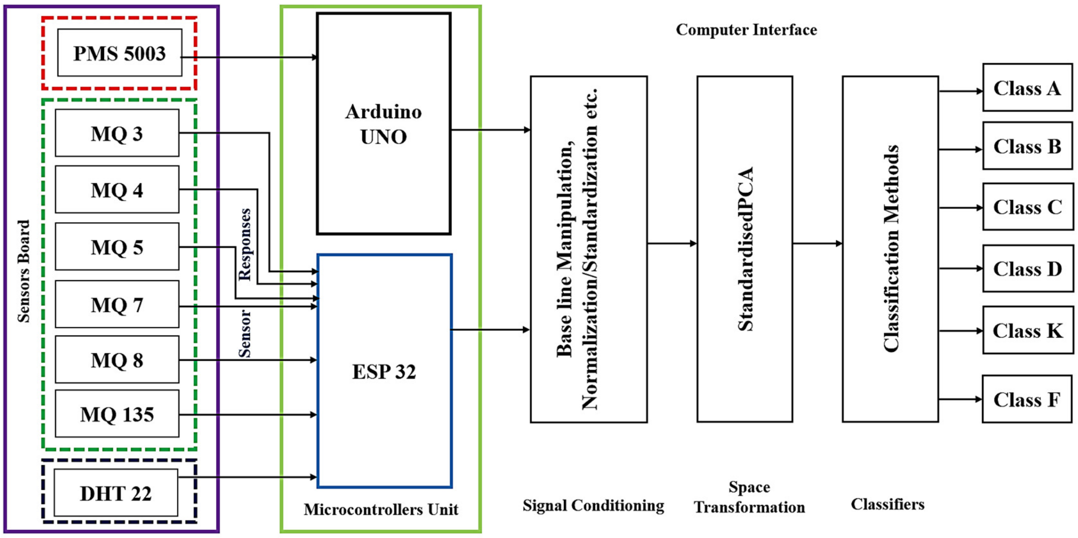


Figure 4. Schematic diagram of the proposed ID2S4FH for detection of all types of fire classes.

The structure of this paper is as follows: In the first section, we discuss the introduction and main purposes of the studies that were conducted. Section 2 describes the materials and methods, including the sample preparation, the building of the proposed ID2S4FH device, the measurement process, the processing of the measured data, and the development of a machine-learning model. The results and discussions are included in Section 3. We conclude the work in Section 4

2. Materials and Methods

We tested our proposed hypothesis by designing and fabricating the proposed intelligent decision support system (ID2S4FH), as shown in Figure 4. Further details are given under various subsections as follows:

2.1. The Design Concept and Principles

In this proposed work, we implemented the ID2S4FH using a two-stage approach. In the first stage, we generated the ambient air's signature patterns using a six-element tin-oxide metal-oxide (MOX)-based gas sensor array, a temperature and humidity sensor, and a particulate matter (PM) sensor. Tin-oxide MOX-based gas sensor elements are naturally nonselective and respond to various VOCs, gases, and odours with different sensitivities [25]. When an array of such gas sensor elements is used, it generates unique signature patterns for different VOCs, gases, and odours. By using pattern recognition techniques, the respective VOCs, gases, and odours can be clearly identified [25]. In the second stage, we processed this surveillance data in its raw form and the analysis space domain using certain pre-processing transformation methods and training certain classifiers. Details of the considered sensors, their detection ranges and target VOCs, gases, and odours, and the pins to which they were interfaced with the microcontroller are given in Table 3.

When both of these stages operate in a cascade, we can identify the fire class from the signature patterns of the smoke present in the ambient air in real-time. These ID2S4FH nodes can be deployed at different locations in storage and distribution centres (SDCs) such as supermarkets, malls, warehouses, etc. During a fire hazard, the data received from these ID2S4FH nodes can be presented as a fire map for further use by the firefighters. An illustration of an ID2S4FH for real-time fire-class map generation is also given in Figure 2.

The proposed approach of using ID2S4FH-based fire-map generation is a non-destructive and non-invasive approach, and various signature patterns belong to the considered VOCs, gases, and odours. We can crisply correlate the patterns with the respective burning materials. The unique signature patterns of smoke generated by burning the considered 16 types of materials are first labelled for the respective fire classes. The raw sensor array responses are analysed in the analysis space transformation domain by applying popular transformations where the data shows distinct and well-separated clusters.

Table 3. Details of the sensors used for the fabrication of ID2S4FH [26–30].

S. No	Sensor Name	I/O Pin	Target Gas/Odour/PM	Detection Ranges (PPM)
S1	PMS5003 (TX, RX)	RX, TX	PM 2.5 and PM 10	1 micron–10 microns
S2	DHT22	25	Temperature and Humidity	−40–125 (°C)
S3	MQ3	32	Alcohol, Ethanol, Smoke	25–500
S4	MQ4	33	Methane, CNG	300–10,000
S5	MQ5	34	Natural Gas, LPG	300–10,000
S6	MQ7	35	CO	10–500
S7	MQ8	36	Hydrogen	100–10,000
S8	MQ135	39	Air Quality	10–1000

2.2. The Prototype

The prototype includes a six-element tin-oxide metal-oxide (MOX)-based gas sensor array, a DHT22 sensor, and a PM sensor which generates real-time signature patterns of the smoke present in the ambient air. The proposed e-nose design's major component is a glass gas chamber. The airflow diagram in the gas chamber is shown in Figure 5.

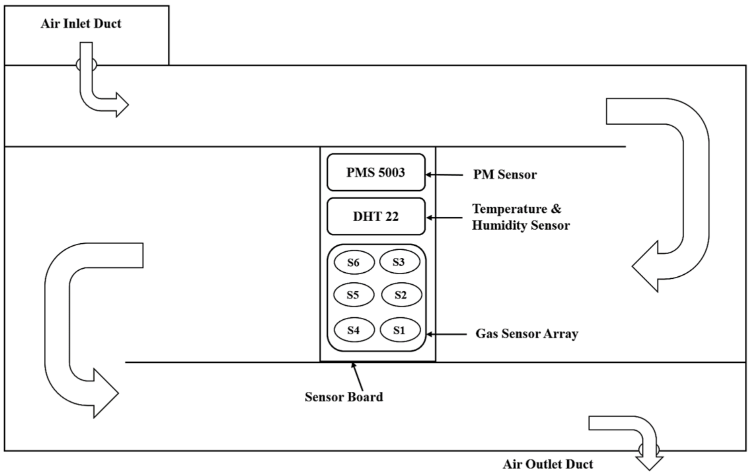


Figure 5. Airflow diagram of the gas chamber used in the proposed prototype of ID2S4FH.

Inside this gas chamber, all the sensors are fitted on the sensor board, and wire connections are made with the microcontrollers. The ratings of the various sensors and devices used in this ID2S4FH are shown in Table 4.

It comprises an electronic control and computer units for real-time data acquisition and processing. The electronic module contains two 32-bit microcontrollers, one for the PM sensor operations while the other interfaces with the rest of the sensors. Using an integrated development environment (IDE), a basic communication protocol was set up between the microcontrollers and the computer to send the data generated during the experiment and to synchronize the beginning and end of the data capturing. The circuit diagram of the PCB designed for the proposed ID2S4FH is shown in Figure 6.

Table 4. Ratings of the components as used in the prototype.

Components	Input Voltage	Power Ratings
PMS 5003	5 V	100 mA
Arduino UNO	5 V	50 mA
Arduino TX/RX pins	3.3 V	40 mA
ESP32	5 V	130 mA
ESP32 GPIO pins	3.3 V	40 mA
DC-DC Buck converter	5 V	2.5 A
DHT22	3–5 V	2.5 mA
MQ sensor	5 V	150 mA

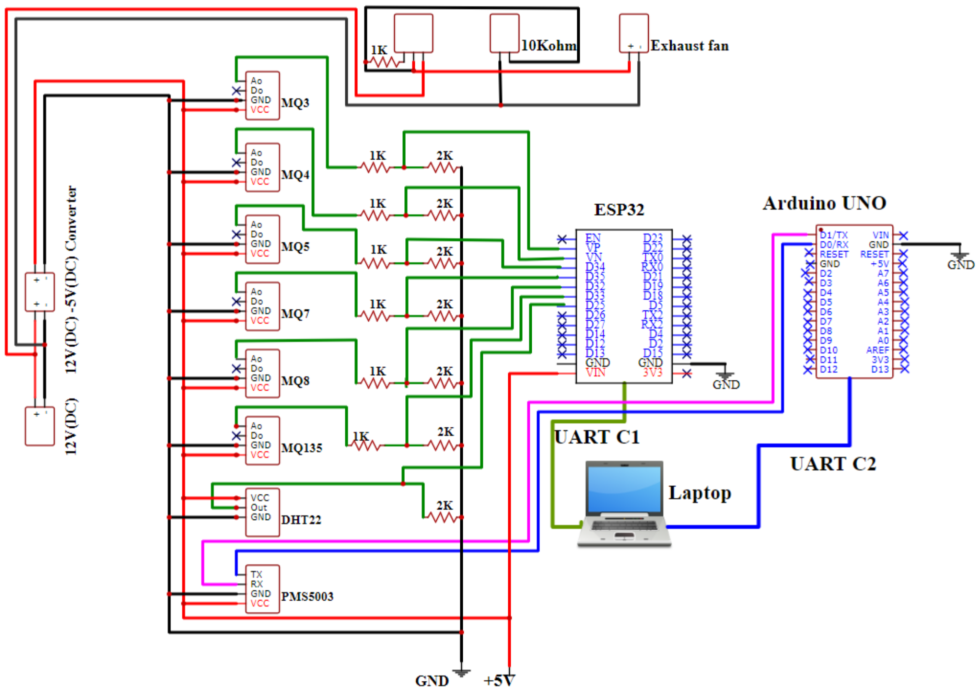


Figure 6. Circuit diagram of the PCB designed for the proposed ID2S4FH.

Post-fabrication, the ID2S4FH prototype has dimensions of 29 cm × 21 cm × 12 cm, providing a total interior volume of 7.308 L (7308 cm^2). Details of the sensors used in the fabrication of the proposed ID2S4FH are given in Table 3. The physical view of the fabricated ID2S4FH is shown in Figure 7a–c.

2.3. The Experiment

In this experiment, we considered 16 types of burning materials to generate VOCs/ gases/odours belonging to the six classes of fire types. Details of the experiment are given in Table 5.

Table 5. Distribution of samples in dataset I and dataset II.

Fire Class	Raw Materials	Dataset I (Training Set)	Dataset II (Testing Set)	Total Samples	Data Collection Time (mints.)
Class A	Cloth	145	5	150	15
	A4 paper	145	5	150	15
	Wood	145	5	150	15

Table 5. *Cont.*

Fire Class	Raw Materials	Dataset I (Training Set)	Dataset II (Testing Set)	Total Samples	Data Collection Time (mints.)
Class B	Paints	145	5	150	15
	Grease	145	5	150	15
	Kerosene	145	5	150	15
	Diesel	145	5	150	15
Class C	Rubber	145	5	150	15
	PVC	145	5	150	15
	Wire	145	5	150	15
Class D	Butter	145	5	150	15
	Mustard oil	145	5	150	15
	Refined oil	145	5	150	15
	Coconut oil	145	5	150	15
Class K	Magnesium	145	5	150	15
Class F	LPG	145	5	150	15
	Total	2320	80	2400	240

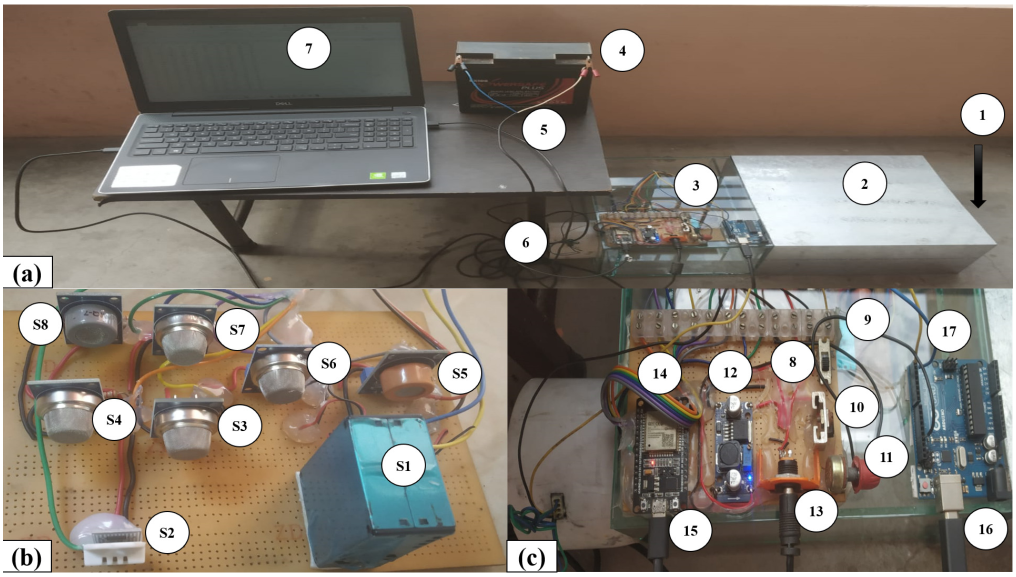


Figure 7. (**a**–**c**) Hardware description of ID2S4FH for fire smoke detection. 1: Gases/odours inlet; 2: air duct; 3: sensor chamber; 4: power supply (12 V DC); 5: power cable; 6: exhaust fan; 7: laptop for sensor response capturing into text format; S1: sensor 1, S2: sensor 2, S3: sensor 3, S4: sensor 4, S5: sensor 5, S6: sensor 6, S7: sensor 7, S8: sensor 8, 8: on–off switch; 9: internal–external wire connecting point; 10: heat sink; 11: voltage regulator; 12: buck-converter; 13: power distribution point; 14: ESP 32; 15: UART Cable-I; 16: UART Cable-II; 17: Arduino Uno.

We integrated eight sensors, viz., six tin-oxide-based gas sensor elements, one temperature and humidity sensor, and one PM sensor on the PCB board of the ID2S4FH. We burned 16 types of materials belonging to six classes of fire smoke. It can be observed from Table 5 that Class-A types of fire smoke are released by the burning of cloth, paper, and wood, while Class-B types of fire smoke are released by burning paints, grease, kerosene, and diesel. The burning of rubber, PVC, and electrical wire releases Class-C fire smoke, and Class-D fire smoke is released by burning butter, mustard oil, refined oil, and coconut oil. Class-K and Class-F types of fire smoke are released by burning magnesium and LPG, respectively. The following experimental procedure was adopted for collecting the experimental dataset:

1. For the first 30 min (t = 0–30 min.), the gas chamber is closed, all the sensors are activated under the prescribed rated operational conditions, and the baseline responses of the sensors are recorded under the steady-state conditions. It is observed that the sensor responses become static during the period.
2. For the next 15 min (t = 31–45 min.), one of the 16 materials (as listed in Table 5) is burned, its smoke is fed into the gas chamber, and sensor array responses are captured continuously, which start at t = 0 min.
3. For the next 30 min (t = 45–75 min.), the gas chamber is purged with fresh ambient air, and during this period, the sensors go into recovery mode and the starting baseline responses are achieved again.
4. The above steps 1, 2, and 3 are repeated again until sensor responses for the fire smokes of all the considered categories have been covered.

Accordingly, each experimental phase continues for 75 min and raw sensor responses are captured for one of the 16 materials and repeated for all the 16 types of materials as considered. Therefore, the experiment was carried out for a total of 1200 min (75 min × 16 materials), covering all six fire smokes classes, per the NFPA standards. Throughout the experiment, we ensured that the sensor responses returned to the baseline responses and that no sensor poisoning occurred. Furthermore, sniffing and purging of the ID2S4FH gas chamber was carried out using an exhaust fan, which maintains a laminar flow in the gas chamber of the ID2S4FH.

2.4. The Dataset

During the experimental procedure, the total experiment time was 1200 min (20 h); during this period, 12,000 samples were captured at the sampling rate of 10 samples per minute. Further details of the dataset and the samples collected are given in Table 5. Regarding the samples belonging to the six classes of fire smoke, a total of 2400 samples were captured for the sixteen considered materials. The dataset contained 450 samples of Class A (cloth, paper, and wood), 600 samples belonging to Class B (paints, grease, kerosene and diesel), 450 samples belonging to Class C (rubber, PVC, and electrical wire), 600 samples of Class D (butter, mustard oil, refined oil, and coconut oil), 150 samples of Class K (magnesium), and 150 samples of Class F (LPG). The signature patterns captured under the considered six classes of fire smoke are shown in Figure 8a–f.

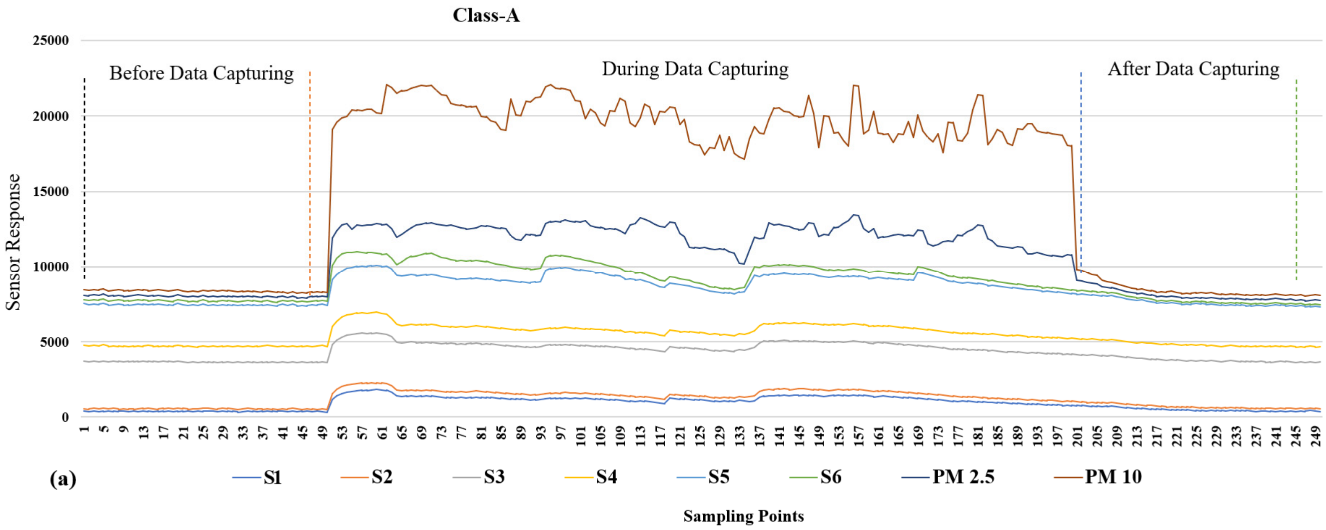
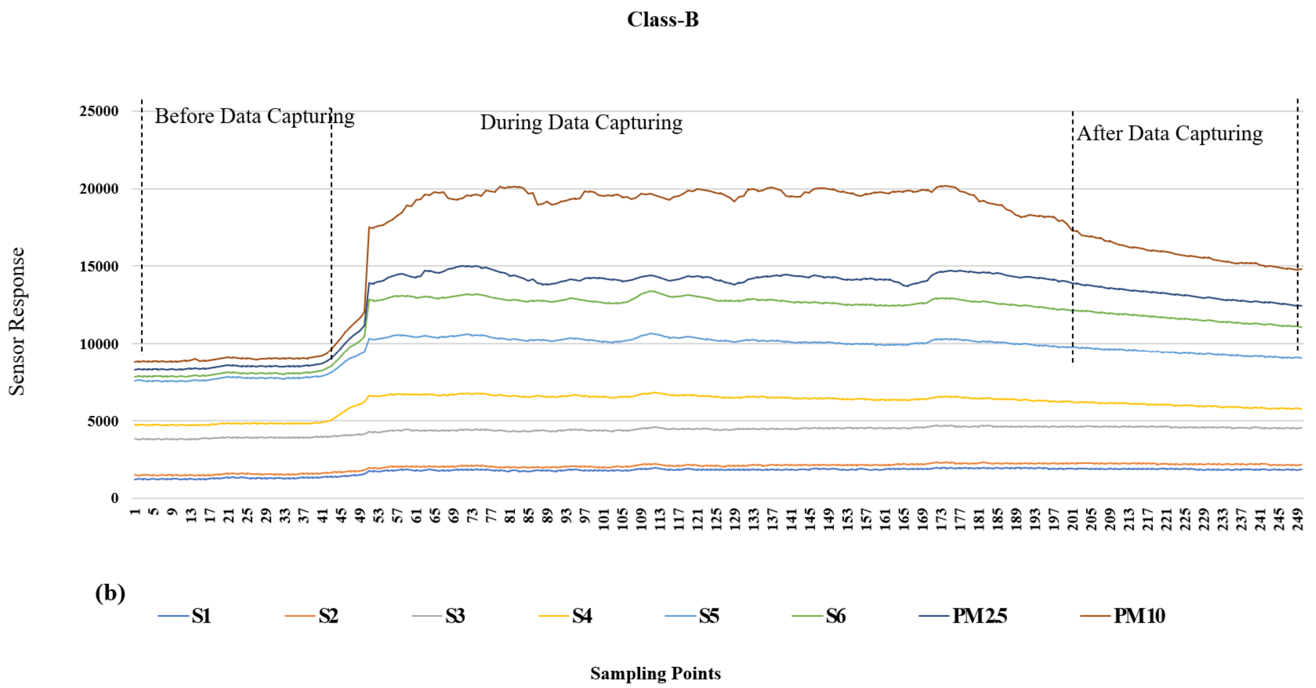
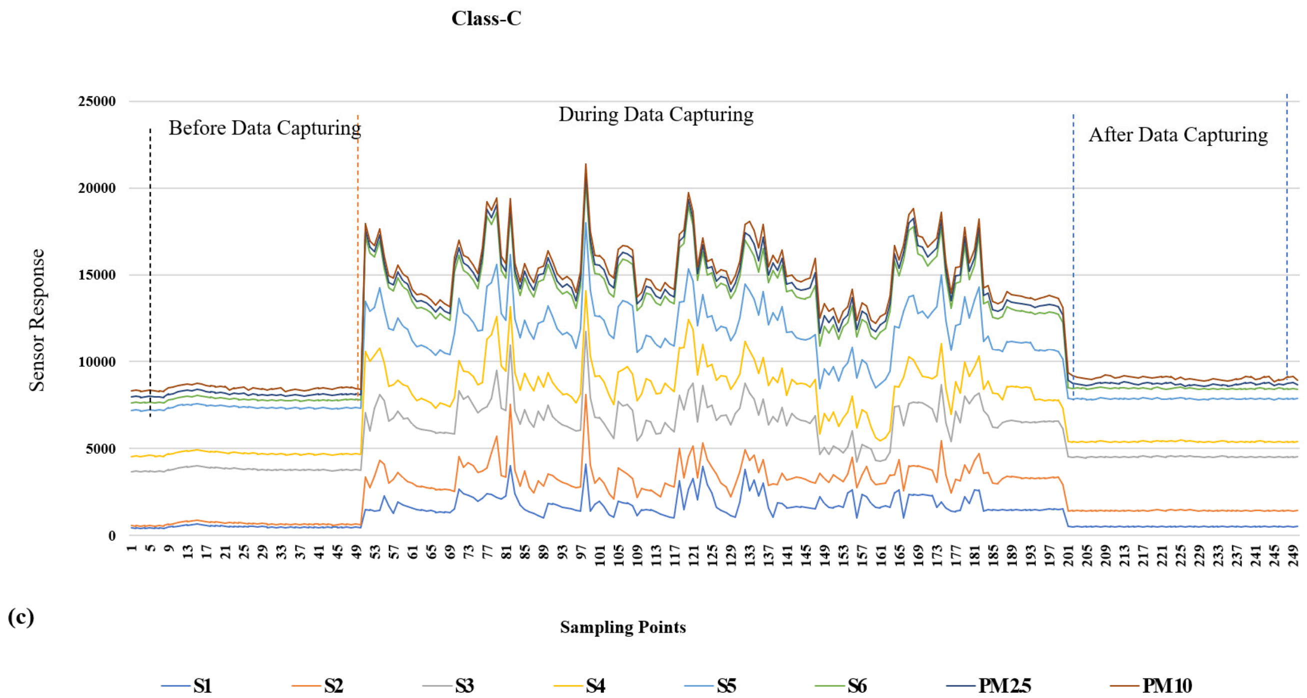


Figure 8. *Cont.*





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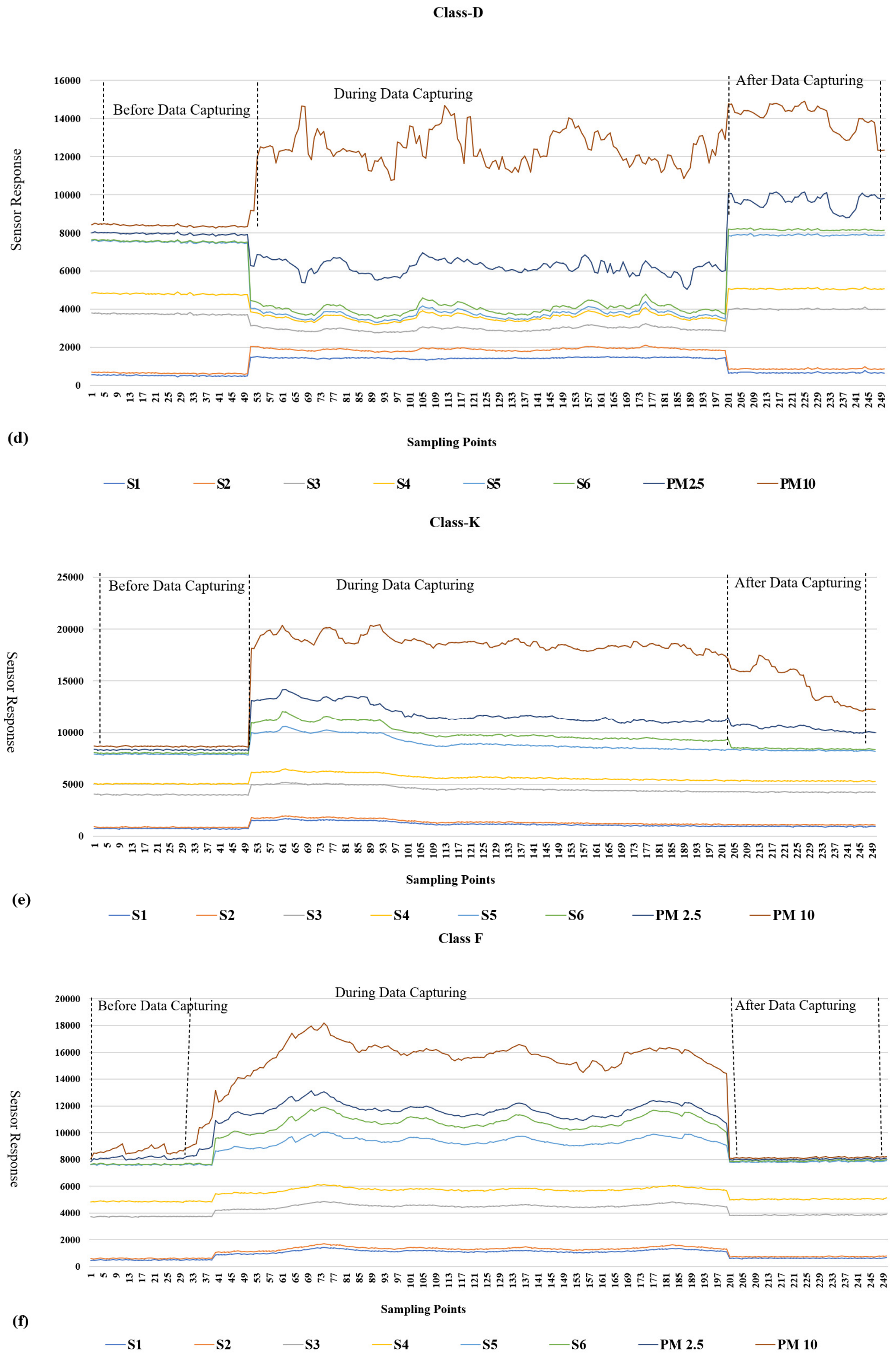


Figure 8. (**a**–**f**) Representative sensor responses of the six classes of fire smoke.

The captured dataset was then segregated into two sets, i.e., training and testing datasets. Accordingly, the training dataset consisted of 145 × 3 = 435 samples for Class A, 145 × 4 = 580 samples for class B, 145 × 3 = 435 samples for Class C, 145 × 4 = 580 samples for Class D, and 145 samples each for Class K and Class F, respectively. Furthermore, for testing purposes, we used 15 samples for Class A, 20 samples for Class B, 15 samples for Class C, 20 samples for Class D, and five samples each for Class K and Class F, respectively, called the testing dataset. The sensor responses and respective temperature (°C) and humidity (RH, %) of the different classes of fire are shown in Table 6.

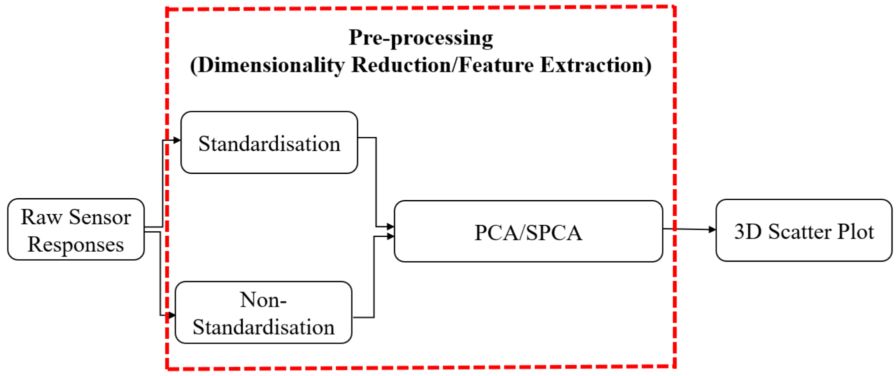
Table 6. The sensor responses and respective temperature (°C) and humidity (RH, %) of different classes of fire.

MQ 3	MQ 4	MQ 5	MQ 7	MQ 8	MQ 135	Temp, (°C)	Humid, (%)	Class
1702	475	3293	1380	3119	993	27.8	62.4	A
1759	321	3233	1314	3696	1360	27.7	64.3	
1395	267	3231	1173	3927	664	23.6	76.4	
1754	208	2336	2302	3709	2480	22.8	75.3	B
1386	242	2364	1373	3257	1226	22.9	65.8	
1050	351	3184	1143	3600	2531	24.8	99	
1523	256	3229	1184	3765	1018	45.6	33.6	
3065	2358	3985	1730	2121	2221	30.2	99	C
3137	1340	3963	2235	3987	1958	26.8	99	
783	156	3096	1045	3167	807	23	84.3	
1007	176	3152	1200	3435	1202	25.1	60.1	D
671	132	3102	1091	2892	992	25.4	51.4	
1083	181	3060	1103	3470	1090	21.5	64.6	
1506	1837	3719	3495	2928	3791	27.1	99.9	
1469	387	1021	495	112	278	25	82.3	K
790	151	3101	1088	3151	843	23	81.1	F

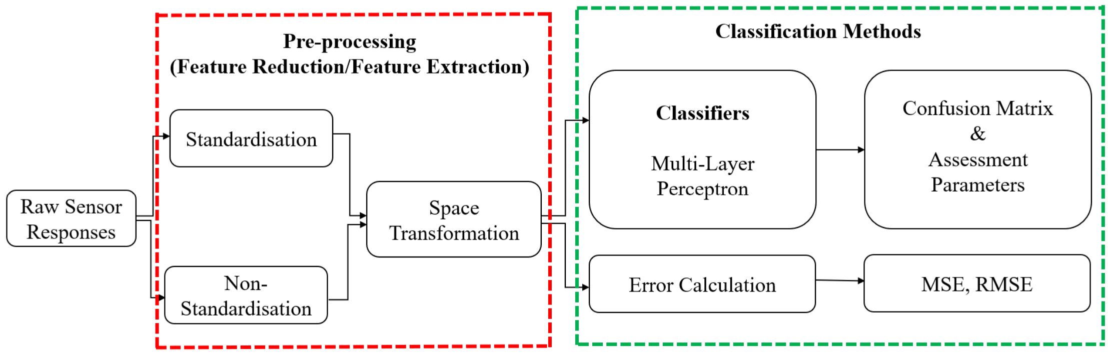
The testing data were separated beforehand and were not used during the training or validation of the classifiers at any stage. They were considered unknown test samples and formed the basis of the ID2S4FH performance test to generate a real-time 'fire-map'. Figure 8a–f shows the representative sensor responses of the six fire smoke classes.

2.5. Contextual Background of Data Pre-Processing and Classifiers

This work was based on the performance enhancement of the proposed ID2S4FH by designing the classifier in the analysis space domain approach as proposed by [9]. It has been observed that a classifier performs better when it is trained in a transformation space where the data show well-separated clusters with good inter-cluster separation. An illustrative diagram depicting the transformation process and its performance assessment is shown in Figure 9a,b. Accordingly, the raw sensor responses were first transformed into the analysis space domainparticularly in the standardised principal component analysis (SPCA) domain. SPCA is a very effective method used for feature extraction as well as for dimensionality reduction [9,12]. For the performance enhancement of the ID2S4FH, we used SPCA as the method for feature extraction. We utilised all the PCs for training and testing the classifier used in the ID2S4FH without any information loss. Furthermore, for the sake of three-dimensional visualisation, we used the first three principal components for the 3D scatter plot.



(a) Block Schematic of Transformation Process



(b) Block Schematic of Performance Assessment Process of IDSS

Figure 9. (**a**,**b**) An illustrative diagram depicting the transformation process and its performance assessment.

Once we obtained the SPCA-transformed version of the raw sensor responses, consisting of the 2400 sample vectors with nine element sample vectors, the transformed dataset was then segregated again into two parts, i.e., the training and testing datasets consisting of 2320 and 80 samples in the SPCA-transformed domain, respectively. In addition to SPCA, we also designed classifiers in the principal component analysis (PCA), kernel principal component analysis (KPCA), and Linear Discriminant Analysis (LDA) domains for comparison purposes [9,17]. Furthermore, we used many popular classifiers such as KNN, NB, LR, DT, SVM, and MLP. Further details of these classifiers can be found in the literature [9,13,21–24]. Among these popular classifiers, the MLP-based classifier outperforms the other types of classifiers. The model configuration details of the different classifiers are shown in Table 7. The schematic diagram of the proposed data pre-processing and the designed classifier are shown in Figure 10a,b.

Table 7. Model configuration details of different classifiers.

Classifiers	Parameters
KNN	Algorithm: auto, leaf_size: 30, metric = minkowski, n_neighbors: 5, p: 2, weights: uniform, cv:5
LR	fit_intercept: True, intercept_scaling: 1, max_iter: 100, multi_class: warn, penalty: l1, random_state: None, solver: warn, warm_start: False, cv:5
SGD	Loss: hinge, penalty: l2, alpha:0.0001, l1_ratio: 0.15, fit_intercept: True, shuffle: True, verbose:0, epsilon:0.1, n_jobs: None, random_state: None, learning_rate: optimal, early_stopping: False, n_iter_no_change:5, class_weight: None, warm_start: False, average: False, cv:5
DT	Criterion: gini, splitter: best, min_samples_split: 2, min_samples_leaf:1, random_state: None, max_leaf_nodes: None, class_weight: None, cv:5

Table 7. *Cont.*

Classifiers	Parameters
NB	Priors: None, var_smoothing: 1×10^{-9} cv:5
SVM	C:1, kernel: rbf, degree: 3, cache_size:200, class_weight: None, verbose: False, max_iter: -1, random_state: None, cv:5
RDA	Solver: svd, shrinkage: None, priors: None, store_covariance: False, tol: 0.0001, covariance_estimator: None, cv:5
MLP	Hidden layer sizes:11, activation function: Relu, solver: adam, batch size:100, learning rate: adaptive, max iteration: 100, cv:5

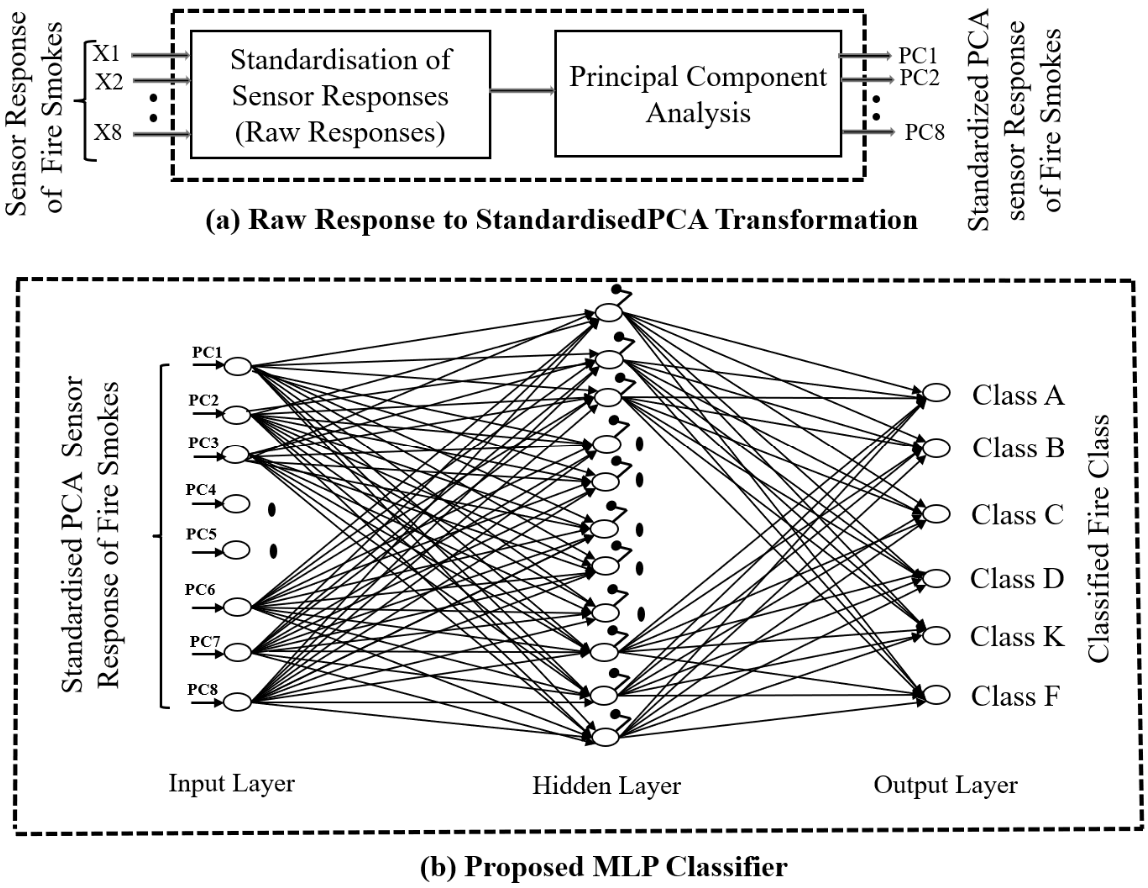


Figure 10. (**a**,**b**) Schematic diagram of the proposed SPCA transformation process and the MLP classifier.

3. Results and Discussion

The proposed work was carried out using Python 3.10.0 software running on a computer, and the ID2S4FH prototype was interfaced with the computer using an integrated development environment (IDE).

3.1. VOCs/Gases/Odours Sensor Response Patterns

As shown in Figure 8a–f, fire smokes belonging to different classes of fire have distinct visible patterns, indicating that MLP classifiers can be used successfully to classify the respective classes of fire smoke with good performance. Most prior research has used large-sized gas sensor arrays (e-noses) or PM sensors alone. As discussed in most of the published literature, their experiments need to be wider to cover all six classes of fire smoke.

In this work, we have considered six types of tin-oxide MOX gas sensor elements (Table 3), which are sensitive to different VOCs, gases, and odours. Being nonselective in nature, they have significantly unique responses. Moreover, it has been observed that materials belonging to different fire classes release distinct amounts of particulate matter. Before starting the exposure to specific fire smokes from respective materials, the gas sensor and the PM sensor attain a baseline value and show steady responses. Once exposure to specific fire smoke is started, there is a significant change in sensor element responses. Once we purge the gas chamber to ambient air, it reverts to a steady-state baseline response, indicating that the sensor elements have not been poisoned or saturated. Class-wise sensor responses are shown in Figure 11a–f. In each fire class, fire smoke materials in the same class also form distinct clusters, indicating that the fire smokes within the same subclass can also be identified successfully.

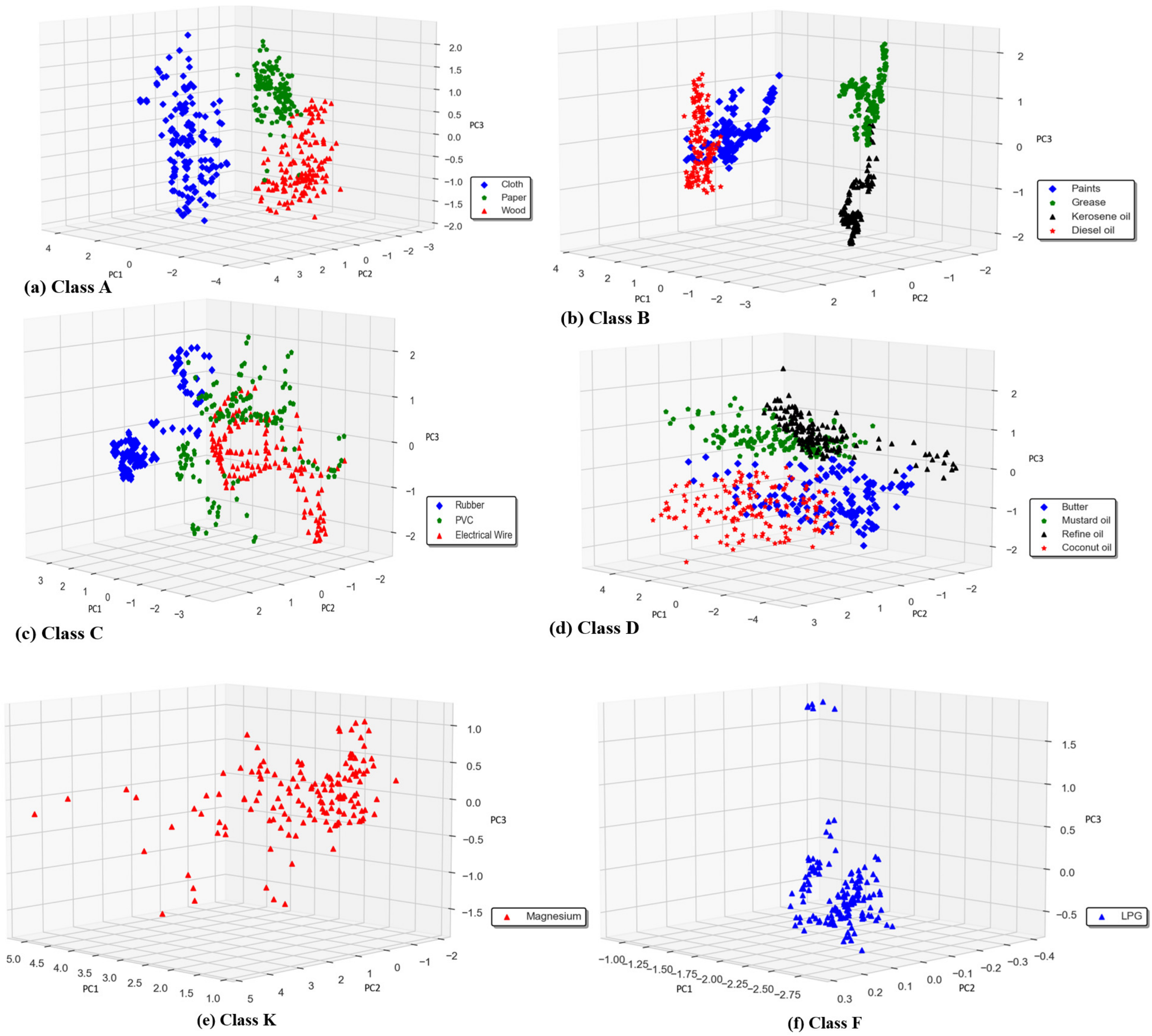


Figure 11. (**a**–**f**), 3D Scatter plots of SPCA-transformed responses of six classes of fire smoke.

3.2. Efficacy of Analysis Space Transformation Approach

In this work, we employed one temperature and humidity sensor (to ensure that the operating conditions remain the same). In contrast, six tin-oxide MOX-based gas sensor elements provide unique sensor response patterns corresponding to the 16 types of materials for releasing six fire smoke classes. The PM sensor was also used, which generates PM values belonging to PM 2.5 and PM 10 concentrations in the respective types of fire smoke. The 3D scatter plot for the raw sensor responses and the respective SPCA-transformed sensor responses, comprising the responses obtained from the gas sensor array and the PM sensor, is shown in Figure 12a,b. It can be observed that the clusters belonging to the six classes of fire smoke, in their raw form, are overlapping and not very clearly distinguishable. Furthermore, as proposed, the same dataset shows far superior clusters with good inter-cluster separation in the corresponding SPCA transformation domain. It is interesting to note that the corresponding scatter plots only consider the gas or PM sensor responses.

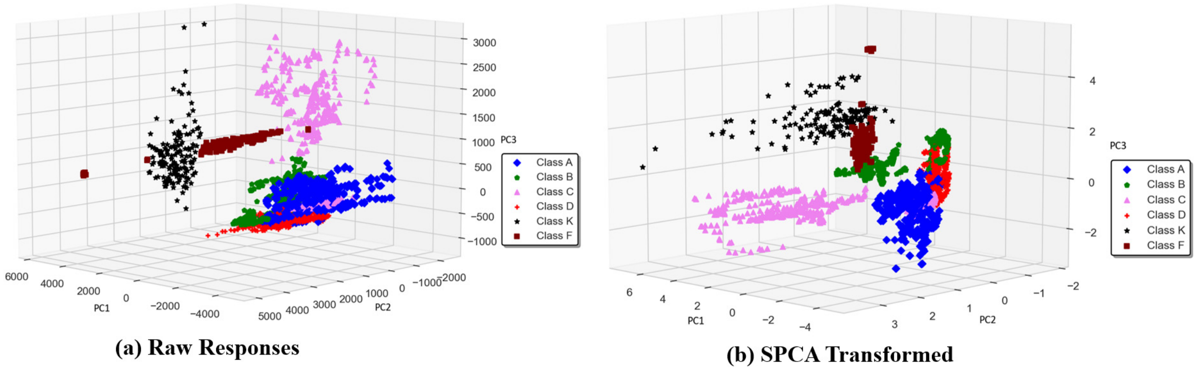


Figure 12. (**a**,**b**). 3D scatter plot of raw and SPCA-transformed responses (gas and PM sensors, jointly).

3.3. Performance of ID2S4FH Classifier for Classifying the Fire Classes

As described in Section 2.5, several performance metrics are considered for multiclass classification, such as accuracy and MSE. Six types of fire smoke data and their sixteen subclasses were classified by employing multiple classifiers and regressors, viz., KNN, DT, NB, SGD, ANN, LR, RDA, and SVM with linear, polynomial, and RBF kernels to evaluate the selected sensor, as discussed in Table 6. The MLP classifier has been the best-performing classifier. The differences between the actual and predicted values for the six classes of fire smoke were evaluated using MSE as the performance parameter, as shown in Figure 13. Furthermore, the classification performance of the ID2S4FH trained and tested in the SPCA domain using the responses of the gas and PM sensors jointly, using 80 unknown test samples, is shown in Figure 14. For the sake of further clarity, the confusion matrix of the classification performance of the MLP classifier is shown in Figure 15, which shows the 'all correct' classification of the considered 80 unknown samples taken from the testing dataset, not used for training the classifier models in the SPCA transformation domain. Another observation is that the MLP classifier's classification performance when trained and tested using only the PM sensor response was found to be ineffective, as shown in Figure 16a,b.

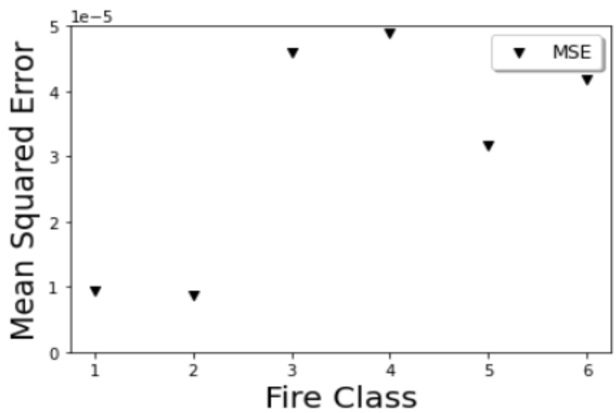


Figure 13. MSE for classification of six classes of fire smoke using MLP classifier trained in SPCA transformation domain.

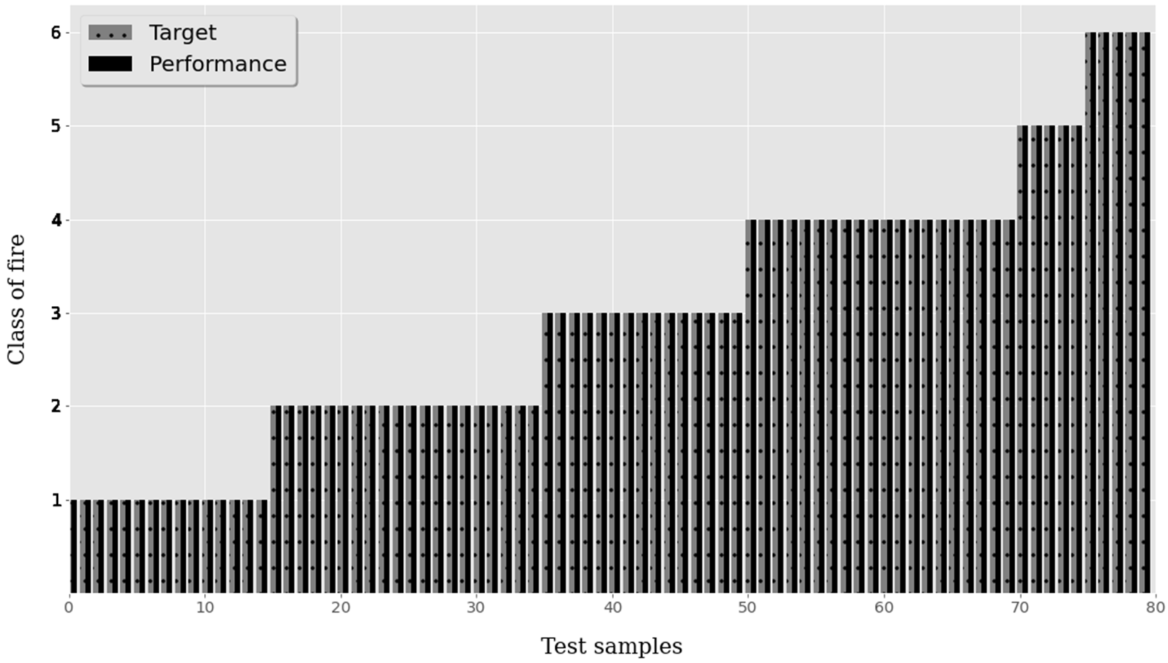


Figure 14. Classification performance of the ID2S4FH designed in the SPCA transformation domain.

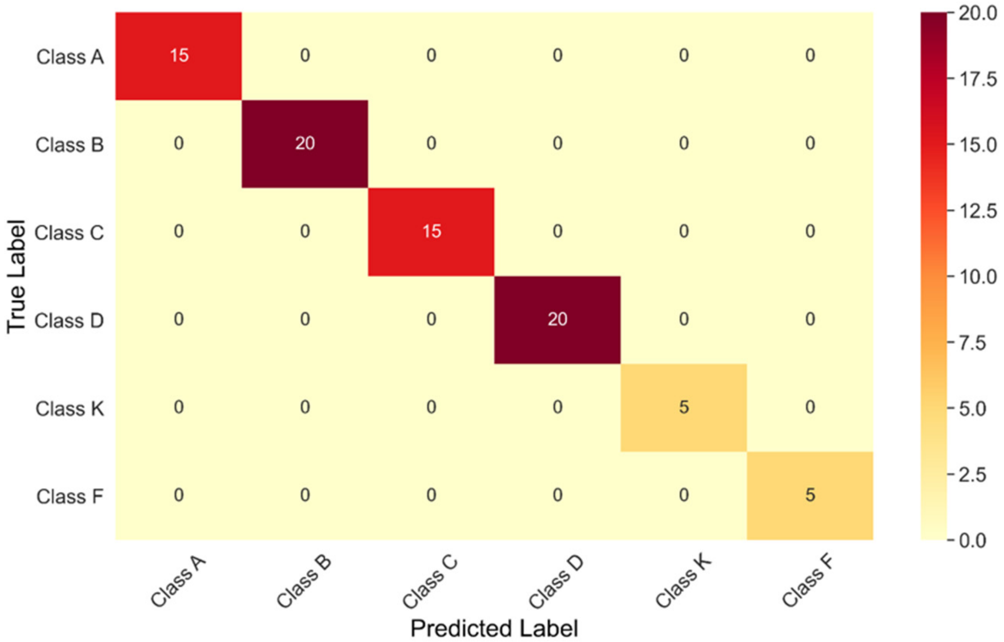
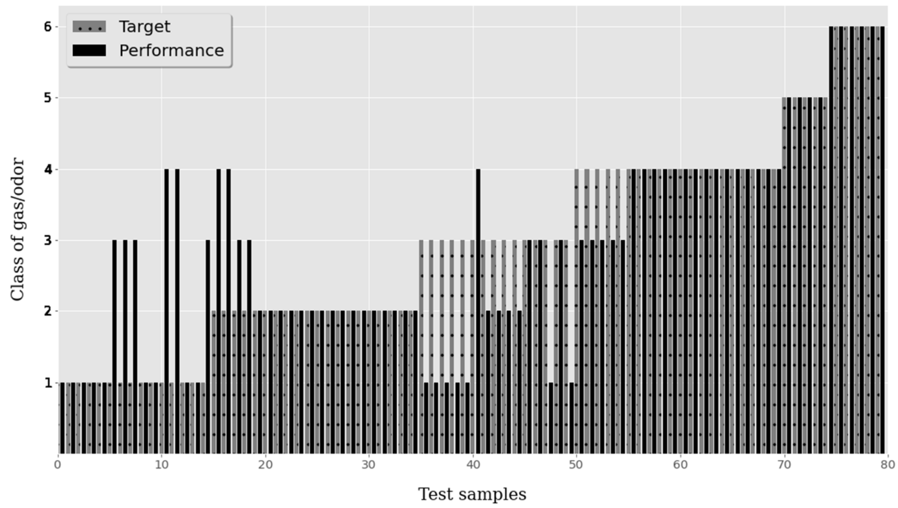
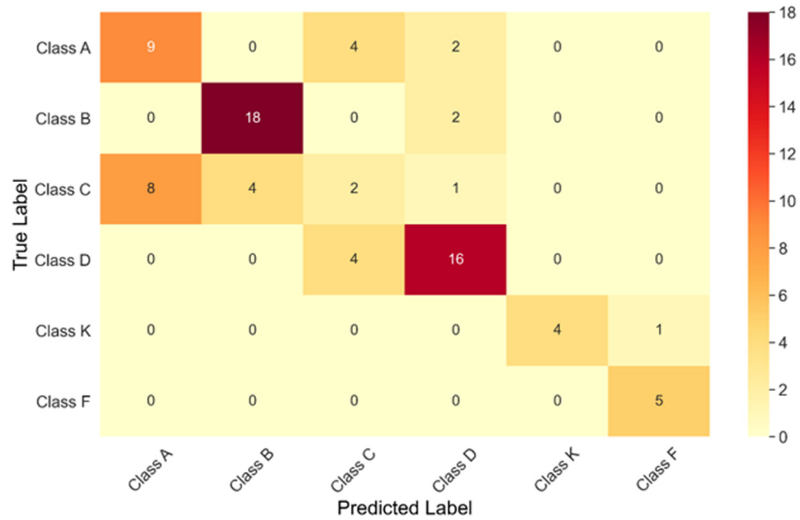


Figure 15. The confusion matrix for the classification performance of the MLP classifier.

We adopted evaluation indices, including accuracy, used a fivefold cross-validation during the performance assessment of the MLP classifier. A graph-based comparative performance of the classification accuracy for various classifiers is shown in Figure 17.



(**a**) **Performance of PM Sensor only**



(**b**) **Confusion Matrix of PM sensor values only**

Figure 16. (**a**,**b**) Performance of classifier trained in SPCA-transformed domain using PM sensor values only.

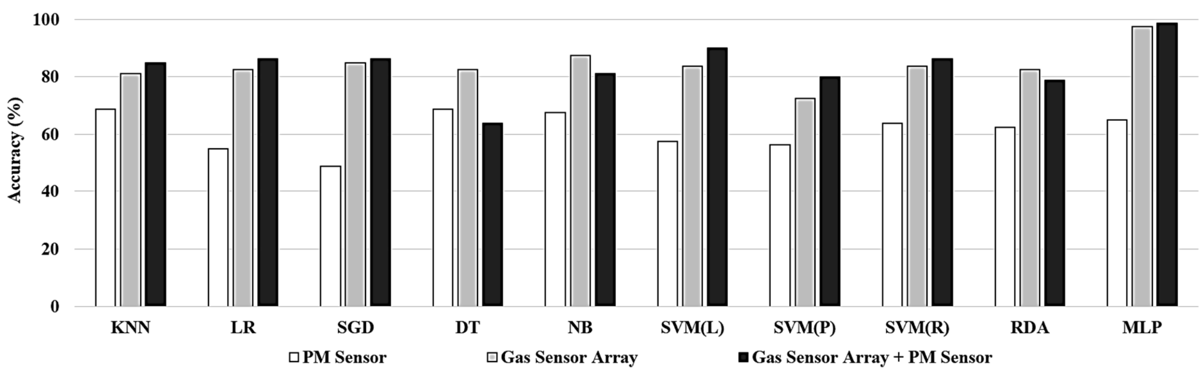


Figure 17. Comparison classification performance of PM sensor, gas sensor, and mixture of gas sensor and PM sensor.

4. Conclusions and Future Work

In this study, we developed an ID2S4FH to accurately classify the six fire classes from the smoke released by burning 16 considered materials. We used 80 unknown test samples to test the performance of the proposed ID2S4FH for the accurate identification and classification of fire smoke belonging to six distinct fire classes. We achieved 'all correct' performance results for the considered 80 test samples, which were not used during the training and validation process of the classifier design process. By considering cross-sensitive elements in the six-element gas sensor array, in conjunction with the PM sensor and a temperature and humidity sensor, we have successfully developed an ID2S4FH that can be used universally to create fire maps in real-time during a fire hazard in storage and distribution centres (SDCs). The proposed ID2S4FH is very stable and durable due to the use of tin-oxide MOX-based gas sensor elements and is accurate because the PM sensor and MLP-based classifiers are included. To the best of the authors' information, this work is the most comprehensive and promising development of an IGSS for real-time generation of maps of 'Classes of Fire'. The proposed ID2S4FH can be deployed as a disaster management system to identify and control fire hazards in various SDCs and places. In the future, a multi-node ID2S4FH network can be designed and deployed across large SDCs to secure such places for real-time fire hazard monitoring and mitigation.

Author Contributions: Conceptualization, K.K., S.H.A. and N.S.R.; Methodology, K.K., A.V.S. and N.S.R.; Software, K.K., R.S.; Validation, N.S.R., A.S. and S.H.A.; Formal analysis, N.S.R. and S.H.A.; Writing—original draft and Visualization, K.K. and N.S.R.; Writing—review, A.V.S., A.S., R.S., N.S.R. and S.H.A.; Editing, A.V.S., A.S., R.S., N.S.R. and S.H.A.; Supervision, N.S.R.; Funding acquisition, N.S.R., A.S. and S.H.A. All authors have read and agreed to the published version of the manuscript.

Funding: No funding available for support.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The dataset used in this study is available and permitted on request.

Acknowledgments: We acknowledge the support of our research group members to permit the use of data for academic and research purposes.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

ANN	Artificial Neural Network
ICA	Independent component analysis
KPCA	Kernel principal component analysis
MLP	Multilayer perceptron
MSE	Mean squared error
NFPA	National Fire Protection Association
PCA	Principal component analysis
QPCA	Quadratic principal component analysis
RMSE	Root mean squared error
SVM	Support Vector Machine

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