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Multi-sourced sensing and support vector machine classification for effective detection of fire hazard in early stage.

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Multi-sourced sensing and support vector machine classification for effective detection of fire hazard in early stage

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***Abstract* –** Accurate detection and early warning of fire hazard are crucial for reducing the associated damages. Due to the limitations of smoke-based detection mechanism, most commercial detectors fail to distinguish the smoke from dust and steam, leading to frequent false alarms and costly evacuation unnecessarily. To tackle this issue, we propose a fast and cost-effective indoor fire alarm system for real-time early fire detection under various scenarios, whilst significantly reducing the false alarms. Multimodal sensors are integrated to acquire the data of carbon monoxide, smoke, temperature and humidity, followed by effective data analysis and classification. For ease of embedded implementation, the support vector machine (SVM) is found to outperform the Random Forests (RF), K-means, and Artificial Neural Networks (ANN). On a public dataset and our own dataset, the proposed system performs promising, with the values of the precision, recall, and F1 of 99.8%, 99.6%, and 99.7%, respectively.

Keywords – Fire incident detection; Sensor fusion; Machine learning; Alarm systems; fire safety.

1. Introduction

Fire incidents can produce a desperate situation for the buildings and users even before they can realise the fire occurrence. A burning table lamp, a lit cigarette, overheated electrical equipment, or any of these can constitute a potential source of ignition [1]. In recent years, the dramatic changes in materials and the construction methods of buildings have led to an increment of fire growth rate. It is a vital issue for the building furnished with highly flammable synthetic materials that react as fire accelerants, resulting in a challenging task for the current fire alarms to detect the fire and rouse the residents in a timely manner [2].

1.1 Background introduction

According to the nuisance test conducted by the UK Fire Protection Association (FPA)[1] , the intelligent detectors outperform the traditional optical and ionisation smoke detectors in the stability to false stimuli, including vapor, toaster smoke and welding. However, the capabilities of the technologies are still not generally well known by the fire and rescue services. In UK, the false alarm rate remains a high level despite the mandatory requirement for householders to install a suitable detector in an appropriate location. The fire & rescue incident statistics[2] published by the U.K Home Office shows that, in England alone, 555 795 incidents were attended by fire and rescue services in the year 2019, among which 41% were accounted as false alarms. Within the real 59% of cases, fires events only occupied 28% of the incidents, where the remaining were for the non-fire incidents. In other words, only 28% of attended cases were real fire events. “Due to apparatus” from the report was the culprit that accounts for 67% of the false alarms, which has caused a huge loss of human and financial resources.

It is reported that, until recently, detectors that solely relying on the smoke detection mechanism still dominate around 60% of the market share [3]. Smoke detectors however provide only limited protection due to the shortcomings such as not reacting to non-smoke fires and can be tricked by steam, dust, cigarette smoke which leads to the high false alarm rate. Multi-sensor detectors on the other hand, measure more than one fire signature, such as the temperature, smoke concentration, carbon monoxide (CO), carbon dioxide (CO2), etc [4]. Although it can be costly, replacing the fire alarm system with multi-sensor detectors would be a more effective choice to intervene the unwanted alarm activations rather than other actions such as enhancing the maintenance level of the system or correctly using appropriate approved detectors.

As fire characteristics regarding the smouldering and flaming fires are different, there are several discriminative fire signatures under different situations. To determine the proper signatures to be employed for our purpose of early fire detection, Table 1 compares the characteristics with remarkable differences between smouldering and flaming

[1] Available: ABI FPA detection demonstration report 2018
[2] Available: UK home office, Fire & rescue incident statistics, England, year ending December 2019

stage from all the fire phenomena presented in [5], from which the heat is of cause an important signature, but it is not sufficiently discriminative and may lead to false alarms. Besides the heat, the smoke (aerosol) in smouldering stage tends to be lighter and spreading quickly. With the fire being developed independently, the smoke tends to be dark, heavy and strongly absorbing. There is also the trend that smouldering fire emits much CO and little CO_2. In contrast, flaming fire emits much CO_2 and little CO. Thus, the CO concentration can be considered as another important signature for early fire incidents. The gas sensors detecting such fire emitting gas accordingly have the potential in early fire detection [6]. The challenge, however, is that the volatiles generated by the nuisances may lead to unwanted false alarms. As a result, fire detection systems incorporating gas sensors heavily rely on machine learning (ML) and pattern recognition techniques for providing a robust and reliable detection.

Table 1: Characteristics of smouldering fires and flaming fires [7].

Type of fire / Properties and fire phenomena	Smouldering fires	flaming fires
Type of smoke (aerosol)	light smoke	Dark smoke
Optical properties of smoke	Quickly spreading	Strongly absorbing, spreading little
Aerosol volume	High	High (except pure alcohol: none)
Heat convection	Low to medium	High
Combustion gases	Much CO, little CO_2	Much CO_2

Machine learning techniques have the advantage to deal with multiple variables effectively by learning their relationships for classification. To achieve effective fire detection, various models have been developed, using different machine learning tools such as Adaptive Neuro-Fuzzy Inference [7], surveillance cameras and support vector machine (SVM) for early fire detection [8], and multi-stage pattern recognition video images analysing [9], unsupervised modified K-means clustering for detecting fire flame pixels [10], as well as deep learning approach e.g. convolutional neural network (CNN) [1], and deep neural network (DNN) [11]. Within these methods, the visual-inspection based approaches have the advantage of a long detection range and wild working environments such as the forest. Although deep learning models enables a more flexible classification, the relevant equipment can be much more expensive yet the performance can still be severely affected due to insufficient training and modelling. Moreover, such detection systems have the shortcomings in terms of delayed response time, due mainly to the complexity in dealing with the imagery data and difficulty in acquiring clear images of the smoke or flame in early stage after the fire ignition [12]. The physical and chemical sensor-based fire detectors, in contrast, measure indicators such as temperature and carbon monoxide, which can thus enable the system to identify the fire events in the early stage. Although many vision-based fire detection systems have been developed, they aim mainly to detect outdoor fire events whereas we focus on the design of a cost-effective and effective indoor solution for early fire detection. The fusion of multi-sensor readings further can thus improve the reliability of the system whilst significantly reducing the false alarms.

1.2 Related work in multi-sensor fusion and early-stage fire detection

Some research works have been focused on fire detection in the early stage using multi-sensor fusion based approaches. In study [7], smoke, temperature and humidity sensor readings are collected for indoor fire detection, where neuro-fuzzy logic is used to determine fire occurrences and send notification via the Global System for Mobile communication (GSM). In Rachman et al. [13], fuzzy logic interfaced with multi-sensor is also implemented with a low average error. In [14], a similar system is developed for fire detection in an electric car model, by combining the Arduino microcontroller and fuzzy logic using data readings collected form temperature sensors, flame sensors, and smoke sensors, respectively.

Actually, multisensory fusion has been widely adopted in smart home environments. In Chou et al. [15], a multi-sensor data fusion based smart home system is developed, where artificial intelligence enabled interfacing with a wearable device is used for remote controlling of the home appliances and locating the position of home residents. The Probabilistic Neural Network (PNN) classifier is adopted in the system for dealing with the temperature and CO concentration readings. Similarly, a Trend Predictive Neural Network (TPNN) based system is introduced in Nakıp et al. [16] to deal with six sensors' measurements, in which eight sets of the multi-sensors are deployed at different locations of a room to improve the accuracy and sensitivity. The study has successfully decreased the false positive rate, though the false negative rate still needs to be improved.

In Lee et al. [17], metal oxide gas sensors were utilised for fire detection. In Salhi et al. [18], multi-sensor readings were acquired in a building environment and interfaced with different machine learning methods against gas leakage and fire hazard. However, the sampling frequency in the study is relatively low, which may affect the performance of early fire investigation, where the sampling frequency during our data acquisition is improved for better tracing the trend of the fire characteristics accordingly investigating the fire as early as possible.

Although various approaches have been proposed for the detection of fire hazard, most of them have difficulty in detecting fires at an early stage, suffering from a relatively high false alarm rate, which often show unsatisfactory performance for indoor fire detection. The study in [19] also remarks that existing commercially available smoke detectors are unable to provide proper protection to building occupants as they are primarily designed for alerting flaming fires. To tackle this particular challenge, in this paper, we have proposed a multi-sensor based system for effectively early detection of indoor early stage fire incidents. With a microcontroller unit (MCU) Arduino UNO[3], the

[3] Available: Arduino UNO rev3

proposed system is cost-effective, and the performance has been validated in different experimental scenarios. Another by-product contribution is the collected datasets, on which the SVM classifier outperformed two other classifiers, benefitting the hardware implementation as SVM is less resources-demanding than deep learning models.

The rest of the paper is organised as follows: Section 2 presents the detailed system description, including software-based and hardware-based designs, and the system implementation, followed by the description of experimental settings. Section 3 discusses the experimental results and the system performance when applied to public available dataset and our own dataset, respectively. Conclusions and future works are given in Section 4. The nomenclature used in this paper is listed in the appendix.

2. System Design and Implementation

2.1 System overview

In our proposed system, we need conduct various simulations in an enclosed space to acquire data, with a sampling rate of 3.7Hz, followed by data modelling and classification. The system architecture for both data acquisition and real-time detection is shown in Figure 1. In the red frame, the software-based processing part handles the inputted data and performs real-time detection. The data is documented and evaluated through MATLAB. To achieve improved performance and simplify the system design for easy implementation using the hardware, the optimal classifier was selected from different methods by comparing the results applied on both experimental dataset and sample dataset. We execute all experiments on a computer with a 2.6-GHz CPU and 8 GB RAM, where the process of fire classification takes less than 0.1 second of responding time after models constructed. Then, as shown in the blue frame, the operation program controls the hardware and switch among three different operation modes based on the classification result. The hardware implementation design can be obtained from the orange frame.

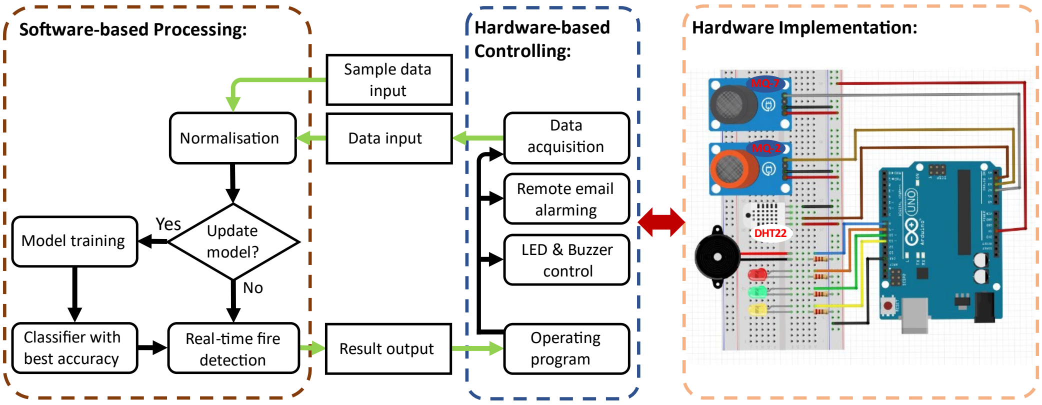

Figure 1: System Architecture.

2.2 Software-based processing

In the software-based processing part, the inputted data needs to be normalised first for reducing the inconsistency caused by different amplitude ranges. This is essential for consistently measuring of the difference from various sensors. Next, three popularly used ML approaches were applied, including the SVM, Random Forest (RF), and K-means.

The main concept of SVM is to find the optimal hyper-plane that separates instances from different classes by finding out the maximum margin between the support vectors, and these instances are closest to the other class. The "Kernel trick" is one of the crucial ingredients of SVM, which can help to transfer the low dimensional input space to a higher dimensional feature space thus enables an improved classification accuracy. In this study, one of the commonly used nonlinear kernel functions, the Radial Bias Function (RBF) is adopted as it tends to produce high performance. For the RBF kernel, the tuning parameters include the cost parameter C, and the degree of dependency parameter γ [20]. The parameter γ defines how much a single training instance may affect the performance, whilst the parameter C controls the acceptance of misclassification against the maximised margin of the decision function. The lower the γ value is, the further the effect that each support vector will have. In other words, a small γ leads to a nearly linear hyperplane with less curvature that may not be able to capture the complexity of the data. On the contrary, a high γ may have the problem of over-fitting. For parameter C, a higher C value may force the decision function to classify the training data correctly but result in longer fitting time and fewer support vectors. Moreover, the error rate will no longer be changed when C increases to a certain threshold. Thus, we need to find the optimal combination of the parameters with the lowest error rate.

There are several widely used methods for automatic parameter tuning, such as grid search, random search and Bayesian optimisation. In this study, the grid search was used as it has the advantage of high resistance to the over-fitting problem. As a common wisdom [21], grid search, one of an exhaustive searching methods, is applied with the cross validation technique to identify the best pair of the hyperparameter, namely the C and γ, by maximizing the achieved prediction accurately. The main concept of the cross validation is to separate the labelled data into two non-overlapped subsets, namely the training set and the testing set. In this study, a 5-fold cross-validation is used for grid search based parameter tuning, e.g. 80% of data used for training and the remaining 20% for validation. Herein the range of the hyperparameters are set to [-10,10] for the parameter C, and [-8, 8] for γ, both with an increment step of 1. Consequently, the SVM models is trained with all candidates of C and γ and validated through the testing dataset. The best performed pair of hyperparameters is then used for the prediction and classification.

Random Forest [22] is an easy-implemented classifier that collects uncorrelated tree predictors aggregated into a combined decision-making. Thus, the ensemble predictions can be more accurate than the result produced by a single tree and overcome the shortcomings of each individual tree classifier. For another ML technique, K-means, the basic principle is to identify k cluster centres (or centroids) before allocating each instance into the nearest centroid iteratively until the point-to-cluster-centroid distances have been minimised. In our implementation, the K-means++

algorithm is used, as it can determine the centroid seeds for K-means clustering via a heuristic process to improve the efficiency and efficacy [10].

The model configurations for RF and K-means are simpler than that for SVM. For RF, the number of trees needs to be specified, where the larger the tree number is, the higher the performance should be. However, the improvement of accuracy can be negligible when the number of trees exceeds a certain threshold, herein this parameter is set to 150 for balancing the performance and efficiency. For K-means, the centroid number is set to 3 for the three situations (no-fire, smouldering, and flaming). The maximum iteration number is set to 100 due to the clustering distances can be minimised in both the public dataset and our dataset with much fewer iteration.

To further validate the performance of the three classifiers, a sample dataset[4] was employed, containing the desired three features corresponding to three different situations. Among the 100 samples of the data set, 40 are accounted for the flaming, 30 belong to smouldering fire situations, and the remaining 30 are no-fire situations, in which stimuli data acquired from kitchen environment is also contained. The values of temperature are recorded with degrees Celsius, and smoke and CO concentration in ppm (parts-per-million).

The quality of classification can be assessed through the confusion matrix which lists the number of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) for each class. Therefore, the AR (Accuracy Rate), PR (Precision Rate), RR (Recall Rate) and F1 Score can be determined for evaluation, where Q_P and Q_N refer to the quantity of positive and negative, respectively.

$$AR = \frac{TP + TN}{Q_P + Q_N} \times 100\% \tag{1}$$

$$PR = \frac{TP}{TP + FP} \times 100\% \tag{2}$$

$$RR = \frac{TP}{TP + FN} \times 100\% \tag{3}$$

$$F1 = \frac{2 \times \mathrm{PR} \times \mathrm{RR}}{PR + RR} \times 100\% \tag{4}$$

2.3 Hardware-based operation & alarming

As shown in the blue frame in Figure 1, the operation program controls three LEDs for providing the visible notifications of the three operation modes, where the green LED gives the notification of no-fire situation at a certain flashing frequency until the software-based program detects fire. The green LED will be switched off and yellow LED will be switched on if the smouldering fire is detected, and red LED will be used to alert the flaming fire. Meanwhile, both flaming and smouldering situations will have audible notification provided by a buzzer with tones in different frequencies. Also, the data and time of the event will be recorded and sent to the pre-specified email address.

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[4] Available: Fire dataset provided in CN104766433A

The remote email notification function sends the alarming email from MATLAB through the SMTP (Simple Mail Transfer Protocol) server on the TCP (Transmission Control Protocol) port 465. Compared to the Internet of Things (IoT) network or Global System for Mobile (GSM) communications, one of the advantages of using SMTP is that extra hardware modules are not required, so that the hardware size can be tinier. It is worth noting that when using the SMTP server, the SMTP authentication is required, which means both sending and receiving parties must mutually accept and support the authentication procedure that the server supports. For instance, if the email is sending from a Gmail account, the client should enable accessing less secure apps in google account settings [5] manually to avoid authentication being rejected.

2.4 Implementation

As shown in the implementation circuit within the orange frame in Figure 1, the gas sensors used in our system are the Metal Oxide Semiconductor (MOS) type gas sensors which belong to the MQ family. These semiconductor sensors are the gas sensors of low prices, operating in various working conditions. Their specifications and approximate cost are shown in Table 2. The MQ-2 gas/smoke sensor is capable of detecting smoke, alcohol, hydrogen, methane, and other flammable gas composites with a high sensitivity and reliable data measurement. Another gas sensor, MQ-7, is highly sensitive to CO with a relatively wide detecting range and stable measurement. DHT22 is selected for monitoring ambient temperature as from the datasheet[6] it has a relatively wide detection range from -40 ºC to 80 ºC and measures humidity in Relative Humidity (RH). In addition, the components were connected to the Arduino UNO. Note that the MATLAB program needs not be downloaded to the MCU.

Table 2: Sensors' specifications and approximate cost.

Sensor	Cost (£)	Range of measurement	Sensitivity	Repeatability
MQ-2	2.85[7]	300-10000ppm Smoke	See Figure 2 (a)	Not given
MQ-7	3.56[8]	20-2000ppm CO	See Figure 2 (b)	Not given
DHT-22	4.24[9]	-40℃-80℃ 0-99.9%RH	0.1℃ 0.1%RH	±0.2℃ ±0.3%RH

Figure 2 presents the sensitivity characteristics from the datasheets of the MQ-2[10] and MQ-7[11] sensors in their standard temperature and humidity condition, where Rs is the sensor resistance in target gas with different

[5] Available: Google less secure app access setting
[6] Available: DHT-22 datasheet
[7] Available: MQ-2 provided by Pololu
[8] Available: MQ-7 provided by sparkfun
[9] Available: DHT22 provided by DFROBOT
[10] Available: MQ-2 datasheet
[11] Available: MQ-7 datasheet

concentrations, and R0 in (a) and (b) respectively are the sensor resistance at 1000ppm hydrogen (MQ-2) and 100ppm CO (MQ-7). For DHT 22, in the datasheet it shows a good measuring range and sensitivity as well as good repeatability. Although the temperature in fire situations generally grows to over 80 ºC, the DHT-22 sensor is still selected as the temperature will not be such high at the early stage. In addition, the typical temperature and humidity characteristics are also compared from the datasheets of the gas sensors. Compared to the normal working situation at around 20°C, sensors suffer from the loss of sensitivity at 20-30% when the temperature increases to 50ºC, which may affect the working temperature range of the whole system. Due to a relatively narrow working temperature range of the MQ sensors, the system has to be capable of effectively detecting of the fire as early as possible. Also, according to the study in [23], it is reported that 60°C is the highest breathable temperature of the saturated air. Therefore, in order to ensure the reaction time, 50 °C can be taken as the temperature limit for the system to perform data analysis, Once the temperature of the saturated air exceeds 50 ºC, the system will start to alert. Hence, the DHT-22 with detection range up to 80 ºC and strong anti-interference ability satisfies the current needs. In addition, the humidity detection function of DHT-22 allows us to test the effect of humidity to the system without any extra components.

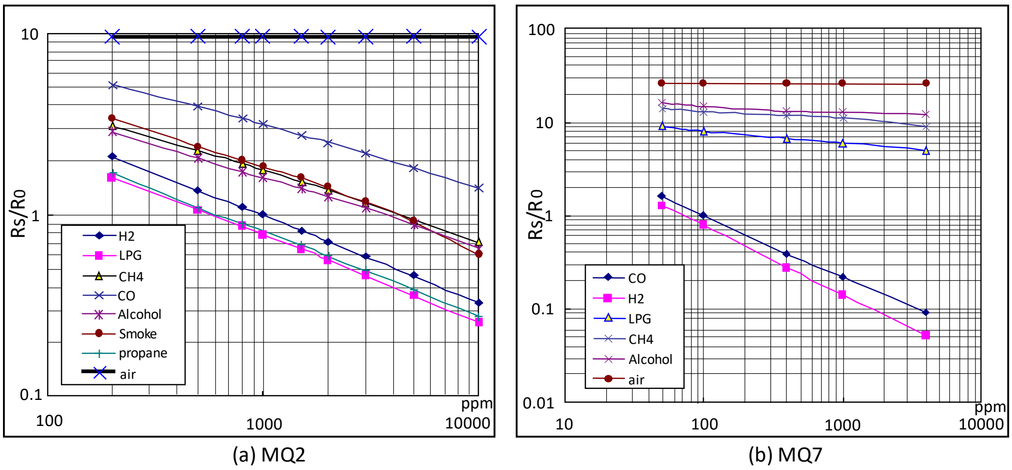

Figure 2: (a) Sensitivity Characteristics of MQ-2 at 20 ℃, 65%RH, (b) Sensitivity Characteristics of MQ-7 at. 20 ℃, 65%RH

2.5 Experimental settings and data acquisition

Different experimental scenarios have been simulated for data acquisition in the proposed system, using a glass case of 0.15m wide, 0.15m long, and 0.08m deep, where there are several holes on the top for air circulation with the sensors settled around them. Table 3 summarises the experimental settings of the nine scenarios, where the humidity was also detected by the DHT-22 sensor. All the measurements were started once the source was ignited or settled in the case with a sampling frequency of 3.721Hz. Before each fire or stimuli test, the room is cleaned up to ensure that the sensors' readings are close to the readings in the TNE condition thus to maintain a good repeatability of the experiments. The scenarios TNE, TS1, TS2, TF1, TF2, and TF3 were undertaken in the same day and same environment. The other scenarios were undertaken in another day with similar environments to ensure the consistency of data acquisition. Additionally, due to the repeatability of the gas sensors is not given by the providers, we have conducted another two normal environment scenarios have been simulated in the same place with similar environmental conditions for evaluating the repeatability quantitatively through the Coefficient of Variation (CV), which is defined as the ratio of the standard deviation to the mean.

Since the semiconductor gas sensors were employed here, the leakage of flammable gas is likely to become nuisance that causes the false alarm. Hence, two comparable experiments were arranged to use 5ml lighter fluid settling 5cm straight underneath the sensors and 15cm away from the sensors. To produce the dust environment, 10 grams of flour, the small particle that is common in households, were blowed to be saturate the case. As a result, 3800 instances in total have been documented for analysis, and the results are reported in the next section. Our acquired data are available on Github: https://github.com/SiYC/Fire-experimental-dataset.

For sensor calibration, chemical-based gas sensors for fire detection need to be exposed to the fire standard conditions. The standard fire rooms are often used to perform experiments under different fire scenarios, though the access to such facilities can be very expensive [24]. Sandbox Electronics[12] has provided a method for MQ sensor calibration, where the "initial" resistance R0 is the main target of the calibration process. This is achieved by sampling and averaging the sensor readings for a certain period under the clean air condition. With the determined R0, the ratio of Rs/R0 can be used as the input for modelling, where a linear formula can be adopted to approximate the relationship as shown in Figure 2 when converting the analogue output into concentration values in ppm. However, both the MQ sensors in Figure 2 are nonlinear, which means that the operation may affect the data integrity. The further calibration with high specification meters will be left as the future work. In this study, as all the data have been normalised before modelling and the prediction test, the calibration accuracy may not affect the result significantly.

Table 3: Experimental settings in TNE (Test Normal Environment), TS (Test Stimuli), and TF (Test Fire) scenarios.

	Scenarios	**Source settings**
TNE	Normal environment	/
TS1	humidifying	humidifier
TS2	heating	4 smokeless candles
TS3	gas leakage	5ml lighter fluid (5cm)
TS4	gas leakage	5ml lighter fluid (15cm)
TS5	dusty	10g flour
TF1	paper flaming	2g paper
TF2	cotton smouldering	3g cotton
TF3	paper smouldering	2g paper

[12]Available: Sandbox Electronics, MQ-2 Smoke/LPG/CO Gas Sensor Module

3. Results and discussion

3.1 Sample data analysis

Table 4 summarises the performance for the three different classifiers where SVM and RF have used 80% of the dataset for training and the rest for testing. To further evaluate the effect of the multi-sensor model adopting the temperature, smoke, and CO sensors, the performances of the models employing different combinations of the sensor readings are also given for comparison. Each experiment was repeated 10 times and the average results are reported.

As seen in Table 4, thanks for the combination of readings from all these sensor, the classification results have achieved the best. Both SVM and RF have achieved the accuracy and F1 score over 85%, significantly outperforming the K-means by about 38% in accuracy and 30-45% in F1, and also outperform the models using single or two sensors. In addition, the SVM surpasses the RF model by about 2% in terms of the accuracy and the F1 score in the three sensors scenarios, which has clearly demonstrated the efficacy of the SVM model.

To further evaluate the performance in predicting the three situations of flaming (1), smouldering (2), and no-fire (3), the confusion matrixes are presented in Figure 3. For better visual effects, the values are reported in percentage and each row adds up to 100%. As can be seen, no-fire instances are more likely to be confused with the smouldering situation in the single and two sensors scenarios. Also, there is a trend among the three classes that no-fire situation shows a lower TP and TN rate, and accordingly higher FP and FN rates compared to the other classes. The reasons could be the insufficient dataset quantity and the stimuli within the no-fire observations which is acquired in the kitchen environment.

Table 4: 10 times testing results (1-flaming, 2-smouldering, 3-no-fire).

Method	Sensors	AR (%)	PR (%)	RR (%)	F1 Score (%)
SVM	All	**89.50**	**88.49**	**88.65**	**88.55**
	Temp + Smoke	83.50	82.61	82.40	82.36
	Temp + CO	85.00	85.29	84.52	84.66
	Smoke + CO	70.00	69.73	68.73	69.09
	Temp	79.50	78.23	78.25	78.18
	Smoke	43.00	36.65	40.04	37.67
	CO	57.00	57.11	60.21	57.25
RF	All	**87.50**	**86.74**	**87.23**	**86.80**
	Temp + Smoke	85.50	84.49	84.54	84.23
	Temp + CO	83.50	82.91	83.20	82.70
	Smoke + CO	73.00	73.59	72.37	72.84
	Temp	81.00	79.13	79.08	79.08
	Smoke	49.50	46.89	46.78	46.45
	CO	63.50	65.51	64.27	64.14
K-means	All	50.00	49.10	48.39	48.66
	Temp + Smoke	**62.30**	**57.62**	**58.38**	**57.40**
	Temp + CO	48.00	46.50	45.13	45.19
	Smoke + CO	23.90	21.57	26.30	22.77
	Temp	52.40	43.19	47.42	44.67
	Smoke	23.80	25.09	26.03	23.64
	CO	48.50	50.98	47.18	47.63

As mentioned, the temperature in the early stage usually cannot reach to that in the flaming stage, resulting in the unsatisfactory performance in classifying the smouldering and no-fire cases when relying solely on the temperature data. Hence, as shown in Figure 3 (m), (n), (o), although the flaming situations are almost correctly identified, smouldering and no-fire situations tend to be confused when only using the temperature data. It is worth noting that although the K-means model with the temperature and smoke readings has yielded 62.3% overall accuracy and 57.4% F1 score, outperforming the three sensors scenario, the higher FN rate of the no-fire situations have indicated its limitation. Compared to the models using the single sensor data, multi-sensor fusion has the advantage of significantly refined results in detection of the smouldering and no-fire situations, which has successfully reduced the false alarms and saved the cost in this context.

In addition, considering the single source of the stimuli data may cause the inferior capability of the model in discriminating between smouldering and no-fire situations, our experiments have emphasised more on the false stimuli data acquisition as shown in section 2.4. In summary, the SVM model has overall better performance than other models for fire detection in terms of the accuracy and F1 metrics. The robustness of employing the three features in SVM and RF based models has also been validated. For the K-means model, the combination of the temperature and smoke sensors can be the best choice, and the FP and FN rates can also be suppressed by using multiple sensors, however, the overall performance cannot reach the acceptable level.

3.2 Experimental data analysis

From the experiments, we have collected the dataset comprising 3800 instances (smouldering – 700, flaming – 400, no-fire – 2700, including normal – 1000, humidifying – 500, gas leakage 5cm – 400, 15cm – 300, heating – 400 and dusty – 200 observations). Figures 4-6 presents the sensor observations in different experiment scenarios specified in section 2.4. It can be seen from TS1 that out of the three sensors, humidity changes affect the CO and temperature sensors, resulting in slightly higher observations than the normal situation. From TS2, the heating scenario, as the candle keeps burning, a small amount of CO has been detected. TS3,4 and 5 are conducted in the same environment, so the basement of the three test scenarios can be taken from the fist fifty instances. TS3/4 are the gas leakage experiments using lighter fluid. Both smoke and CO sensors are highly sensitive to the gas volatising, which is due to the mechanism of such semiconductor gas sensors. TS5 has used a blower to blow off the small particles, therefore, the temperature increased as the blower also generates heat slightly. However, both gas sensors keep stable during the experiments comparing the ST3/4 except an obvious change of smoke data at 450 to 470 instances, which is due to the hardware connection issues. Such a problem also occurred on the CO senser during the paper smouldering test, indicating the hardware implementation need to be enhanced.

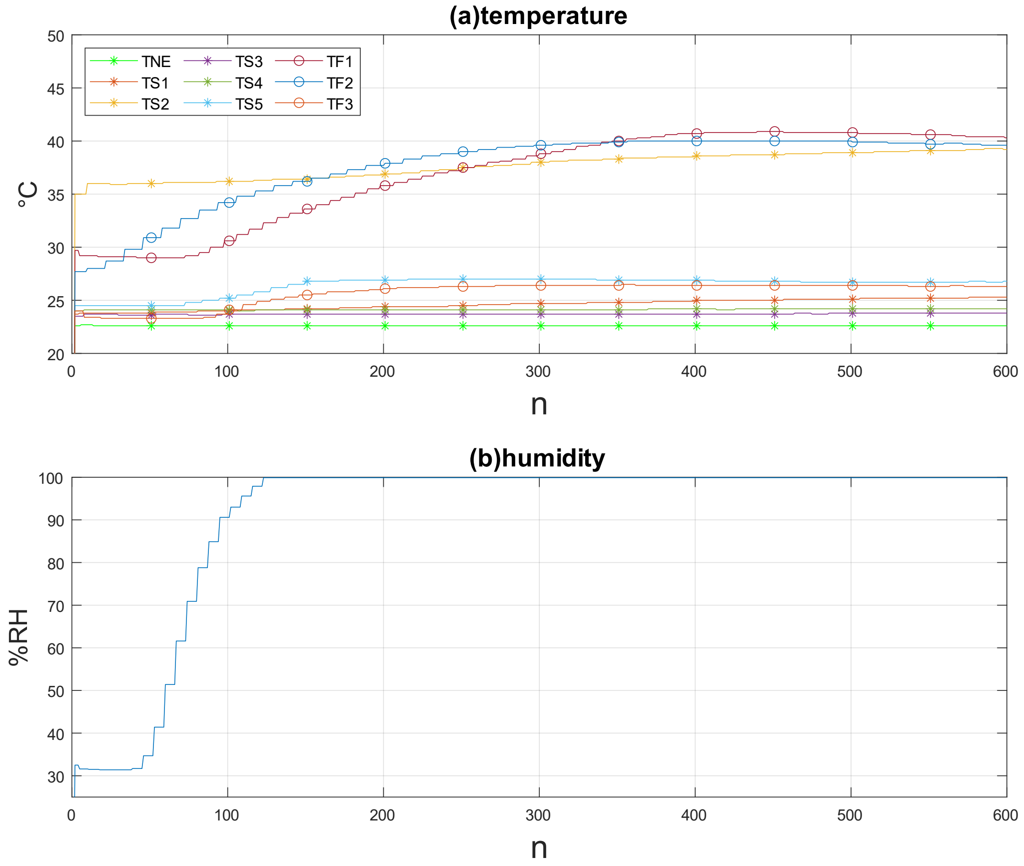

Figure 3: (a)Temperature observations in various experiment scenarios, (b) Humidity observations of DHT-22 sensor in TS1 humidity environment testing.

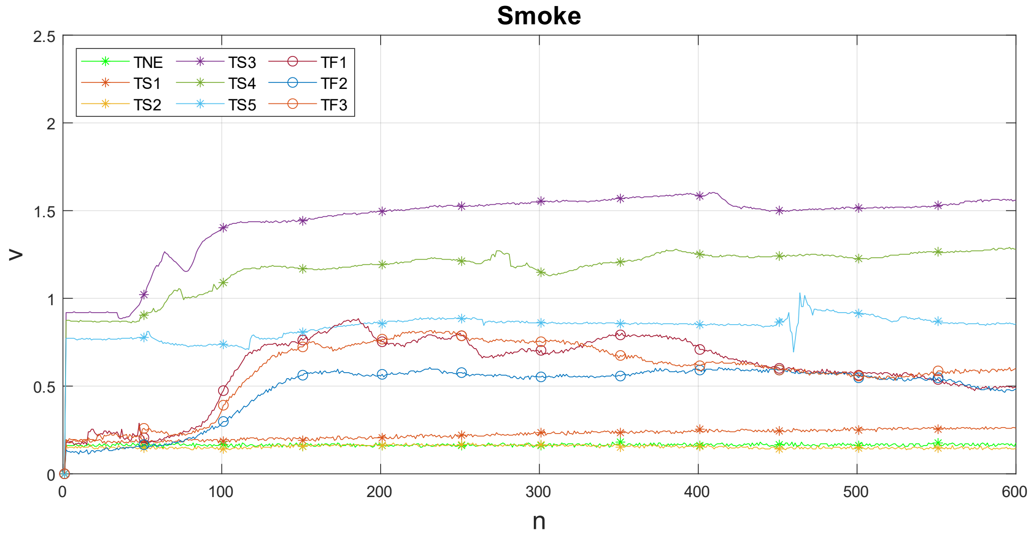

Figure 4: Smoke observations of MQ-2 in various experiment scenarios.

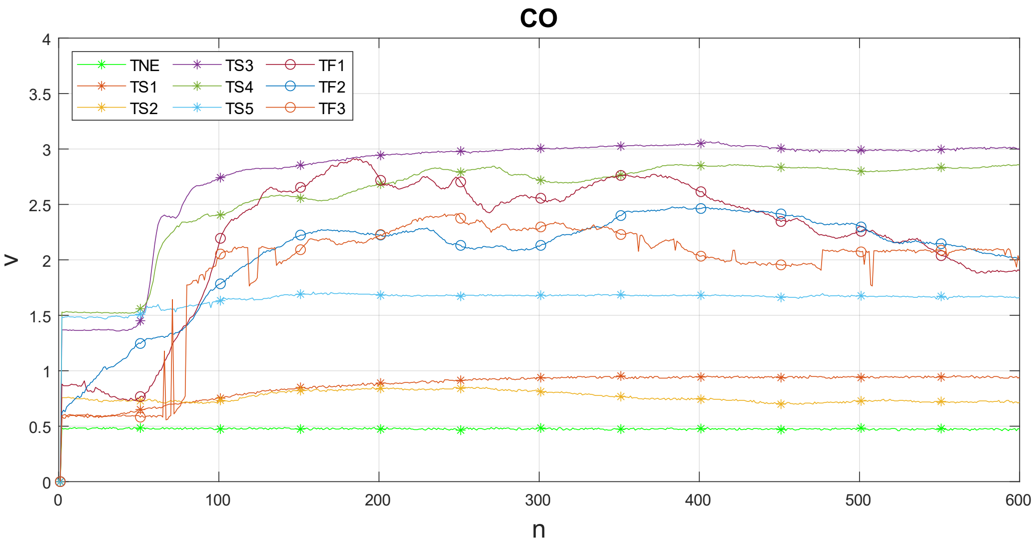

Figure 5: CO observations of MQ-7 in various experiment scenarios.

Compared to TF3, the scenario of paper smouldering, TF1, paper flaming has higher temperature values which is same with our subjective observations. However, TF1 shows similar smoke and CO observation values with TF3 which is probably due to the limitations of relatively small simulation space and few amounts of combustibles, leading to the combustibles not completely reaching the flaming phase at first although an open flame was observed. The smoke and gas emissions of TF1 gradually decline follows to the temperature reaching the highest value after 400 instances, indicating the fire achieved the flaming phase. In terms of TF2, cotton smouldering, it was observed that the CO observations are like the paper flaming and smouldering scenarios while generating less smoke. However, the temperature increases rapidly which even exceeds paper flaming scenario in the first 350 instances. In addition, the smoke generation is less than the other two fire tests.

During the measurement, noise is inevitable, in which sensors' noise is the primary concern in our experiments. According to ISO/IEC 25012 [25], the five main data quality criteria are used as referring indicators for evaluating the data quality in the experiments. The corresponding strengths and weaknesses to these five data quality criteria are summarised in Table 5. As the sensitivity of the gas sensors may vary as the temperature and humidity change, the experimental environment was chosen to be as close to the standard condition specified in the manual as possible. Also, to ensure the stability and credibility of sensors' readings during the experiments, the gas sensors have been preheated as suggested in the datasheets. Regarding the data processing, to mitigate the noise that may affect the modelling performance, pre-processing is applied to remove outliers caused by the transmission noise from the data to get rid of any data spikes. For the fire scenarios, we only retain the instances after the sensor readings become relatively stable. All these have helped to minimize the effect of noise in our developed system.

In addition, the CV values are calculated for measuring the repeatability of the system, which are found to be 0.08% for the temperature, 8.85% for the smoke, and 5.93% for the CO. The results show that the temperature sensor is highly reliable with a CV less than 1%. The CV values of the gas sensors have exceeded 5%, due mainly to the high sensitivity of the semiconductor sensors to the environmental variations. While the repeatability of the gas sensors is not ideal, it is still acceptable as the CV values of both sensors are within 6-9%.

Table 5: Experimental settings in TNE (Test Normal Environment), TS (Test Stimuli), and TF (Test Fire) scenarios.

Data Quality Characteristic	**Strengths**	**Weaknesses**
Accuracy	The DHT22 sensor from the datasheet has a high accuracy in measuring the temperature and humidity, i.e. ± 0.5℃ and 2% RH.	The accuracy of the gas sensors is unclear from the datasheet; also the performance of the sensors, especially the gas sensors will be affected by ambient temperature and humidity.
Completeness	The data sampled at a frequency of 3.7Hz can acquire timely records for tracing the variation of the measured fire signatures during different experimental scenarios. The measured ranges of the humidity, temperature, smoke and CO are 31.4%-99.9%RH, 22.6-40.9℃, 0.1320-1.6031v, and 0.4594-3.0645v, respectively.	For a full representation of the experiments, humidity data can be recorded in each individual scenario, and some data ranges can be extended.
Consistency	The data of each measurement maintains equivalent format and unit during all the process.	The data consistency can be improved through recording the gas sensors readings in ppm, which requires the calibration process.
Credibility	The data is relatively reliable since the sensors' setup follows the corresponding manuals and noise removal is performed in the data processing stage.	The reliability can be improved through performing the calibration process.
Currentness	Data measured by the sensors that need to be updated to the computer under specific time periods are updated frequently in real time during the experiment.	Data need to be recorded for events that occur under certain conditions e.g. components disconnection.

In summary, the smoke sensor shows a strong immunity to high temperature and moisture nuisance. All three sensors were barely affected by the dusty environment produced by flour particles. Nevertheless, both the CO and smoke sensor react drastically to the flammable gas emitted by lighter fluid. And regarding the fire tests, the fire has relatively higher temperature when it reached the flaming phase with a decreasing smoke and CO values which validates the characteristics in Table 1.

To verify our device with the SVM, different sizes of training dataset were applied by taking 38 (1%) to 760 (20%) instances. The procedure was repeated 10 times and the results is shown in Figure 7. It can be seen the maximum accuracy achieves nearly 100% from taking 4% of the experimental dataset as training dataset. The average accuracy increases rapidly from 91.4% when taking 1% training instances to 99.2% when the training data size reached 5% and keeps a high level as the training data size further increases. The minimum accuracy also exceeds 98% from the training data size achieving 7%, indicating the classification effect of the system becomes stable and good overall. The SVM results with 380（10%) training instances are presented in Table 6. The ANN is also employed with the same training and testing division ratio for comparison. For ANN, Scaled Conjugate Gradient (SCG) backpropagation, a commonly used training algorithm is selected, where the number of hidden layers can vary from 1 to 2-3 and even more, depending on the input features. The number of neurons in the hidden layer is another concern which is usually decided through trial and errors. In this study, we used 1 hidden layer with 18 neurons to minimise the error rate. The procedure was also repeated 10 times.

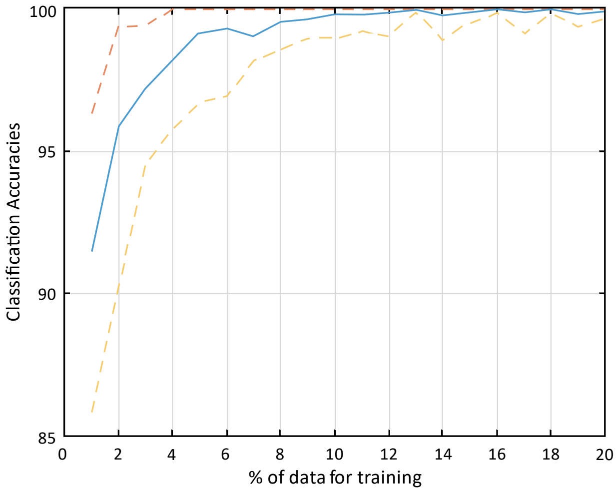

Figure 6: Comparison of classification accuracies in 10 runs with different training data sizes: blue-average, red-maximum, yellow-minimum.

In Table 6, it can be observed the that both methods have similar and overall good performance, where SVM outperforms ANN with 0.2% and 0.04% higher F1 scores in flaming and smouldering situations, whilst ANN produces higher precision rate than SVM, leading to a higher F1 score in no-fire situation. However, regarding the running time including model construction and data prediction, ANN on average, takes 1.04s (27.15%) longer than SVM, which validates the efficiency of the model chosen in this study. The running times for RF and K-means are 3.76s and 1.38s, respectively, Although the K-means runs quite fast, the performance is not ideal.

Table 6: Prediction performance for the three classes with 380 (10% of the experimental dataset) training data points.

Method	SVM				ANN			
Class	PR (%)	RR (%)	F1-score (%)	Running time (s)	PR (%)	RR (%)	F1-score (%)	Running time (s)
No fire	99.89	99.99	99.94	2.79	99.98	99.95	**99.96**	3.83
Flaming	99.97	99.26	**99.60**		99.17	99.67	99.40	
Smouldering	99.53	99.55	**99.54**		99.62	99.40	99.50	
Average	99.80	99.60	**99.69**		99.59	99.67	99.62	

Among the three classes, the results show the trend that algorithms perform better in predicting no-fire, validating the increment of experimental scenarios in the no-fire situation improves the classification performance. The flaming situation that performs best in the sample dataset, in contrast has a relatively low F1 score because of the lower recall rate. The reasons are that the patterns of the three features in flaming and smouldering situations are not discriminative enough as the fire did not reach the flaming phase before 400 instances as shown in the Figures 5-6. Meanwhile, the number of flaming data points is less than the other two classes, leading to the smouldering data could be misclassified to flaming and accordingly the reduces the recall rate.

True Class	TF1	TF2	TF3	TN	TS1	TS2	TS3	TS4	TS5		
TF1	3555	52								98.6%	1.4%
TF2	35	2653								98.7%	1.3%
TF3			3571					19	3	99.4%	0.6%
TN				9007						100.0%	
TS1					4493					100.0%	
TS2						3621				100.0%	
TS3			5				2703	7		99.6%	0.4%
TS4			11					2698		99.6%	0.4%
TS5			14						1753	99.2%	0.8%
	99.0%	98.1%	99.2%	100.0%	100.0%	100.0%	100. 0%	99.0%	99.8%		
	1.0%	1.9%	0.8%					1.0%	0.2%		
Predicted Class	TF1	TF2	TF3	TN	TS1	TS2	TS3	TS4	TS5		

Figure 7: Confusion matrix of 9 scenarios (TS1-humidifying, TS2-heating, TS3/TS4-glas leakage(5cm/15cm), TS5-dusty, TF1-paper flaming, TF2-cotton smouldering, TF3-paper smouldering) that randomly using 10% for training and repeated 10 times.

To further understand the impact of each source, we performed the classification 10 times with nine classes where each class corresponds to a fire or stimuli source with same training dataset used in determining the performance for the three classes classification with taking 380 (10% of the experimental dataset) as training data points. As shown in Figure 8, TF1 and TF2 are most likely to be confused, due to their similar observations in temperature and CO. In addition, TS4 and TS5 were misclassified to the paper smouldering situation. The reasons are first, relatively low temperature but high CO and smoke were observed in TF3, which is like the characterises that TS3/4 shows. Second, the dust stimuli test was conducted in the same environment as TS3/4, leading to a higher smoke and CO values than the normal level shown in TNE. Also, as is discussed, the temperature in paper smouldering is not as high as cotton smouldering situation, resulting in lower recall rate that observations with higher smoke and CO values could be misclassified. In summary, the system shows an overall good performance in discovering fire events with the average accuracy value of 99.83% when taking 10% instances as training dataset. Additionally, during the experiment, the temperature sensor has shown a poor resilience that decreases slowly from the highest level to the normal level, which may have influence on data acquisition. Hence, the experimental data would be improved by replacing with a temperature sensor with lower deviation and arranging more fire scenarios of both flaming and smouldering situations.

4. Conclusions

Existing fire detection system tends to very sensitive, yet it fails to distinguish certain scenarios e.g. the smoke from dust and steam. Also, most of the commercially available fire detectors and vision based methods have no advantage in early fire detection whilst reducing the false alarm rate in the building/residential environment. As a result, false alarms can be reported frequently, leading to heavy costs to the business and society. In this study, we employed the temperature, smoke and CO sensors to cover the shortages of each individual sensor with a microcontroller unit that makes the proposed system cost-effective, and the performance has been fully validated in different scenarios. In analysis of the sampled data, scenarios using different sensor combinations are evaluated, which have also validated the robustness of using the employment of the multi-sensors. Another by-product contribution is the collected datasets, on which the SVM classifier has produced the best overall performance than the three other classifiers, including K-means, Random Forest and ANN, benefitting the hardware implementation as SVM is less heavy-load than deep learning models.

However, the proposed technique still has some limitation that need to be tackled. First, as a result of the sensor calibration, precise readings of gas concentration, temperature and relative humidity data as well as improved repeatability of the gas sensors are crucial for reducing the impacts of sensitivity noise. Second, for optimal performance of the system, an alternative sensor with a wider measuring range and higher specifications e.g. sampling frequency and the MCU will be beneficial in the future work. Also, we will build a tidy prototype, with the N-channel metal–oxide–semiconductor field-effect transistor (MOSFET) used as a switch to better maintain the humidity and temperature readings. In addition, following the EN54 standard, more comprehensive experiments on numerous fire sources will also be carried out to investigate the sensitivity of the detector in different and typical aerosol spectrum to build a large dataset, whilst integrating the sensor array for suppressing the uncertainty of using the sole sensor for each measurement. Finally, with the increased data volume, the system can be further expanded with the organisational memory model that utilises interpretive and semantic knowledge for improving the system reliability. The long-term target will be an online recommendation system for providing better adaptiveness to individual users, in which the evaluation of data quality using the international standard e.g. ISO/IEC 25012 is also desirable.

Appendix

Table 7: Nomenclature used in this paper.

Symbol	Meaning	Symbol	Meaning
C	RBF cost parameter	Q_P	Quantity of positively classified instances
γ	RBF degree of dependency parameter	Rs	Sensor resistance during measurement
k	Number of cluster centroids	R0	Sensor resistance in clean air
Q_N	Quantity of negatively classified instances		
Abbreviation	**Meaning**	**Abbreviation**	**Meaning**
ANN	Artificial Neural Network	MOSFET	metal–oxide–semiconductor field-effect transistor
AR	Accuracy Rate	PNN	Probabilistic Neural Network
CNN	Convolutional Neural Network	ppm	parts-per-million
CO	Carbon Monoxide	RAM	Random-Access Memory

CO2	Carbon Dioxide	PR	Precision Rate
CPU	Central Processing Unit	RF	Random Forest
CV	Coefficient of Variation	RH	Relative Humidity
DNN	Deep Neural Network	RR	Recall Rate
F1	F1 score	SCG	Scaled Conjugate Gradient
FN	False Negative	SMTP	Simple Mail Transfer Protocol
FP	False Positive	SVM	Support Vector Machine
FPA	Fire Protection Association	TCP	Transmission Control Protocol
GSM	Global System for Mobile Communications	TF	Test Fire
IoT	Internet of things	TN	True Negative
LED	light-emitting diode	TNE	Test Normal Environment
MCU	Microcontroller Unit	TP	True Positive
ML	Machine Learning	TPNN	Trend Predictive Neural Network
MOS	Metal Oxide Semiconductor	TS	Test Stimuli

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