Chapter 4

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

Modern societies and industrial sectors are serviced through storage and distribution centers (SDCs) such as supermarkets, malls, warehouses, etc. Large quantities of supplies are stocked here, e.g., food grains, clothes, shoes, pharmacies, electronics, plastics, edible oils, electrical wires/equipment, petroleum products, painting materials, etc. Fires due to the burning of these materials are categorized in six classes, viz., Class A, Class B, Class C, Class D, Class K, and Class F. A thumb rule on firefighting also says “never fight a fire if you do not know what is burning”. A fire is extinguished better when the right type of fire retardant is used. 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 real-time signature patterns of the ambient air. We have burnt sixteen different types of materials belonging to six classes of fires and created a dataset consisting of 2400 samples. The sensors array responses are then preprocessed and analyzed using various classifiers trained in different analysis space dmains . Among these classifiers, four classifiers achieved ‘all correct’ identification of fire classes of 80 unknown test samples, and the lowest mean squared error (MSE) achieved is 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.

4.1 Introduction

The 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 notification to those near the fire, which may help people to vacate the burning area and to the appropriate care unit to efficiently extinguish the fire. The

International Fire Service Training Association (IFSTA) has characterised a fire event 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 [153]. 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/odors and particulate matter (PMs) [154]. 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 odors are emitted before smoke particles. At the same time, PM can be sensed using laser-based PM sensing phenomena when the fire gives rise to steep PM concentrations [155]. While the primary fire indicators are ambient heat, flame, air quality, smoke and air track, sensors and actuator technology have recently seen a lot of activity and have become a key component of real-time assessment [156].

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 4.1.

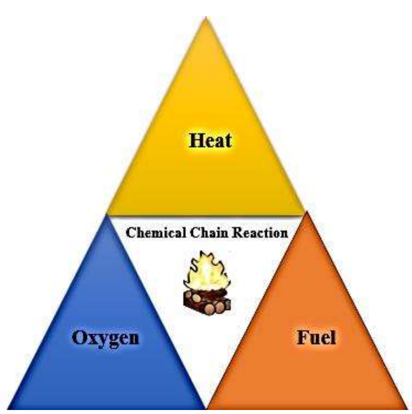


Figure 4.1. The fire triangle tetrahedron (fuel, oxygen and heat)

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 [156].

Based on the kind of material being burnt 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 – refine, 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 4.1.

Table 4.1. Recommended extinguishing agents for various classes of fire.

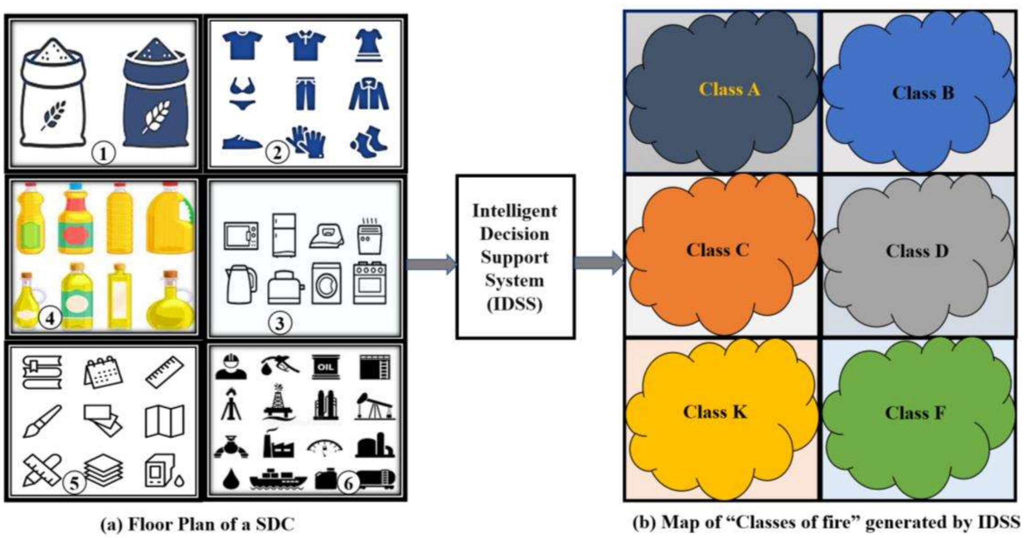
Fire Class/ Extinguishers	Water	Water Mist	Foam	ABC Dry Powder	CO2	Wet Chemical	Specialist Powder
Class A	√	√	√	√			
Class B		√	√	√	√	√	
Class C		√		√			
Class D							√
Class K		√		√	√		
Class F							√

It references 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 creates a blanket-like cover over the fuel. Dry Powder removes the fire’s heat and deprives it of oxygen [157].

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 [157]. 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 respective sources of fire and their subcategories.

As a response, an Intelligent Decision Support System (ID2S4FH) can detect the classes of fires 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 4.2.



1: Grains Store; 2: Cloth Stores; 3: Edible Oil; 4: Electrical & Electronics; 5: Stationary; 6: Oil & Liquids

Figure 4.2. (a), (b) Illustration of an ID2S4FH for real-time fire class map generation.

The ID2S4FH consists of a pattern recognition (PR) system to detect various VOCs, gases and odors released due to the burning of various materials during the fire. It consists of a gas sensor array with a PM sensor and a temperature & 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 4.3.

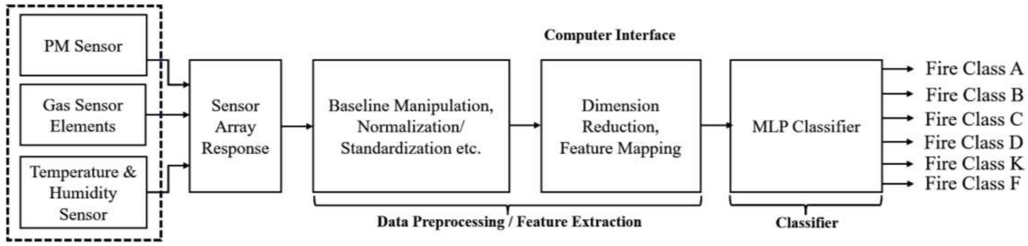


Figure 4.3. Basic block schematic of an Intelligent Decision Support System (ID2S4FH) for fire class detection.

In the ID2S4FH, multiple sensors are used to capture the fire-linked signature patterns and analyse the same using various pattern recognition methods, sometimes by mimicking the human olfactory system, which is essentially an extended version of popular electronic noses (E-nose) [158]. E-noses have been popularly used to detect the presence and types of explosives, food and beverage quality assurance, process monitoring, cosmetics and fragrances, medical diagnostics and health monitoring, and automotive and aerospace applications.

In 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 [81]. Among these, semiconductor metal oxide gas sensors are highly-sensitivity, low-cost, and have a longer operational lifetime [49],[81]-[82]. Various researchers have used various commercially available instruments and processed the data using machine-learning methods like Bayesian classification, Convolutional Neural Networks (CNN), Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Networks (ANN)-based classifiers for identification of VOCs, gases and odors 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 [83]. D. Guttmacher et al. have performed experiments on fires of wood, cotton, foam, and alcohol under standardized (EN54) test fire scenarios and found that MOS sensors have faster response time [8]. Adib et al. have 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 board (PCB) from their burning smells [84]. Wu et al. have created an E-Nose for 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 microcontroller; and used Principal Component Analysis (PCA) and ANNs for identification of the fire materials [85]. Tam et al. have

Table 4.2. Comparative study of the proposed contributions with respect to published literature

Ref.	Contributions and Limitations of the Reference	Contributions to our proposed work
[82]	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 own e-nose prototype with 06 gas sensor elements and have classified 16 different types of smoke belonging to six classes of fire.
[49]	Used SPCA transformation ANN for only four gases and classified them accurately and developed if suitably for real-time applications.	We have used SPCA-transformed MLP for all six classes of fire and classified them accurately in real time.
[83]	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 own gas sensor array-based system, used three MLP models, and classified all six classes of fire for real-time applications.
[84]	Used e-nose to detect cotton, beech, and printed circuit board (PCB) from their burning smells and classified the same using LDA method.	Our e-nose system detects all six types of fire classes using PCA and SPCA for pre-processing the dataset while we designed and tested 08 different types of classifiers to achieve high performance classification.
[85]	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 for all VOCs, gases and odors detection, and releases from fire smoke.
[86]	Used cooktop igniting using 14 sensors and SVM, RF, and DT for the	We have achieved 100% accuracy using SPCA-transformed MLP for

	fire smokes obtained by burning oils from canola, maize, olive, sunflower, and soy, achieving 96.9% accuracy using SVM.	identifying 16 different types of smoke releasing materials belonging to 06 types of fire classes..
[87]	Classified wildfires by using PM 2.5 and PM 10.0 sensor data.	We have detected all kinds of fires using a PM sensor (PM2.5 and PM 10) along with a six-element gas sensor array and a Temperature and Humidity sensor to achieve 100% accuracy over all the test samples.
[88]	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) along with a six-element gas sensor array and a Temperature and Humidity sensor to achieve 100% accuracy over all the test samples.

developed a system for the prevention of cooktop igniting 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 using SVM to predict the pre-ignition situations [86]. Further, Rajput et al. demonstrated high sensor array response in more efficient analysis spaces. They used standardized PCA (SPCA) with simpler ANNs to achieve 100% accurate classification and quantify the considered hazardous gases/odors [49]. 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 [87]. Findlay et al. used a single CO sensor and a PM sensor to identify wildfires before they started [88]. Sahal et al. have 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 [168]. A table highlighting the major contributions of our work with the previously published literature has been placed shown at Table 4.2.

In this paper, we have developed an ID2S4FH using six-element Tin Oxide based gas sensor elements, with one digital temperature and humidity sensor and one PM sensor for Particulate Matters (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 4.4.

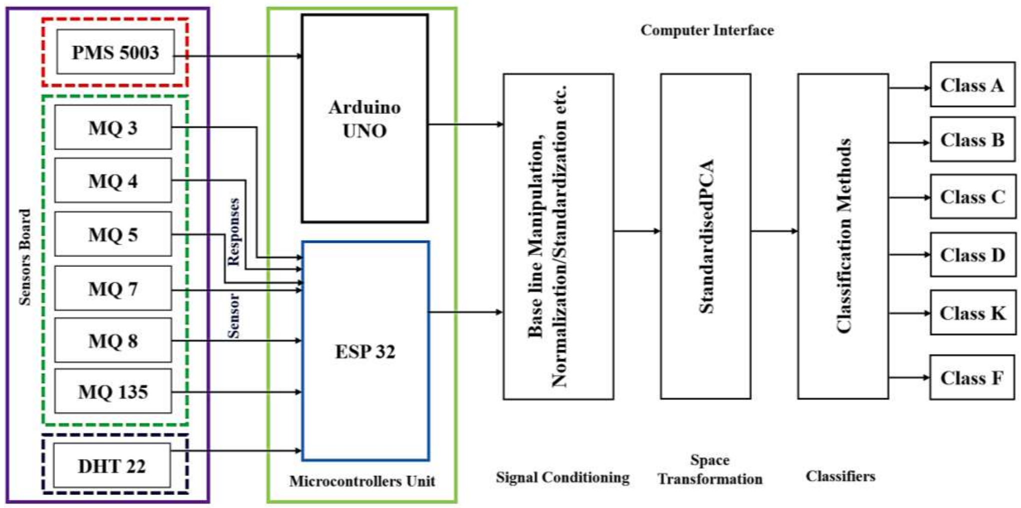


Figure 4.4. Schematic diagram of the proposed ID2S4FH for detection of all types of fire classes.

We have captured the gas sensor array and PM sensor responses in real-time in an interfaced computer while burning 16 types of the considered 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 is very well segregated and shows well organized clusters [83]-[85], [159]. Further, K Nearest Neighbor (KNN), Naïve Bayes (NB), Logistic Regression (LR), Stochastic Gradient Descent (SGD), Decision Tree (DT), Support Vector Machine (SVM) with different kernels and multi-layer perceptron (MLP)-based classifiers for achieving superior classification performance over the considered dataset of sixteen types of fire smoke [86], [160]-[162]. The MLP-based classifier trained using 2320 training data samples in the SPCA transformed analysis space domain outperformed all the other transformation spaces as considered and achieves 'all correct' classification accuracy of the 80 test samples belonging to the six classes of fire. The proposed ID2S4FH has been aimed at being portable, easy to use and affordable.

4.2. Materials and Methods

We have tested our proposed hypothesis by designing and fabricating the proposed intelligent decision support system (ID2S4FH), as shown in Figure 4.4. Further details have been given under various subsections as follows:

4.2.1. The Design Concept

In this proposed work, we have 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 non-selective and respond to various VOCs, gases and odors with different sensitivities [163]. When an array of such gas sensor elements is used, it generates unique signature patterns for different VOCs, gases and odors. By using pattern recognition techniques, respective VOCs, gases, and odors can be clearly identified [163]. In the second stage, we process this surveillance data in its raw form and in 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 odors, along with the pins to which they have been interfaced with the microcontroller, are given in Table 4.3.

Table 4.3. Details of the sensors used for the fabrication of ID2S4FH [21]-[25].

S. No	Sensor Name	I/O Pin	Target Gas/Odor/PM	Detection Ranges (PPM)
S1	PMS5003 (TX, RX)	RX, TX	PM 2.5 & PM 10	1 micron – 10 microns
S2	DHT22	25	Temperature & Humidity	-40 - 125(°C)
S3	MQ3	32	Alcohol, Ethanol, Smoke	25 - 500
S4	MQ4	33	Methane, CNG	300 - 10000
S5	MQ5	34	Natural Gas, LPG	300 - 10000
S6	MQ7	35	CO	10 - 500
S7	MQ8	36	Hydrogen	100 - 10000
S8	MQ135	39	Air quality	10 - 1000

When both of these stages are operated 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 centers (SDCs) such as supermarkets, malls, warehouses, etc. During an event of a fire hazard, the data received from these ID2S4FH nodes can be presented in the form of a fire map for further use by the firefighters. An illustration of an ID2S4FH for real-time fire class map generation has also been given in Figure 4.2.

The proposed approach of using ID2S4FH -based fire-map generation is a non-destructive and non-invasive approach, and various signature patterns belonging to the considered VOCs, gases and odors, we can crisply correlate with the respective material under fire. The unique signature patterns of smoke generated by burning the considered 16 types of materials are first labelled for 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.

4.2.2. 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 4.5.

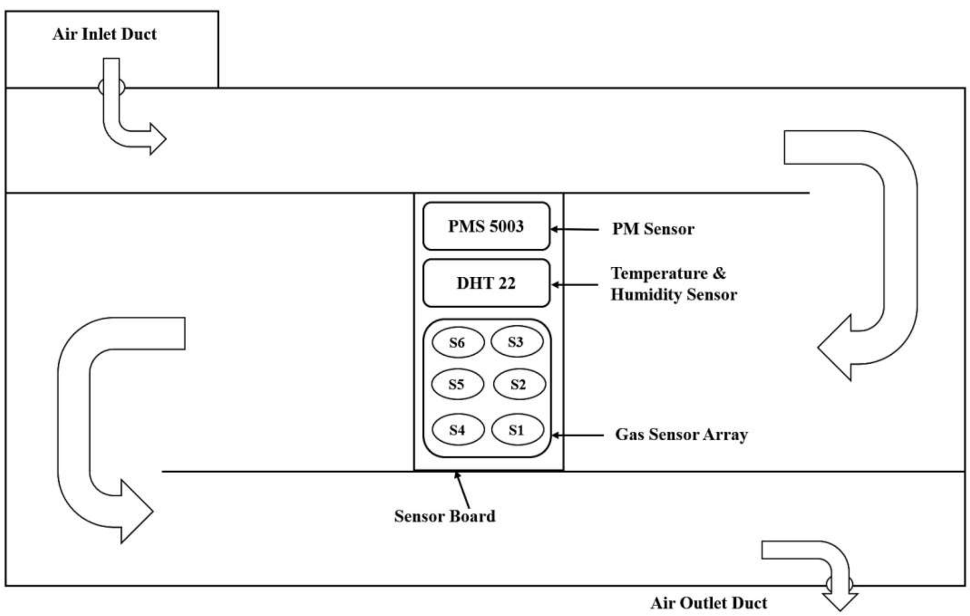


Figure 4.5. Airflow diagram of the gas chamber used in the proposed prototype of ID2S4FH.

Inside this gas chamber, all the sensors are fitted on the sensor board, and wire connections are made with the microcontrollers. The ratings of various sensors and devices used in this ID2S4FH are shown in Table 4.4.

Table 4.4. Ratings of the Components as Used in Prototype.

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

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. By 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 with the beginning and end of the data capturing. The circuit diagram of the PCB designed for the proposed ID2S4FH has been shown in Figure 4.6.

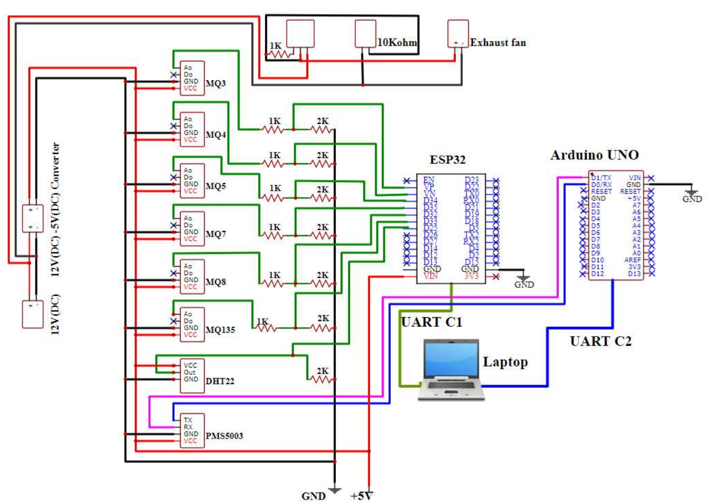


Figure 4.6. Circuit diagram of the PCB designed for the proposed ID2S4FH.

Post fabrication, the ID2S4FH prototype has a dimension of 29 cm x 21 cm x 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 have been given in Table 3. The physical view of the fabricated ID2S4FH has been shown in Figure 4.7 (a) – (c).

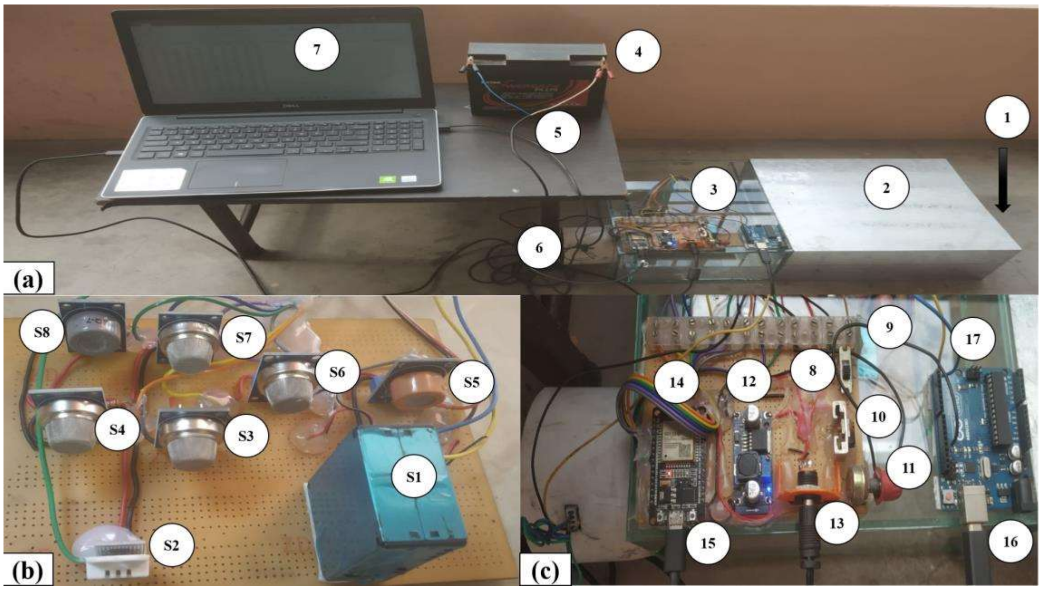


Figure 4.7. (a), (b), (c) Hardware description of ID2S4FH for fire smoke detection.

1: Gases/odors 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

4.2.3. The Experiment

In this experiment, we have considered burning 16 types of materials to generate VOCs/Gases/Odours belonging to the six classes of fire types. Details of the experiment has been given in Table 4.5.

Table 4.5. 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 (minutes)
Class A	Cloth	145	5	150	15
	A4-Paper	145	5	150	15
	Wood	145	5	150	15
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
	Refine	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

We have integrated eight sensors, viz., six Tin-oxide based gas sensor elements, one temperature & humidity sensor and one PM sensor on the PCB board of the ID2S4FH . We have burnt 16 types of materials belonging to six classes of fire smoke. It can be observed from Table 4.5 that Class-A type 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. 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 minutes (t = 0 – 30 mins.), the gas chamber was closed, and all the sensors are activated under the prescribed rated operational conditions, and 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 minutes (t = 31 – 45 mins.), one of the 16 materials (as listed in Table 5) is burnt, and its smoke is fed into the gas chamber and sensor array responses are captured continuously, which was started at t = 0 mins.
3. For the next 30 minutes (t = 45 – 75 mins.), 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 fire smokes of all the considered categories have been covered.

Accordingly, each experimental phase continues for 75 minutes 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 is carried out for a total of 1200 minutes (75 minutes × 16 materials), covering all six fire smokes classes, per the NFPA standards. Throughout the experiment, we have ensured that the sensor responses return to the baseline responses and that no sensor poisoning occurs. Further, sniffing and purging of the ID2S4FH gas chamber is carried out using an exhaust fan which maintains a laminar flow in the gas chamber of the ID2S4FH .

4.2.4. The Dataset

During the experimental procedure, the total experiment time was 1200 minutes (20 hours); during this period, 12000 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 smokes, a total of 2400 samples were captured for the sixteen considered materials. The dataset contains 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, 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 4.8 (a) – (f).

The captured dataset was then segregated into two sets, i.e., training and testing datasets. Accordingly, the training dataset consisted of $145 \times 3 = 435$ samples for class A, $145 \times 4 = 580$ samples for class B, $145 \times 3 = 435$ samples for class C, $145 \times 4 = 580$ samples for class D and 145 samples each for class K and class F, respectively. Further, for testing purposes, we have 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.

Testing data was separated beforehand and were not used during the training or validation of the classifiers at any stage, are considered unknown test samples and form the basis of the Intelligent Decision Support System (ID2S4FH) performance test to generate real-time 'fire-map'.

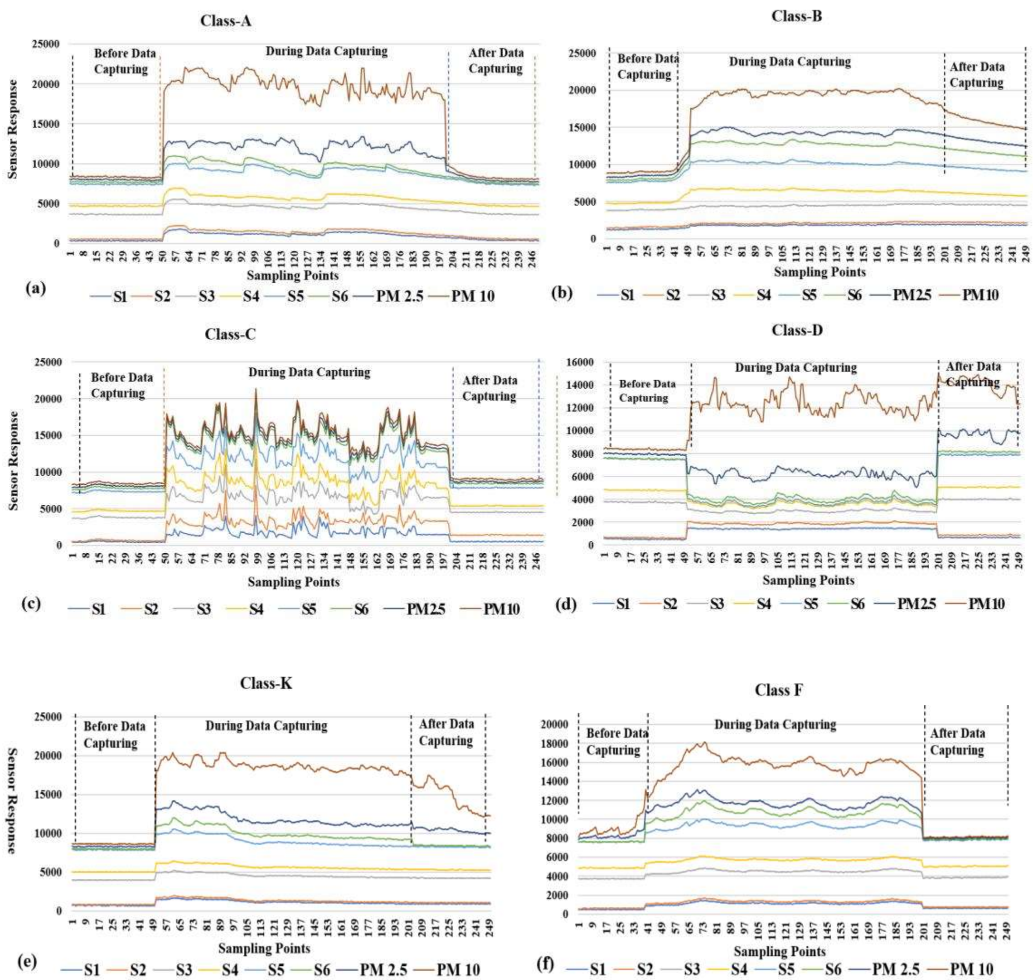
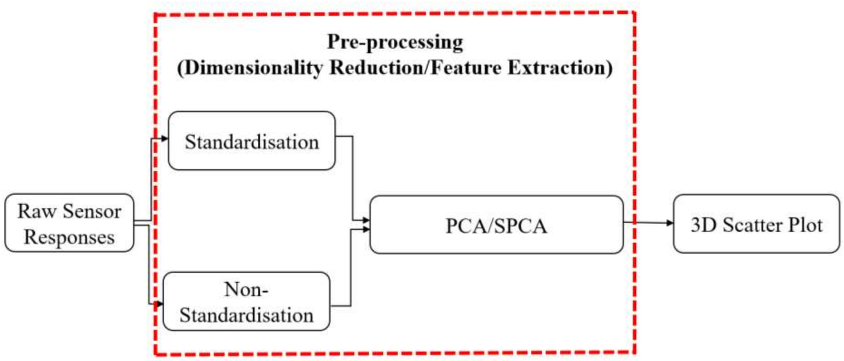


Figure 4.8 (a) – (f). Representative Sensor Responses of six classes of fire smokes.

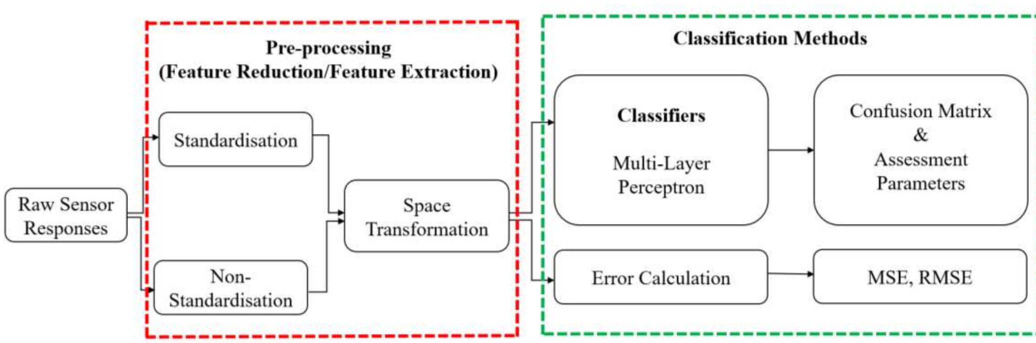
4.2.5. Contextual Background of Data Pre-processing and Classifiers

This work has been based on the performance enhancement of the proposed ID2S4FH by designing the classifier in the analysis space domain approach as proposed by [49]. It has been observed that a classifier performs better when it is trained in a transformation space where the data shows well-separated clusters with good inter-cluster separation. An illustrative diagram depicting the transformation process and its performance assessment has been shown in Figure 4.9 (a) – (b).

Accordingly, the raw sensor responses were first transformed into the analysis space domain, especially in the standardized principal component analysis domain. Standardized Principal Component Analysis (SPCA) is a very effective method used for feature extraction as well as for dimensionality reduction [49],[85]. For the performance enhancement of the ID2S4FH , we have used SPCA as the method for feature extraction. We have all the PCs for the training and testing of the classifier used in the ID2S4FH without any information loss. Further, for the sake of three-dimensional visualization, we have 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 4.9. (a), (b) An illustrative diagram depicting the transformation process and its performance assessment.

Once we have 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 dataset consisting of 2320 and 80 samples in the SPCA transformed domain, respectively. In addition to SPCA, we have also designed classifiers in the Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA) and Linear Discriminant Analysis (LDA) domains for comparison purposes. Further, we have used many popular classifiers such as KNN, NB, LR, DT, SVM and MLP. Further details of these classifiers can be found in the literature [49], [86], [159]-[162]. Among these popular classifiers, MLP based classifier outperforms the other types of classifiers. The schematic diagram of the proposed data pre-processing and the designed classifier are shown in Figures 4.10 (a) and (b).

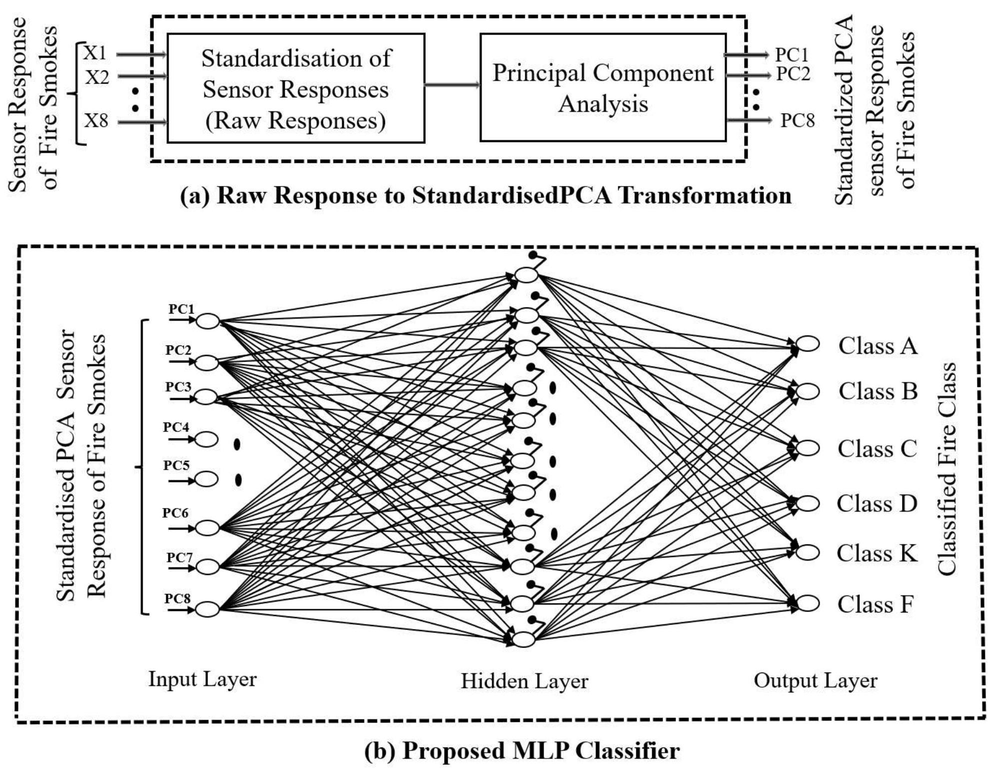


Figure 4.10. (a), (b). Schematic diagram of the proposed SPCA transformation process and the MLP classifier.

4.3. Results and Discussions

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

4.3.1. VOCs/Gases/Odors Sensor Response Patterns

As shown in Figure 4.8 (a) - (f), fire smokes belonging to different classes of fire has distinct visible patterns indicating that MLP classifiers can be used successfully to classify respective classes of fire smoke with good performance. Most of the prior research used large-sized gas sensor arrays (E-noses) or PM sensors alone. As discussed in most of the published literature, their experiments have not been wide enough to cover all six classes of fire smokes.

In this work, we have considered six types of tin-oxide MOX gas sensor elements (Table 4.3), which are sensitive to different VOCs, gases and odors. Being non-selective in nature, they have significantly unique responses. Also, it has been observed that materials belonging to different fire classes release distinct amounts of particulate matter. Before the exposure to specific fire smoke from respective material starts, both 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 have been shown in Figure 4.11 (a) – (f). In each fire class, fire smoke materials in the same class also form distinct clusters, indicating that the fire smokes within the same sub-class can also be identified successfully.

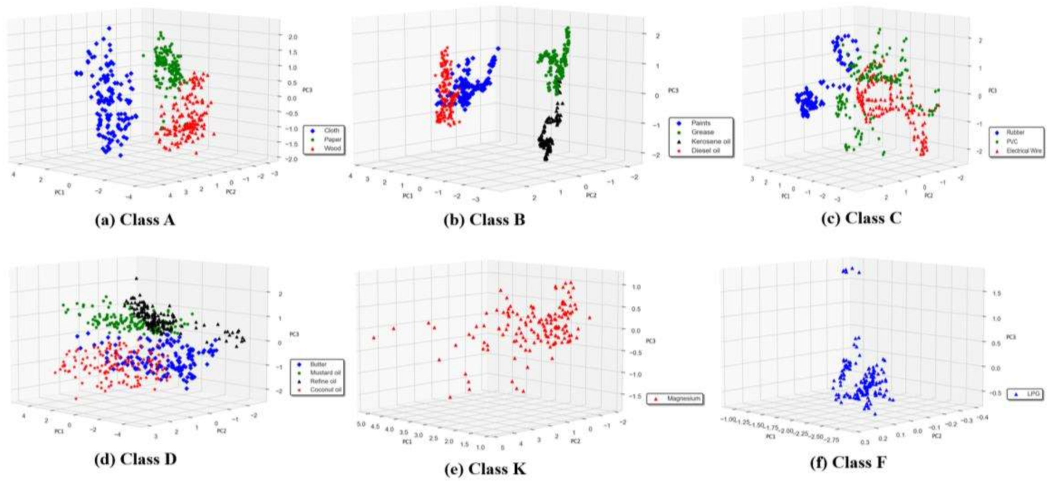


Figure 4.11. (a) – (f), 3D Scatter plots of SPCA transformed Responses of six classes of fire smoke.

4.3.2. Efficacy of Analysis Space Transformation Approach

In this work, we have 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. The PM sensor has also been used, which generates PM values belonging to PM 2.5 and PM 10 concentrations in 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, has been shown in Figures 4.12 (a) and (b). It can be observed that the clusters belonging to the six classes of fire smokes, in their raw form, are overlapping and not very clearly distinguishable. Further, 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.

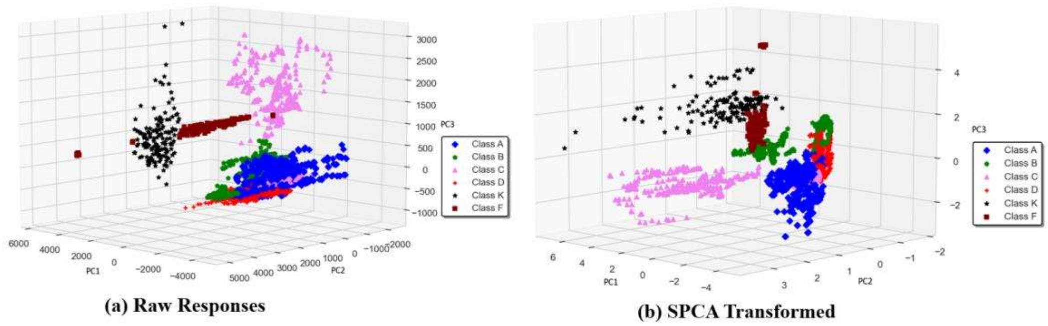


Figure 4.12. (a), (b). 3D scatter plot of raw and SPCA transformed responses (Gas & PM Sensors, jointly).

4.3.3. 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, MSE, and RMSE. Six types of fire smoke data and its 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. The MLP classifier has been the best-performing classifier. The difference between the actual and predicted values for the six classes of fire smokes has been evaluated using MSE as the performance parameter, as shown in Figure 4.13.

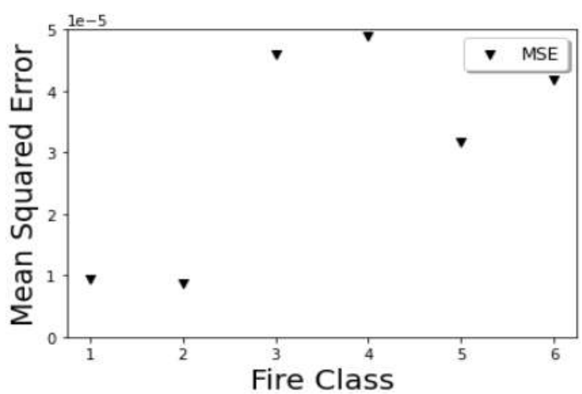


Figure 4.13. MSE for classification of six classes of fire smokes using MLP classifier trained in SPCA transformation domain.

Further, the classification performance of the ID2S4FH trained and tested in the SPCA domain and by using the responses of the gas and PM sensor jointly, using 80 unknown test samples, has been shown in Figure 4.14.

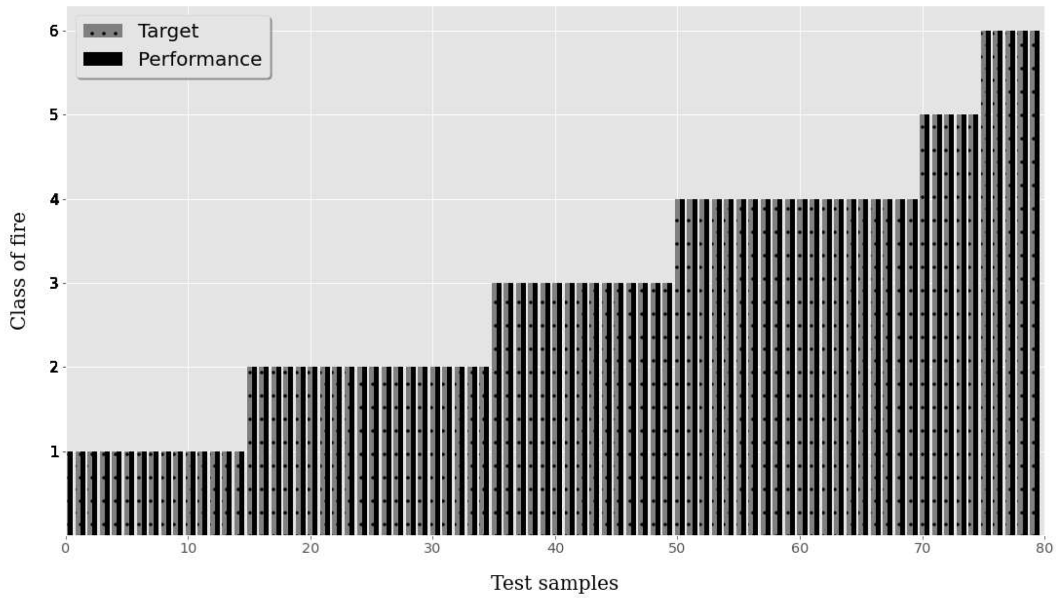


Figure 4.14. Classification Performance of the ID2S4FH designed in the SPCA transformation domain.

For the sake of further clarity, the confusion matrix of the classification performance of the MLP classifier has been shown in Figure 4.15, which shows 'all correct' classification of the considered 80 unknown samples taken from the testing dataset, not used for training the classifier models in SPCA transformation domain.

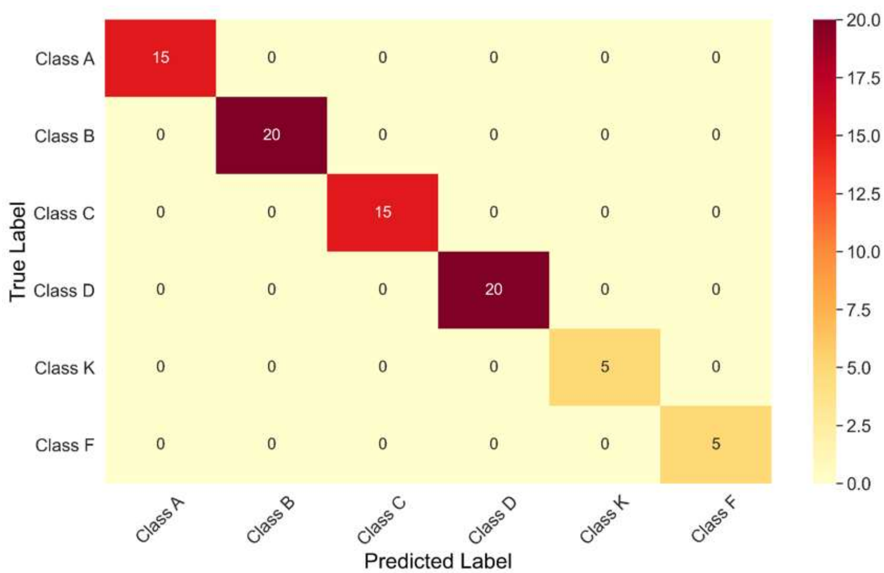
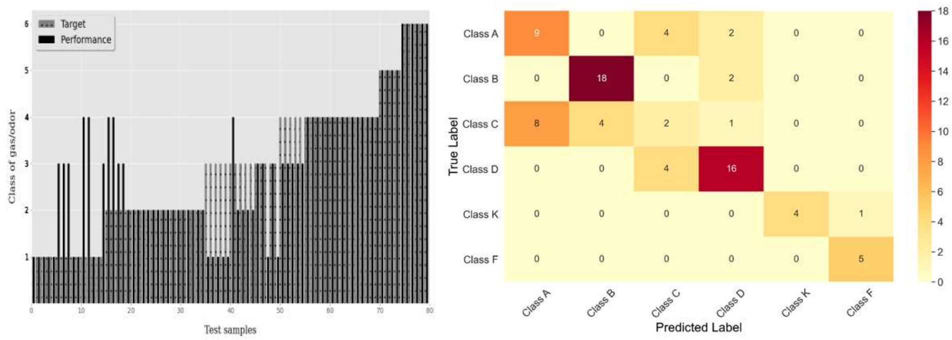


Figure 4.15. The confusion matrix for the classification performance of the MLP classifier.

Another observation which can be made is that the classification performance of the MLP classifier, trained and tested using only the PM Sensor response, has been found ineffective, as shown in Figures 4.16 (a) and (b).



(a) Performance of PM Sensor only (b) Confusion Matrix of PM sensor values only

Figure 4.16. (a), (b) Performance of classifier trained in SPCA transformed domain using PM sensor values only.

We adopted evaluation indices, including Accuracy used a 5-fold cross-validation during the performance assessment of the MLP classifier. A graph-based comparative performance of the classification accuracy for various classifiers has been shown in Figure 4.17.

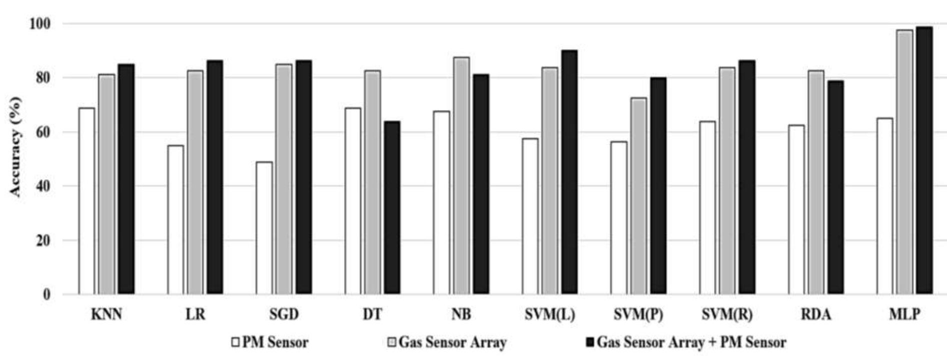


Figure 4.17. Comparison classification performance of PM Sensor, Gas Sensor and Mixture of Gas Sensor.