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Improving the Detection and Warning Fire System on the Smart Campus Area using ANFIS

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Abstract. *The adoption of IoT technology in universities has significantly improved campus security, emergency response, and control systems, particularly through IoT-based surveillance and fire detection systems. Traditional fire detection systems suffer from high false alarm rates, leading to unnecessary resource allocation. This paper proposes an intelligent fire detection system leveraging IoT and adaptive fuzzy systems to enhance accuracy and reduce false alarms. The system uses sensors to collect real-time data, which is analyzed by an Adaptive Neuro-Fuzzy Inference System (ANFIS) to determine alarm levels based on input severity. ANFIS combines fuzzy logic and neural networks, enabling learning and adaptation. Data analyzed by ANFIS is sent to ThingSpeak channels for real-time monitoring. When a fire is confirmed, alerts with fire location, timestamp, and severity are sent via SMS through GSM to the fire management system. The system utilizes cost-effective, small-sized sensors, ensuring repeatable solutions. After training, the ANFIS system achieved 99.59% accuracy, significantly reducing false alarms. It demonstrated faster detection times by reducing the fire detection rate by 28% and maintaining high detection accuracy with fewer sensors, training inputs, and epochs. Utilizing IoT and ANFIS technologies, the system integrates efficiency, speed, and reliability, protecting lives and property and highlighting the importance of safety and technology in serving humanity.*

Keywords: ANFIS, IoT, fire detection, fire alarm, training, Smart Campus.

1. INTRODUCTION

Fires pose a serious threat to universities, as they can cause property damage, injuries, and loss of life [1]–[3 These fires not only result in financial losses but also disrupt academic activities and pose a threat to student safety, faculty, and staff. In addition, traditional fire detection systems used in universities often rely on manual inspection or basic smoke and heat detectors [4], [5 Adaptive Neuro-Fuzzy Inference System (ANFIS)-Internet of Things (IoT) integrated detection targets of the proposed fire system in order to overcome these limitations. Currently, universities rely on traditional fire detection systems that are often inaccurate and inefficient [6]–[10]. These policies increase false alarms, disturbed departures, and student anxiety [11]. Thus, universities must have a reliable fire detection system. The IoT revolution has significantly impacted our lives by enabling devices to connect and communicate, increasing productivity and convenience [12], our proposed system by integrating ANFIS technology with IoT sensors aims to it will significantly increase the accuracy of fire detection in university buildings. Moreover, the integration of ANFIS technology with Internet of Things (IoT) sensors allows for real-time monitoring and data analytics [14]–[16], besides enabling early fire detection, the system can reduce false alarms and enable timely reporting to appropriate personnel, which enables faster response and reduces fire risk.

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The researchers in [17], utilized sensors to measure temperature and carbon monoxide levels. They utilized a Probabilistic Neural Network (PNN) without specifying the accuracy. The researchers in [18] conducted a study using a variety of sensors including those for gas, temperature, humidity, smoke, and heat. The Directional Prediction Neural Network (TPNN) was employed with an accuracy of 99%, where cloud computing or the GSM was not utilized. In [19], a range of sensors was used to measure different levels of CO2, CO, smoke, humidity, LPG, and air temperature, where the K-Nearest Neighbors (KNN) Algorithm was used with an accuracy of 99.71%. The researchers in [11], conducted a study using sensors for smoke, temperature, humidity, and flame. They relied on the ANFIS without specifying the accuracy. The researchers in [20], used sensors for fire, smoke, and temperature detection. They utilized Sugeno Fuzzy Logic without specifying the accuracy. The researchers in [21], conducted a study using sensors for temperature, smoke concentration, and CO levels. They utilized a Backpropagation Neural Network (BPNN) with an accuracy of 99.4%. The researchers in [22] 2022 conducted a study using sensors for gas/smoke, temperature, and humidity. They utilized a Support Vector Machine (SVM) with an accuracy of 99.83%. The researchers in [23], conducted a study using sensors for gases, smoke, and temperature. They utilized Support Vector Classification with an accuracy of 90%. The researchers in [24], used sensors for smoke, duration, and temperature detection. They utilized Support Vector Classification with an accuracy of 90%. The researchers in [24], used sensors for smoke, duration, and temperature detection. They utilized Mamdani Fuzzy Logic without specifying the accuracy. All research in the above literature did not consider cloud computing or Global System for Mobile (GSM) warnings in their research.

Despite the accuracy of research [19], [22] in training its members, it lacks the reliability and effectiveness of the sensors used.

Smoke detectors are designed to detect fires when they are blazing or in the early stages of fire or flame and typically, flame detectors respond faster and more accurately than thermal smoke detectors [5]. In this work, the SGP30 sensor was chosen because it has proven its effectiveness among many sensors for fire detection through gas and smoke sensing according to this study [25]. For flame and temperature detection, the AMG8833 sensor to more reliable.

While cameras can be valuable tools in fire detection and detection systems, they also have their disadvantages Limited visibility, Vulnerability to environmental conditions, complexity of analysis, Privacy concerns, and High cost [5].

2. MATERIALS AND METHODS

2.1. Architecture of Proposed FAMS

The diagram below in Figure 1 shows the structure of the proposed system for early fire detection and warning. The system includes sensors that collect data such as TVOC, CO2, and flame, which are input as linguistic variables to the ANFIS fuzzy system. The system will be trained on data from previous experiments to determine the severity of the fire based on the input values. The sensor data and fire severity are then sent over the internet to the ThingSpeak cloud for monitoring and taking necessary action based on the resulting fire severity. This includes the ability to alert occupants inside the building and send messages via the internet or communication system to firefighters to request additional assistance with the internal firefighting system.

The system consists of three phases:

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The first phase involves the design of the hardware devices and the configuration of the sensor nodes. The second phase involves MATLAB simulation to train the ANFIS fuzzy system, and the final phase involves programming and configuring the algorithm to integrate the system Diagram.

The workflow of the proposed FAMS is visually represented in the accompanying Figure 2, outlining the sequential steps involved in the system's operation.

Explanation of Figure 1 The operation of the fire alarm system begins with the detection of a fire using various types of detection devices, such as smoke and gas detection sensors, which detect the presence of smoke particles and gas in the air, and heat and flame detection sensors, which measure the temperature of the flame thermally using infrared rays. When a fire is detected, the detection devices send a signal to the central control panel, which processes the signal, determines the exact location and time of the fire, and then sends the data to the cloud via the Internet. The fire data is stored in the cloud, where it can be analyzed to understand fire patterns and take necessary actions to control the fire. Subsequently, necessary decisions can be made, and alerts can be sent to various receiving devices through the cloud. SMS alerts are sent to nearby fire stations and relevant personnel. Audible and visual alarm devices are activated to inform individuals of the fire, and safety systems are activated to extinguish fires as quickly as possible, such as spray systems that release water or chemicals to extinguish the fire.

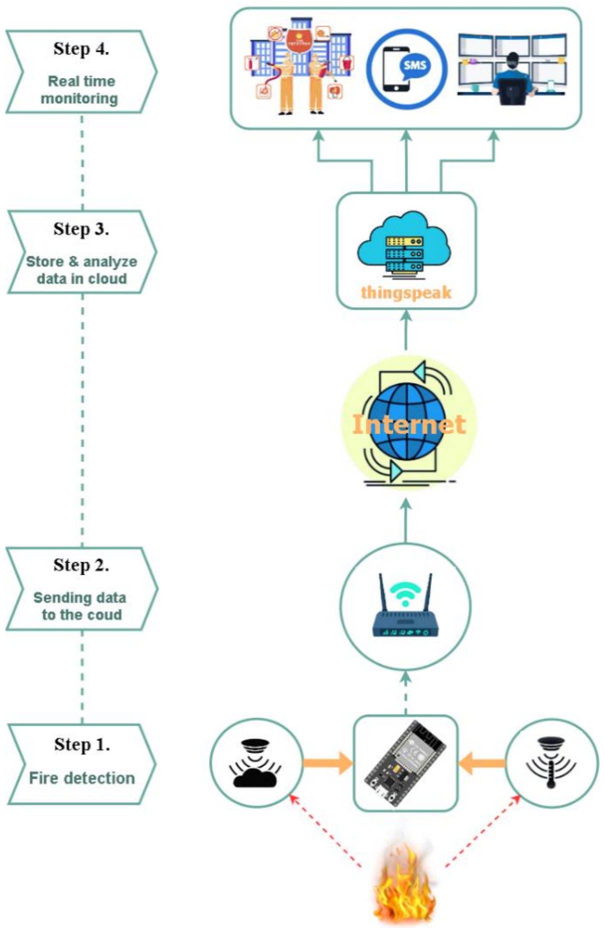

Figure 1 The architecture of the fire alarm system.

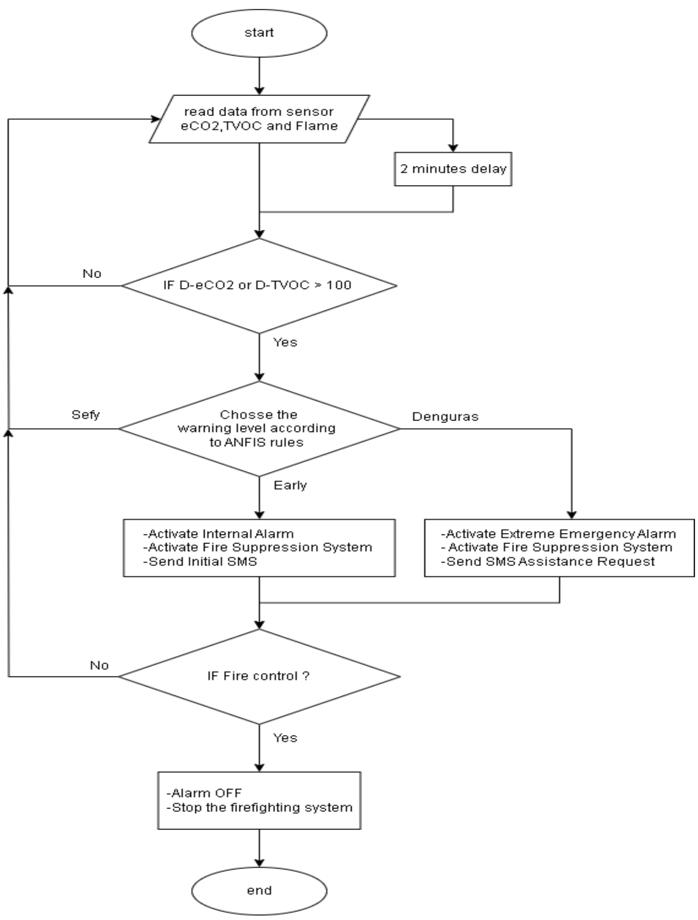

Figure 2 flowchart of FMAS

2.2. Used Hardware in Proposed FAMS

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In the hardware design and setup aimed at detecting the chance of fire by reading flame and smoke sensors, we used an ESP32 Arduino module to connect and integrate the AMG8833 sensors with the SGP30 sensor. This enabled us to accurately collect basic data regarding the presence of flame, total VOCs, and eCO2 levels. To ensure smooth integration of the AMG8833 and SGP30 sensor with the ESP32 Arduino module, we carefully followed the following steps:

1. The Arduino IDE program and libraries necessary for the ESP32 on our computer are installed.
2. We connected AMG8833 and SGP30 to the corresponding pins on the ESP32 Arduino module as shown in Figure 3.
3. A program was developed in the Arduino IDE to retrieve data from the connected IR flame sensors and the SGP30 sensor. This program includes code to collect data, process data, and display results. In addition, it contains code to establish a connection with ThingSpeak, enabling data to be transmitted for display on its interface.

By diligently adhering to these steps, we have seamlessly integrated IR flame sensors and the SGP30 sensor into our IoT project, enhancing our ability to effectively monitor and detect fire sources. The sensors and related items were placed inside a box containing all the practical parts, as shown in Figure 4.

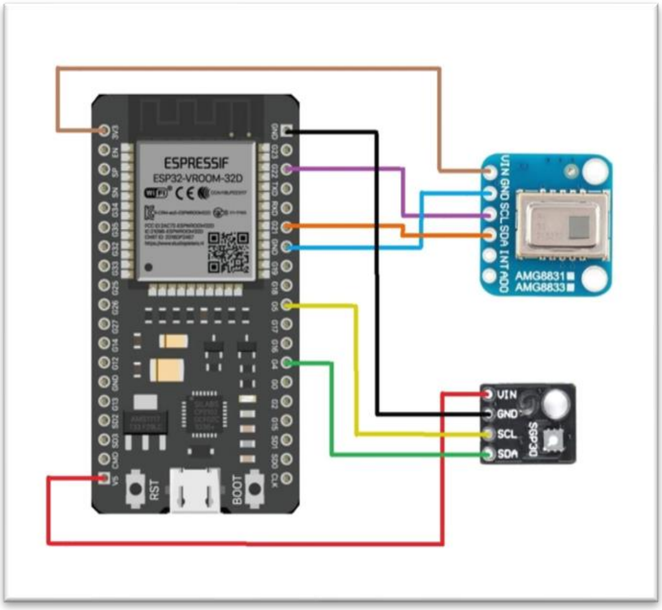

Figure 3 Connect AMG8833 and SGP30 to the corresponding pins on the ESP32 Arduino module.

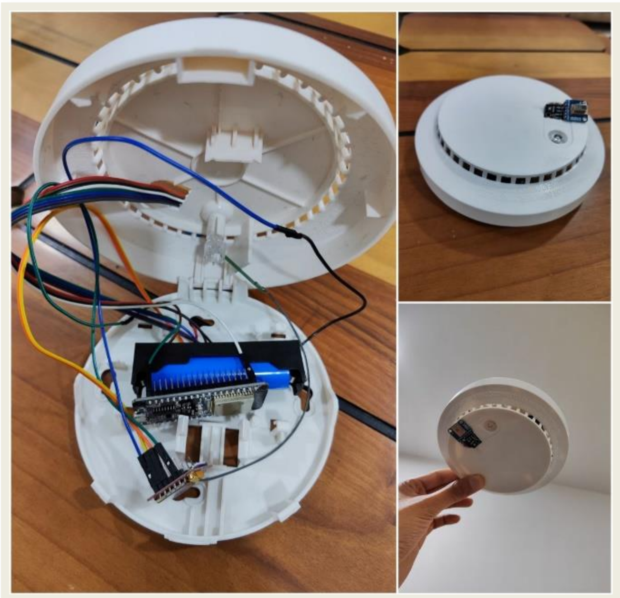

Figure 4 Box containing all the practical parts

2.3. Used Software in Proposed FAMS

The following sections detail everything related to implementing the software for the proposed system.

2.3.1. Collect and structure the database

To collect and structure the database, the data comprises a comprehensive set of values related to inputs and outputs, focusing on key inputs such as eCo2, TVOC, and IR flame. Fire experiments were conducted covering various scenarios, including the burning of wood, plastic, fabrics, cardboard, paper, electricity wires, and other commonly used materials, in a realistic environment reflecting fire challenges. These

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experiments were conducted in a room with precise dimensions of 4 meters in length, 4 meters in width, and 3 meters in height, ensuring an accurate testing environment. Essential sensors were installed in the middle of the ceiling, ensuring high capability in monitoring and measuring environmental variables as shown in Figure 5.

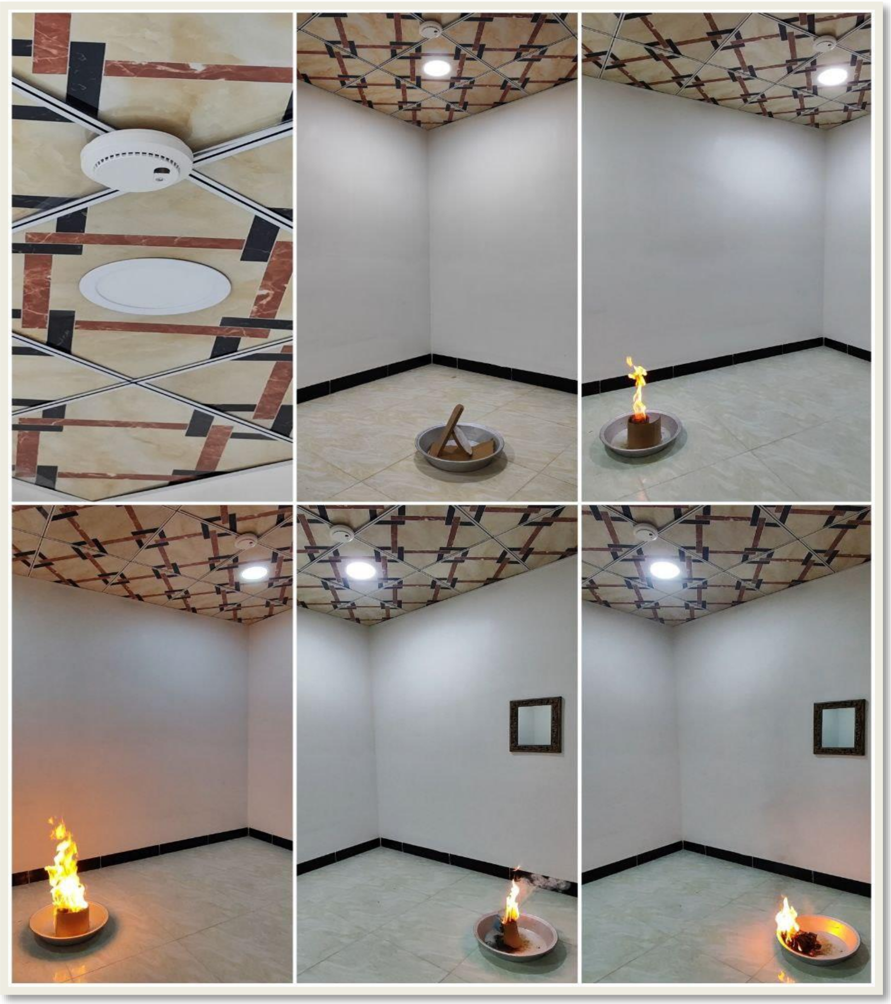

Figure 5 Fire experiment room to collect real data for the database**.**

The software code included in the ESP32 board obtains the sensor readings and displays them in a spreadsheet, as shown in Table 1. Table 1 shows a sample of real-time data collected for the experiment using the Arduin in an Excel spreadsheet. In the absence of a fire, the sensors' reading of the environment is variable and has unstable values at the beginning of operation in relation to a real environment due to the high sensitivity of the sensors. After collecting the initial data from the different sensors, the basic steps of data analysis include determining warning levels by setting warning thresholds for each measured value for different types of burning materials, as shown in Table 2.

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Table 1: Samples of Real-Time Data Gathered from Experimentation

TIME	ECO2(PPM)	TVOC (PPM)	IR FLAME(°C)
05:19:17 PM	400	0	25.25
05:19:18 PM	408	5	25.5
05:19:19 PM	402	8	25.75
05:19:20 PM	406	11	25.75
05:19:21 PM	416	19	26
05:19:22 PM	417	22	25.5
05:19:23 PM	414	17	25.5
05:19:24 PM	425	26	25.25
05:19:25 PM	426	30	25.25
05:19:26 PM	434	32	25.5
05:19:27 PM	433	39	25.75
05:19:28 PM	434	36	25.25
05:19:29 PM	438	42	25.25
05:19:30 PM	452	54	25.5
05:19:31 PM	444	54	25.75
05:19:32 PM	450	55	25.75
05:19:33 PM	457	65	25.5

Table 2: Determining warning levels for each measured for the different types of burning materials

MATERIAL TYPE	ALARM LEVEL	ECO2	TVOC	IR FLAME
CARDBOARD	0	400	0	25.75
	1	534	201	25.75
	2	845	528	26.5
FABRICS	0	400	0	26
	1	712	199	26.25
	2	1093	509	26
WOOD	0	400	0	26
	1	698	200	28
	2	1272	510	29
PLASTIC	0	400	0	25.75
	1	652	240	26.25
	2	752	712	26.5
PAPER	0	400	0	25.5
	1	704	222	26.75
	2	858	514	25.5
ELECTRICITY WIRES	0	400	0	27.5
	1	759	251	25
	2	776	506	25.25
FABRICS	0	400	0	24.75
	1	1000	365	26.25
	2	1317	535	26.25

Next comes the preprocessing of the data, where data cleaning involves removing any missing, contradictory, or noisy values. Then take the difference between the current reading and the reading 2 minutes ago. For the system to adapt to all indoor environments. Then, data normalization is performed to convert all values to a unified range, typically from 0 to 1. Subsequently, the data is divided into two sets, the training set used to train the ANFIS model and the test set used to evaluate the model's performance. Out of the total dataset, which consists of approximately 2000 measured values, 80% is allocated for training data and 20% for testing data.

The purpose of the preprocessing step is to ensure data quality and accuracy before using it for training. Furthermore, dividing the data into discrete groups (training and testing) helps prevent overfitting of the model. Table 3 shows the data processed and prepared for training.

2.3.2. ANFIS for Intelligent Fire Detection.

In fire detection, ANFIS is emerging as a powerful technique, converting raw sensory information into actionable fire detectors. This intelligent system overcomes the limitations of traditional methods and provides a dynamic and adaptive solution for real-time fire management.

At their core, ANFIs effectively blend the power of ambiguity and neural connections. Fuzzy logic enables the system to deal with inherent uncertainties and mismeasurements common in fire situations. Neural networks now introduce variable learning capabilities, enabling the system to refine its understanding of fire patterns based on real-time data This network enables ANFIS to generate robust relationships between three critical components between intrusion and fire hazard is well illustrated. After providing the ANFIS system with training data and determining the number of MF for each input function, the model structure for the ANFIS system can be observed as shown in Figure 6. This allows an understanding of how to build and configure the final model of the ANFIS system.

Table 3: Data After Processing and Preparing it for Training.

eCO2 (INPUT 1)	TVOC (INPUT 2)	IR FLAME (INPUT 3)	ALARM LEVEL (OUTPUT)
0	0	0.0625	0.25
0.25	0.635	0.19	0.75
0.085	0.028	0	0.25
0.089	0.044	0.0025	0.25
0.185	0.284	0.0025	0.5
0.338	0.376	0.035	0.5
0.535	0.995	0.045	0.75
0.312	0.199	0.0025	0.5
0.033	0.039	0.0075	0.25
0.23	0.64	0.185	0.75
0.224	0.306	0.0025	0.5
0.077	0.188	0.02	0.25
0.017	0.022	0.005	0.25
0.499	0.6	0.0175	0.75
0.046	0	0.02	0.25
0.241	0.566	0.1975	0.75
0.09	0.055	0.0075	0.25

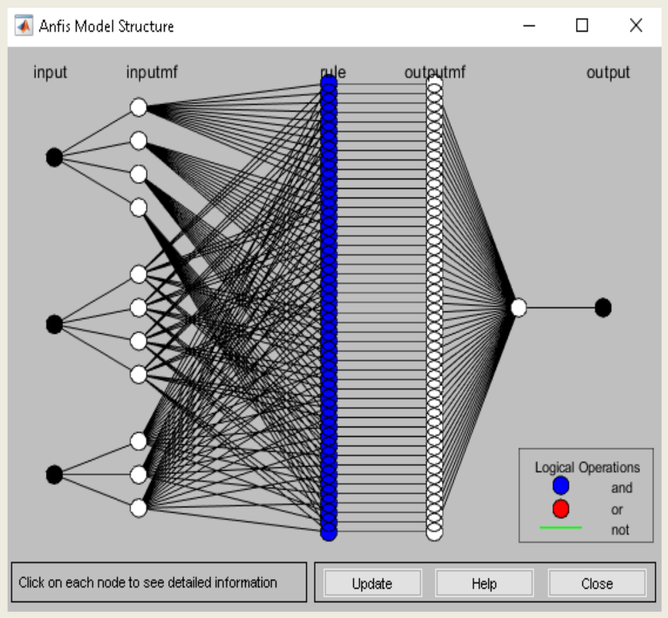


Figure 6 The ANFIS structure

ANFIS seamlessly merges its data, enriching its understanding of fire dynamics. Each of these input features is meticulously processed through Gaussian MF. These functions translate the crisp numerical data into fuzzy sets, representing degrees of membership (low, medium, high) for each variable. This fuzzy representation allows ANFIS to handle the inherent ambiguity and uncertainty associated with fire detection.

The input data is processed using the ANFIS technique to generate the desired alert level based on the input data. ANFIS assigns weights to the input data and correlates it with fire detection outcomes, in real time, by integrating fuzzy interference and neural networks into the smart fire detection and monitoring system. The resulting fuzzy interference model is displayed in Figure 7. The Trapezoidal form of MF is employed to validate the three fundamental inputs as displayed in Figure 8.

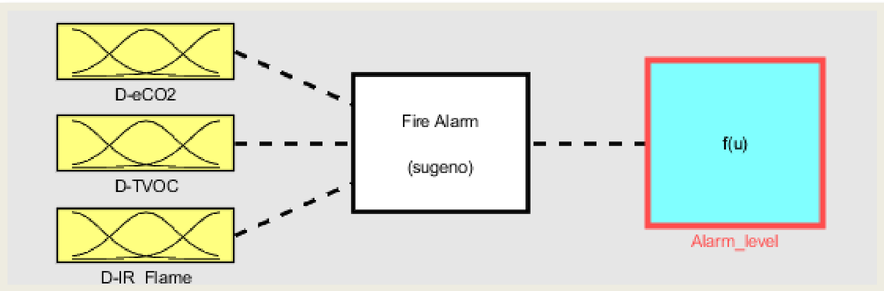


Figure 7 Fuzzy interference model

$$\mu(x) = \begin{cases} 0. & x < k_1 \\ \dfrac{x - k_1}{k_2 - k_1}. & k_1 \le x \le k_2 \\ 1. & k_2 \le x \le k_3 \\ \dfrac{k_4 - x}{k_4 - k_3}. & k_3 \le x \le k_4 \\ 0. & x > k_4 \end{cases}$$

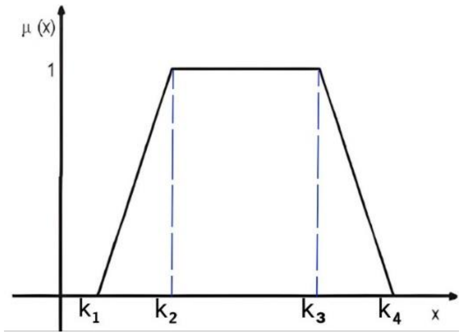
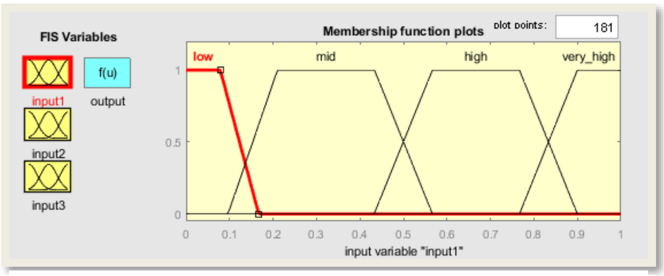


Figure 8 The Trapezoidal form of MF

The MF plots for D-eCO2 (The difference between the current reading and the reading 2 minutes ago), D-TVOC, and D-IR Flame are in Figures (9, 10, 11), respectively.



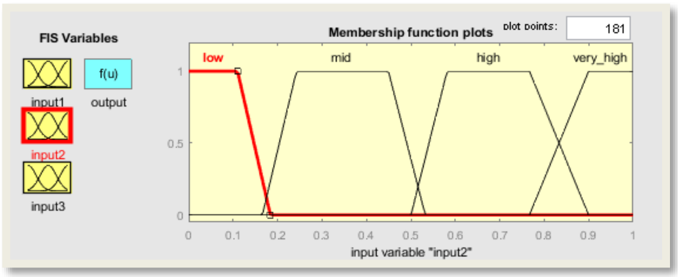
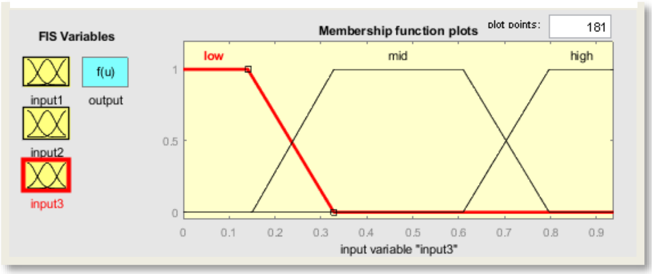


Figure 10 D- TVC

Figure 11 D- IR Flame MF plot



After defining the input and output MF, the training process automatically generates a set of rules. The training process requires the implementation of the Sugeno method to train the fuzzy linguistic labels. The ANFIS was provided with the Training.dat file, which contains the training data collected from the sensors. After successful training, the system generated 48 rules. The generated rules are shown in Figure 12, which illustrates different fire parameters based on the "AND" operator. The ability to delete, add, and modify rules. For the ANFIS training command to work, the initial FIS structure must have a rule for each output MF; that is, the number of output MF must equal the number of rules.

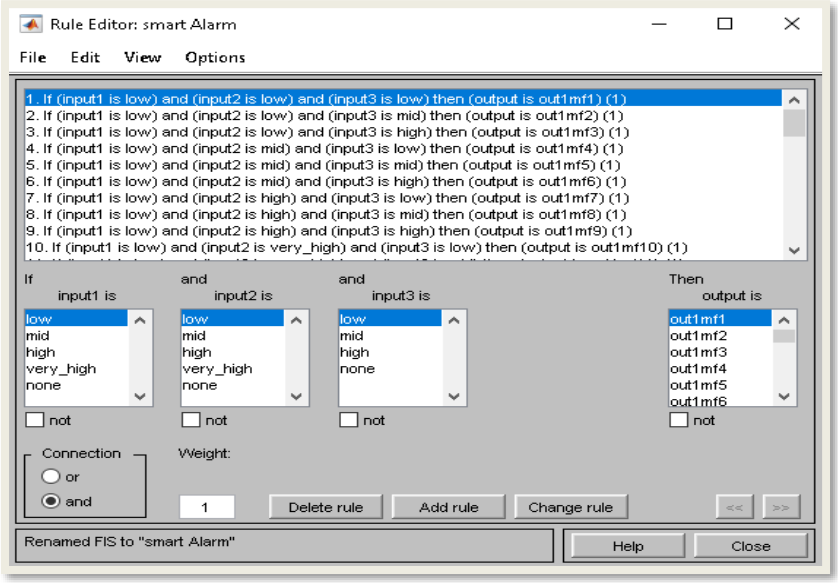


Figure 12 ANFIS generated rules.

2.3.3. ThingSpeak cloud

We have created a ThingSpeak channel to display eCO2, TVOC, Flame, and Fire Chance. Table 4 shows the details of our channels on the ThingSpeak account.

Table 4: Details of Our Channel on The Thingspeak Account

Channel name	**Fire Alarm and Monitoring System**
Channel ID	2272770
Author	enghlf360
Access	Public/private

ThingSpeak uses secure HTTP/HTTPS protocols over the internet. We use this cloud-based platform to analyze data live, where we collect, view, and analyze it continuously.

3. RESULTS AND DISCUSSION

3.1. results of ANFIS training

The FAMS training and testing help with data that shows what real fires look like and what other events that may resemble a fire look like. This training helps the system become smarter at distinguishing real fires, allowing it to send early warnings only when there is a real danger. The ANFIS system was trained on a dataset collected from fire experiments conducted on various materials. The best results were achieved by setting the MF to four for the first input, four for the second input, and three for the third input while increasing the number of epochs to 20. The training showed the best outcomes when the number of epochs was set to 20, resulting in 48 rules with an error rate of 0.0042 and a system accuracy of 99.58%. Figure 4.2 illustrates the training and testing results of the system, showing the accuracy of correctly identifying the warning levels—first, second, or third. Figure 4.2 depicts a correct output with a plus sign (+) and the

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system's output after training with a multiplication sign (*), demonstrating the system's accuracy in identifying the correct warning and risk levels corresponding to different input scenarios.

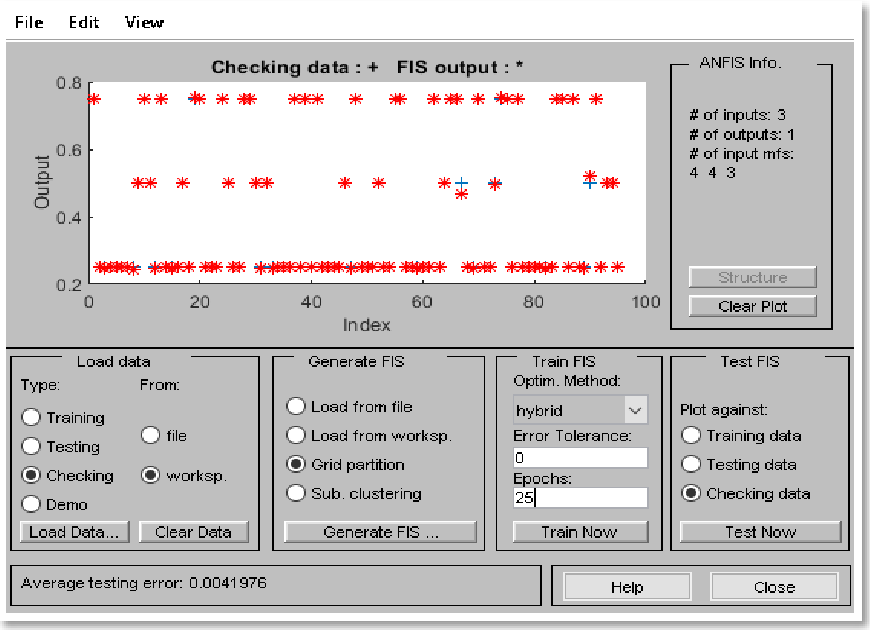

Figure 13 Average testing results.

3.2. Actual test results for FAMS

After completing the early fire detection system and conducting practical experiments on it, testing it on fires of various materials, the results of the practical tests are clarified in the following sections:

3.2.1. Results of detection of fires

The results of distinguishing between real fires and false alarms demonstrate the accuracy and reliability of the fire detection system in differentiating genuine incidents from situations that might trigger false alerts. This analysis aids in evaluating the system's effectiveness in minimizing unnecessary disruptions and ensuring a swift response to genuine fire emergencies. Figure 4.6 illustrates the outcomes of actual fire detection for various materials.

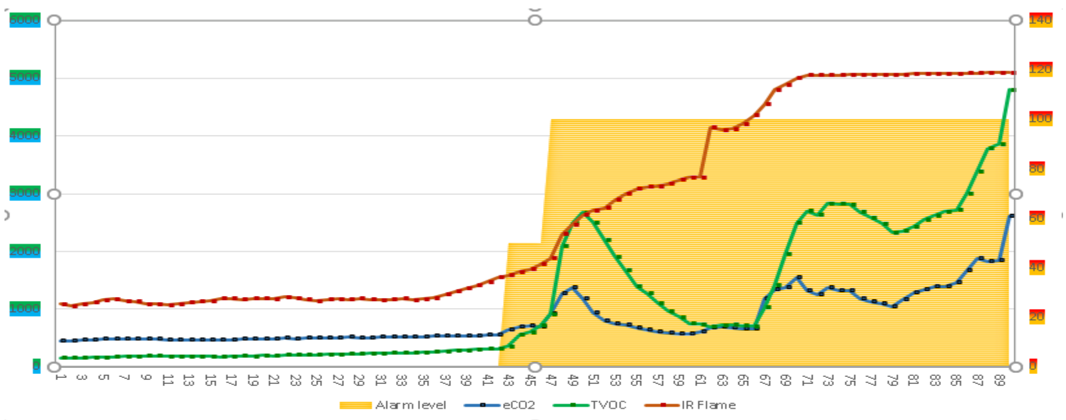

Figure 14 Outcomes of actual fire detection for various materials.

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Figure. 14 illustrates the determination of the alarm level based on the level of danger using the data from the three inputs. Initially, the danger level is zero, indicating no risk before the fire starts or is detected. At the onset of the fire at second 33, only smoke and organic compounds are detected before the flames become visible. Sensors for eCo2 and TVOC begin recording until second 37 when the flames start to rise. At second 42, with an increase in the flame temperature recorded by the IR flame sensor, reliable early fire detection is made, prompting the alarm level to be set to the first level for early fire detection.

The inputs continue to increase, indicating the fire's persistence until second 47, where readings of eCo2, TVOC, and flames reach a high level, approaching danger. Consequently, the alarm level is raised to the second level, indicating fire hazards due to flame temperature and air pollution from smoke and hazardous volatile organic compounds. Between seconds 51 and 63, eCo2 and TVOC readings begin to decrease, but the flame readings remain elevated, maintaining the alarm level at the second level due to continued danger. After second 65, with increased readings, the alarm level is raised again to the second level, indicating fire hazard, until the final second.

3.2.2. Fire Detection Times for Different Material Types

Table 5 shows the fire detection times for various material types at two different levels. The time is measured in seconds, and the table highlights the differences in fire detection speed based on the type of material and the level. This analysis helps to understand which materials require more time to detect fire, which can have a significant impact on fire prevention and safety strategies.

Table 5: Validity of detection and detection time for the system

Scenario	**Material type**	**Detecting fire by FAMS**	**Fire Detection Time (s)**		**The real situation**
			Level (1)	Level (2)	
1	cardboard	Yes	26	33	fire
2	fabrics	Yes	50	68	fire
3	wood	Yes	139	155	fire
4	plastic	Yes	149	172	fire
5	paper	Yes	25	30	fire
6	electricity wires	Yes	164	186	fire
7	cigarette smoke	No	-	-	No fire
8	Gas leak	No	-	-	No fire
9	Water vapor	No	-	-	No fire
10	Air dust	No	-	-	No fire
11	Light the candles	No	-	-	No fire

The table indicates that there is a variation in fire detection times among different material types across the two levels. On average, electricity wires, plastic, and wood are among the materials that take longer to detect fire, posing a greater risk in emergencies. On the other hand, paper and cardboard are detected more quickly.

3.2.3. Monitoring On Thingspeak and Alarm

Monitoring the system via the Thankspeak cloud, as shown in Figure 15, is straightforward.

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- eCo2 chart illustrating the distribution of eCo2 values from the SGP30 sensor, with eCo2 values on the vertical axis and time of measurements on the horizontal axis.
- TVOC chart displaying the distribution of TVOC values from the SGP30 sensor, with TVOC values on the vertical axis and time of TVOC measurements on the horizontal axis.
- IR Flame chart providing the distribution of flame temperature values from the AMG8833 sensor, with flame temperature on the vertical axis and time of temperature measurements on the horizontal axis.
- Alert Level chart determining the warning or danger level from the ANFIS system based on three inputs, with the danger level and alert level on the vertical axis and the time of determining these levels on the horizontal axis.

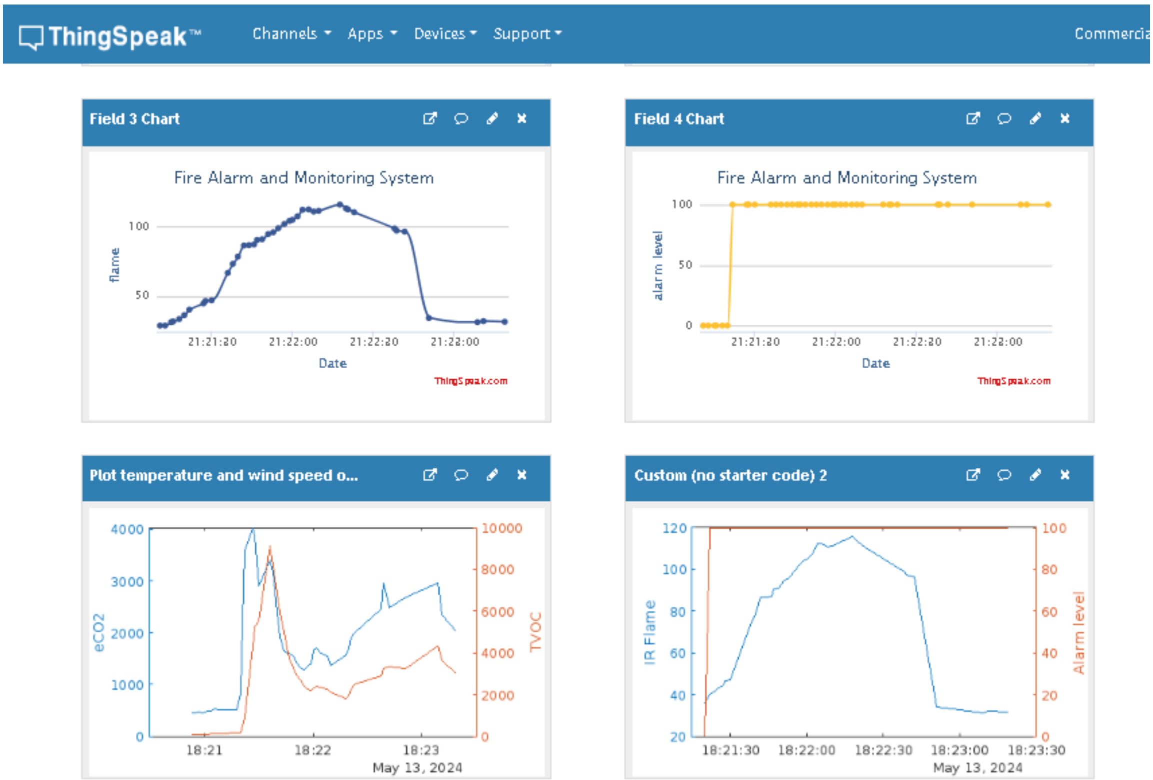

Figure 15 Monitoring the system via the Thankspeak cloud.

3.2.4. Alarm SMS

Upon the detection of a fire and the determination of its level of danger or alert, an SMS message is received via the GSM network from one of the telecommunication companies in Iraq. The message contains detailed information about the fire location, including the specific floor and room, as well as the time of the fire occurrence and the level of danger, along with a request for assistance to control the situation as shown in Figure 16.

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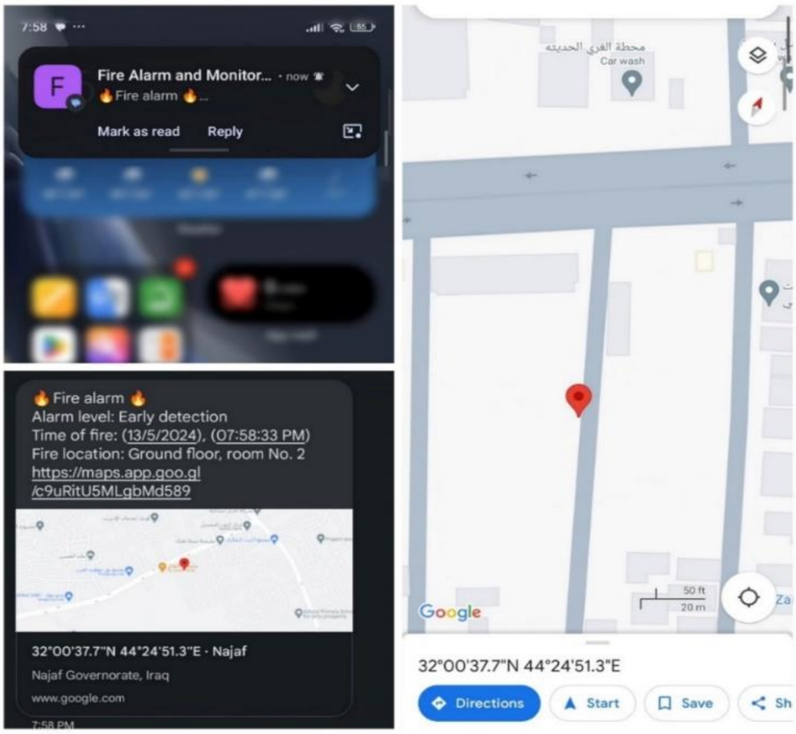

Figure 16 Alert messages from FAMS

3.3 Comparison between the Previous Works and the Proposed Solution

This paragraph focuses on highlighting the key differences between previous solutions and the FAMS. The comparison is made by evaluating several essential criteria, including the number of sensors used, the reliability and sensitivity of the sensors, the type of training system employed, the number of training inputs, the number of fire experiments conducted, the total number of samples used for training and testing, the number of epochs used for training, system accuracy, The average time taken before a fire is detected, and finally, the ability to resolve the issue of unknown values in the output after training. Table 6 presents the details of this comparison:

Table 6: Results and Differences Between Previous Solutions and the FAMS

	[11]	**[21]**	**Proposed FAMS**
Number of sensors used	3	3	2
Reliability and sensitivity of the sensors used	LOW	LOW	HIGH
Type of training system	ANFIS	BPNN	ANFIS
Number of training inputs	4	6	3
Number of fire experiments	-	6	7
The total number of samples for training and testing	-	3500	2000
Number of epochs used	100	50	20
System accuracy	-	99.4%	99.58%
The average time taken before a fire is detected	-	135 S	97 S
Solve the problem of unknown values in the output after training	NO	NO	YES
Using the cloud to monitor, store, and analyze data	NO	NO	YES
Alarm messages via GSM	NO	NO	YES

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The FAMS solution exhibits several improvements over previous work. It achieves fast detection time and comparable accuracy with fewer sensors, interpolation training, and epochs. Moreover, it provides high sensor reliability and sensitivity and solves the problem of unknown values of results after training. This indicates that the proposed FAMS can provide efficient, reliable, and effective fire detection and monitoring.

4. CONCLUSIONS

The FAMS is an effective system for the early detection of fires inner buildings, especially inside college campuses, where excessive-efficiency sensors along with eCo2, TVOC, and flame temperature are applied. The ANFIS machine has been educated on statistics amassed from actual environments and experimental fires involving numerous materials and situations. Based on real-time sensor statistics, the machine determines the extent of the alert and monitors and analyzes records using the Thingspeak cloud platform. SMS alerts containing comprehensive facts about the heart location, severity stage, and detection time are dispatched via GSM networks to help firefighters extinguish fires as fast as possible. The ANFIS system achieves high accuracy, as much as 99.58% after schooling, way to ANN and fuzzy logic features, lowering false alarms and aiding in distinguishing between true and false alarms. The FAMS solution demonstrates several improvements over the previous works. It achieved faster detection times by reducing the fire detection rate by 28% and accuracy with fewer sensors, training inputs, and epochs. Additionally, it offers higher sensor reliability and sensitivity and solves the problem of unknown values in the output after training. By employing IoT and ANFIS technologies, the system integrates efficiency to achieve safety and fire suppression for the protection of lives and public property, highlighting the importance of safety and technology in human service.

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