Comparative Analysis of Naive Bayes and Fuzzy Logic Algorithm in Fire Classification System

[1]Ria Rismayati*, [2] Suriyati, [3]Parama Diptya Widayaka
[1,2]Computer Science, Faculty of Engineering, Universitas Bumigora, Mataram, Indonesia
[3]Electrical Engineering, Faculty of Engineering, Universitas Negeri Surabaya, Surabaya, Indonesia
*e-mail: riris@universitasbumigora.ac.id

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Abstract

Building fires can cause losses in several areas, including property damage, environmental pollution, loss of life, injury, and psychological trauma. Building fires can occur due to several factors such as gas leaks, short circuits, overheating electronic devices, the presence of flammable materials, and human error. In fire mitigation efforts, devices are generally used as early warnings, but their implementation is often less than optimal due to system malfunctions. Therefore, this study aims to develop an early warning system that can detect potential fires before they spread. The methods used in this study are the naïve Bayes and fuzzy logic methods, which then compare each method to determine the most effective method. The results of this study indicate that the naïve Bayes and fuzzy logic methods have successfully classified potential fires well. From 30 experimental data, the naïve Bayes algorithm produced an accuracy of 96%, while the fuzzy logic algorithm produced an accuracy of 100%. The naïve Bayes algorithm shows reliable performance in classifying extreme data while the fuzzy algorithm can detect the 'Danger' status even though not all parameters are in a dangerous condition.

Keywords: *building fires, fuzzy logic, naive bayes, comparative analysis*

1 Introduction

Building fires can cause significant losses, such as loss of life, injury, psychological trauma, loss of property, and environmental pollution [1], [2]. Several factors contribute to fires, including electrical short circuits, gas leaks, human error, the presence of flammable materials, and overheating of electronic devices [3], [4]. To mitigate these risks, buildings generally have early warning systems, but their implementation is often suboptimal due to system failures [5]. Building early warning systems generally use a single parameter, such as the presence of fire, increased temperature, or the presence of gas or smoke in the building [6], [7]. This approach has weaknesses such as low detection accuracy, resulting in false alarms, which activate the building's fire extinguishing system. False alarms disrupt building operations and cause material and non-material losses [8].

To overcome these problems, various studies have been conducted on fire prevention, such as increasing sensor accuracy, developing artificial intelligence-based devices to classify potential fires [9], [10], selecting optimal sensor materials [8], and implementing internet of things (IoT) based on software applications to monitor potential fires in buildings [11]. However, implementing artificial intelligence for an early fire warning system that can accurately and quickly make decisions requires more in-depth study.

In the last decade, technological developments regarding building fire potential detection systems have increased. Research by [12] examined the Building Information Modeling (BIM) method approach to assessing fire potential by referring to the resulting risk index. However, the approach in this research has limitations because it does not integrate sensors in real-time and is in the simulation domain. In addition, research by [13] has succeeded in integrating real-time sensors such as gas sensors (MQ-3), and temperature sensors (DHT22) to detect building fires using fuzzy logic methods, in addition, it examined building fire notification systems. However, in this research, it only focused on data transmission using Simple Mail Transfer Protocol (SMTP) without examining in depth the sensor response for fire mitigation. In addition, research by [14] examined the use of the naïve Bayes method to classify fire potential. The accuracy resulting from this research was 97.76%, however, the weakness of this research is the lack of control system integration for building fire mitigation and is

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only limited to dataset collection without real-time validation in the environment. Meanwhile, research by [15] examined the implementation of deep learning with the inception-v3 model to detect fire and smoke using a camera, however, there are weaknesses in real-time implementation because it requires high computing and large resources.

Based on the literature review, although various studies for fire detection have been developed, there are still limitations that can be studied more deeply. In previous studies, research studies only focused on one aspect such as BIM integration without real-time sensor implementation, fuzzy logic implementation without real-time testing, naïve Bayes implementation without a control system for fire mitigation, and visual fire detection using deep learning but requiring high computation and large costs. Therefore, there is a research gap that examines the implementation of naïve Bayes and fuzzy logic methods to classify potential fires, which are then subjected to comparative analysis to compare more effective methods. In addition, research gaps can also focus on testing fire detection systems in real-time environments. This gap offers a very relevant and adaptive opportunity for further in-depth research.

The novelty of this research lies in the implementation of the naive Bayes method and fuzzy logic to classify the potential for building fires, then conducting trials in a real-time environment to examine the comparative analysis of the two methods to obtain a more effective, efficient, and reliable method. In addition, integrating several sensors such as a temperature sensor (DHT22), a smoke sensor (MQ-2), and an infrared temperature sensor (MLX90614) in real-time to reduce detection errors. So the purpose of this study is to evaluate the level of effectiveness of the naive Bayes method and fuzzy logic to determine a more optimal method in classifying potential fires.

2 Literature Review

Based on the literature study conducted, there are various studies conducted for the detection and classification of potential fires through various computational approaches, sensor integration, and IoT. Research by [14], examines the modification of the naïve Bayes algorithm using the double weighted naïve Bayes method with compensation coefficient (DWCNB), which has succeeded in increasing the prediction accuracy to 98.13% by considering the weighting of each attribute. In addition, research by [16] developed a fire detection system using IoT and Convolutional Neural Network (CNN) by adding a security system in sending videos to the cloud. The accuracy of the fire detection system reached 97.5%. In line with that, research by [17] used the YOLO-V8 algorithm approach in an intelligent fire detection system. The accuracy produced in this research reached 97.1% and was designed to be integrated into smart city infrastructure.

In addition, the implementation of fuzzy logic in fire detection systems has been widely explored. Research by [18] uses a fire signal pattern recognition approach using fuzzy logic and IoT. This research can predict fires 30 seconds earlier compared to conventional alarms. On the other hand, research by [19] uses an Arduino and IoT approach to provide early warnings and monitor fires. In addition, fuzzy logic is also integrated in this research, resulting in detection accuracy of up to 90%. Furthermore, research by [20] examines the integration of fuzzy logic with firefighting robots using a GSM module for fire detection and directing the nozzle to the fire source.

Although various studies have demonstrated the effectiveness of both modified Naive Bayes algorithms and fuzzy logic-based systems in the context of fire detection, most studies are still limited to evaluation through simulation or laboratory environments. Research such as that conducted by [14] and [16] has not tested algorithm performance in real-world conditions with uncontrolled environmental variables. Furthermore, no study has comprehensively compared the performance of enhanced Naive Bayes algorithms and fuzzy logic approaches within the same fire classification system, particularly in terms of accuracy, response speed, and resilience to false alarms. Therefore, research is needed that not only tests both approaches in a real experimental setting using controlled fire sources but also conducts an in-depth comparative analysis to identify the strengths and weaknesses of each algorithm in the context of developing a reliable and responsive fire classification system.

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3 Research Method

This research is conducted according to the following stages: data collection, carried out to perform literature studies and determine the specifications of the equipment to be developed. Subsequently, the stages involve the design of the hardware for the building fire classification system, the design of the Naïve Bayes algorithm, and the design of the fuzzy logic algorithm. The implementation phase then follows, encompassing hardware assembly, comprehensive sensor testing, testing of the Naïve Bayes algorithm, testing of the fuzzy logic algorithm, and a comparative analysis of the two algorithms. Finally, the stage of research result evaluation is conducted. The research block diagram is shown in Figure 1.

Figure 1. Research flow

3.1. Data Collection

In the initial stage, a literature study was conducted to obtain an in-depth understanding of the materials and electronic components to be used in this research, then the specifications of the materials and components used were determined. The purpose of determining the specifications of these components is to find accurate and relevant information before building the tool to help find out the environmental conditions around the tool. The specifications of the fire classification system can be shown in Table 1.

Table 1. Materials and components for fire detectors

No	Componen	Description
1	NodeMCU ESP-32	NodeMCU ESP32 functions as the main microcontroller that can manage and control various components connected in a microcontroller-based system [21].
2	DHT22 Sensor	Serves to measure temperature and humidity in a room [22].
3	MQ-2 Sensor	Serves to measure gas in a room [23], [24].
4	MLX90614 Sensor	Serves to measure temperature using infrared in a room [25].
5	LCD 16x2	Serves to display sensor data.
7	Adapter DC 9Volt	Serves as a power source for the fire detector system.
8	Box	Serves as a protector of electronic components in the tool.
9	Jumper Cable	As a connector between electronic components.

3.2. Design of The Hardware

In the hardware design process, various electronic components such as microcontrollers, sensors, and actuators are used which are integrated into a real-time building fire detection system. The electronic components used include a microcontroller (ESP32), infrared temperature sensor (MLX90614) [25], environmental temperature (DHT22), and gas (MQ-2). In addition, the fire detection system is equipped with a buzzer alarm and a 16x2 LCD which functions as an early warning indicator and displays information in the form of sensor data and system output. The hardware design of the fire detection system can be shown in Figure 2.

Each sensor used in a fire detection system serves as input. Sensors measure environmental parameters such as temperature, humidity, and gas concentration. Sensor measurement data is transferred to a microcontroller for processing, allowing it to be used as input for the naive Bayes and fuzzy logic methods. This microcontroller functions as a control center for processing signals and actuators connected to the fire system. The naive Bayes algorithm is used to classify potential fires using statistical data based on probability, while fuzzy logic is often used as a decision maker based on predetermined if-then rules [26]. Both methods can reliably evaluate the potential for fires in buildings based on sensor data.

If the temperature increases and the gas concentration becomes thicker, an alarm will be activated, which serves as an early warning. Furthermore, sensor data and fire potential classification

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results will be displayed on a 16x2 LCD screen, allowing users to monitor the building's environmental conditions in real time. With this approach, the fire detection system can provide a rapid response to any potential fire threat within the building.

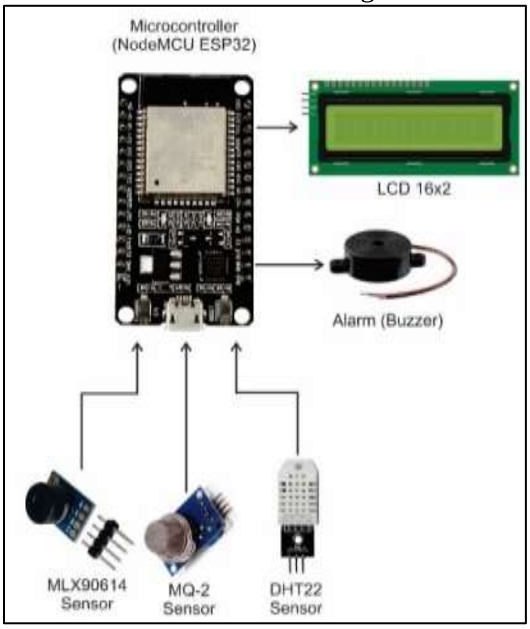

Figure 2 Hardware block diagram of fire detector system

3.3. Design of The Software

3.3.1. Data Tranformation

At this stage, data transformation involves three attribute variables: room temperature, infrared temperature, and indoor smoke. Each attribute has a numeric value obtained from sensor measurements, which will then be transformed into nominal data to meet the requirements of the naive Bayes algorithm and fuzzy logic. The data transformation process can be observed in detail in Table 2, which maps the continuous values from the sensors into the corresponding discrete categories.

Table 2. Attribute data transformation

Attributes	Nominal Data	Numerical Data
Room Temperature	High	>36
	Medium	33-36
	Low	<33
Non-Contact Infrared Temperature	High	>40
	Medium	33-40
	Low	<33
Indoor smoke	Concentrated	>266
	Medium	170 - 266
	Low	<170

3.3.2. Dataset Naive Bayes and Rule Fuzzy Logic

In the Naive Bayes algorithm, training data and fuzzy rules are fundamental components that serve as the basis for learning the model to perform classification. The training data consists of a number of samples that each have known attributes (features) and class labels. Each feature in the data represents a certain characteristic of the observed object, while the class label indicates the category or group to which the object belongs. The attributes used in the training data are room temperature, non-contact infrared temperature, and indoor smoke. While the classes used are safe, alert, dangerous, and very dangerous.

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Table 3. Dataset naive bayes and rule fuzzy logic

No	Room Temperature	Non-Contact Infrared Temperature	Indoor smoke	Room conditions
1	Low	Low	Low	Safe
2	Low	Low	Medium	Safe
3	Low	Low	Concentrated	Alert
4	Low	Medium	Low	Safe
5	Low	Medium	Medium	Safe
6	Low	Medium	Concentrated	Alert
7	Low	High	Low	Safe
8	Low	High	Medium	Safe
9	Low	High	Concentrated	Danger
10	Medium	Low	Low	Safe
11	Medium	Low	Medium	Alert
12	Medium	Low	Concentrated	Danger
13	Medium	Medium	Low	Alert
14	Medium	Medium	Medium	Alert
15	Medium	Medium	Concentrated	Danger
16	Medium	High	Low	Alert
17	Medium	High	Medium	Danger
18	Medium	High	Concentrated	Danger
19	High	Low	Low	Danger
20	High	Low	Medium	Danger
21	High	Low	Concentrated	Very Danger
22	High	Medium	Low	Danger
23	High	Medium	Medium	Danger
24	High	Medium	Concentrated	Very Danger
25	High	High	Low	Very Danger
26	High	High	Medium	Very Danger
27	High	High	Concentrated	Very Danger

3.3.3. Design of Naive Bayes Algorithm

Naive Bayes is one of the supervised learning algorithms in machine learning used for classification tasks. It is based on Bayes' Theorem, a concept in probability theory that relates the probability of an event to conditions or prior knowledge related to the event. The uniqueness of Naive Bayes lies in its ‘naive’ assumption, which assumes that all features in the data are independent of each other, even though in practice, they may have a relationship or correlation. This assumption makes calculations simpler and more efficient, although sometimes less accurate if features are highly dependent on each other. There are several stages in classification using the naïve bayes algorithm:

1) Calculating Prior Probability

The prior probability represents the initial estimation of the occurrence of a class based on the distribution of the training data. In this study, the room conditions are classified into four discrete categories, namely safe, alert, dangerous, and very dangerous, which are set as target classes in the classification model. The prior probability values for each of these classes can be observed in detail in Table 4.

Table 4. Data of prior probability

Room Condition	Total	Probabillity
Very Danger	5	0,278
Danger	6	0,333
Alert	5	0,278
Safe	2	0,111

2) Calculating Likelihood

Likelihood is measuring how often a feature appears in a particular class. Likelihood calculation data can be shown in Table 5-7.

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Tabel 5. Likelihood of room temperature

Room Temperature	Very Danger	Danger	Alert	Safe
High	0,5	0,3333	0,1667	0
Medium	0,1667	0,3333	0,5	0
Low	0,1667	0,3333	0,1667	0,3333

Tabel 6. Likelihood of non-contact infrared temperature

Non-Contact Infrared Temperature	Very Danger	Danger	Alert	Safe
High	0,6667	0,3333	0	0
Medium	0,1667	0,5	0,3333	0
Low	0	0,1667	0,5	0,3333

Tabel 7. Likelihood of indoor smoke

Indoor Smoke	Very Danger	Danger	Alert	Safe
Concentrad	0,6667	0,3333	0	0
Medium	0,1667	0,5	0,1667	0,1667
Low	0	0,1667	0,6667	0,1667

3) Applying Bayes Theorem to Calculate Posterior Probabilities

Bayes theorem combines prior and likelihood to calculate posterior probability, which is the probability that data belongs to a certain class based on its features. The Bayes theorem equation can be shown in Equation (1).

$$P(Class|Feature) = \frac{P(Feature|Class).P(Class)}{P(Feature)} \quad (1)$$

4) Predict the Class with the Highest Probability

After calculating the posterior probabilities for all classes, the algorithm selects the class with the largest probability value as the final prediction.

3.3.4. Design of Fuzzy Logic

Fuzzy logic is a logic system that works with the concept of partial truth (values between 0 and 1), in contrast to Boolean logic (0 or 1). In the context of fire detection, fuzzy logic allows the system to handle parameter uncertainty more flexibly [26]. The stages of the fuzzy logic algorithm are as follows:

1) Fuzzyfication

Fuzzification serves to convert crisp input values into fuzzy membership degree values. The variables used in this fuzzy logic are room temperature, non-contact infrared temperature, and smoke in the room. The results of the membership value conversion can be shown in Figure 3 and Figure 4.

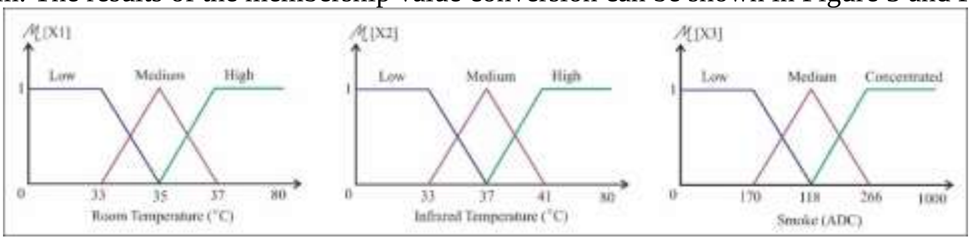

Figure 3. Input member of function

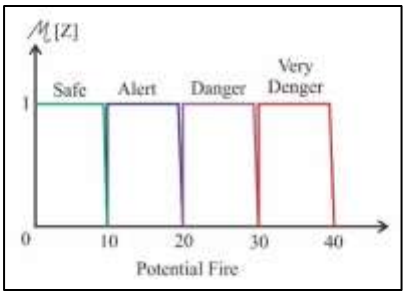

Figure 4. Output member of function

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2) Infrence

In the inference process, the method used is the Sugeno method. Sugeno inference method is one of the fuzzy inference system methods developed by Michio Sugeno in 1985. The Sugeno method uses a linear function output, making it more efficient in the computational process. This model is often implemented in intelligent control systems because it is very good at handling non-linear problems. In the method, fuzzy rules are formulated in the form of 'If-Then' where the antecedent is a fuzzy set, while the consequent is a mathematical equation. The mathematical equation in Sugeno's fuzzy rule base can be shown in Equation (2).

$$if\ x\ is\ A\ AND\ y\ is\ B\ THEN\ z = f(x,y) \quad (2)$$

Firing strength ($\mu(Z_i)$) can be calculated using the min or product operation on the antecedent membership degree, as shown in Equation (3).

$$\mu(Z_i) = \mu A_i(x) * \mu B_i(y) \quad (3)$$

3) Defuzzyfication

Defuzzification is the process of converting fuzzy outputs into crips values. The defuzzification method used is the average expressed in Equation (4).

$$Z_0 = \sum_{i=1}^{n} \frac{\mu(Z_i).Z_i}{\mu(Z_i)} \quad (4)$$

4 Results and Analysis

4.1. Hardware Design Results

This hardware design aims to integrate various components, including power supply, sensors, microcontroller, and alarm, into one packaging unit so that it functions as a potential fire early detection system. The sensors used in this system consist of a temperature sensor (DHT22), a smoke sensor (MQ-2), and a non-contact infrared temperature sensor (MLX90614). Meanwhile, the microcontroller used is the NodeMCU ESP-32, equipped with a 16×2 LCD for data visualisation and a buzzer as an audio indicator. The specifications of the power supply applied are an adapter with an output of 9 Volts and 1 Ampere. The results of the hardware design can be shown in Figure 5.

Figure 5. The results of the hardware design of the fire detection device

4.2. DHT22 Temperature Sensor Testing Results

The temperature sensor testing was conducted to evaluate the level of accuracy and reliability of the sensor in responding to ambient temperature changes. In this test, variations in ambient temperature were induced through controlled combustion, while the temperature readings from the sensor were recorded at 5-second intervals. The data obtained from the sensor will be compared with the data generated by the digital thermometer to identify any measurement deviations by the sensor. The resulting measurement differences will be analyzed to calculate the measurement error. The

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average measurement error value will be used as an indicator to calculate sensor accuracy. The sensor test results are presented in Figure 6.

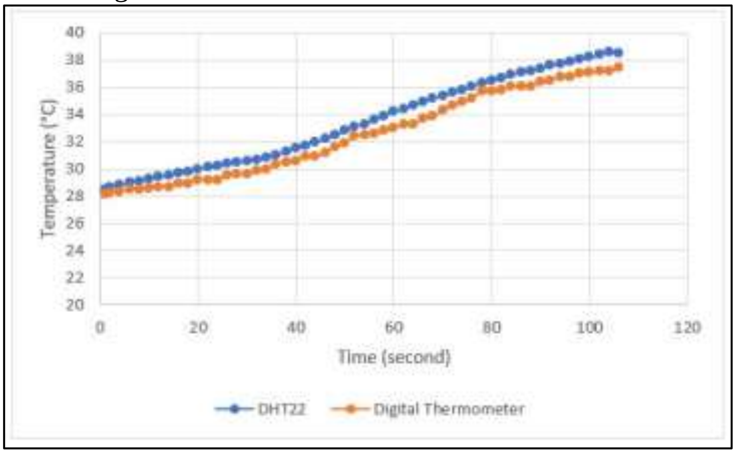

Figure 6. Temperature measurement result graph

Based on the sensor test results in Figure 6, it shows that the DHT22 sensor successfully measures changes in indoor temperature. This is evidenced by the results of the DHT22 sensor measurements that can follow the temperature change trend obtained by the digital thermometer. The average temperature deviation produced by the sensor and digital thermometer is 0.91oC, with an average measurement error of 2.8%, resulting in a measurement error of 97.2%. Based on these results, the accuracy obtained by the sensor is quite high and in accordance with industry standards. Therefore, the DHT22 sensor is an adequate sensor for use in fire detection systems.

4.3. MQ-2 Smoke Sensor Testing Results

The MQ-2 gas sensor test aims to evaluate the sensor's response to changes in indoor air quality, especially when tested to detect smoke and other flammable gases. The test procedure begins with gas measurements in clean air conditions, which are used as a reference, then the test room will be given gas contamination in the form of smoke gradually by burning paper near the sensor, then data collection is carried out periodically every 10 seconds during smoke exposure and in the recovery phase after the fire is extinguished, so that the smoke in the test room is gradually reduced. Based on this procedure, an analysis can be carried out on the results of the sensor test under conditions of exposure and the recovery process. The results of the MQ-2 gas sensor test can be shown in Figure 7.

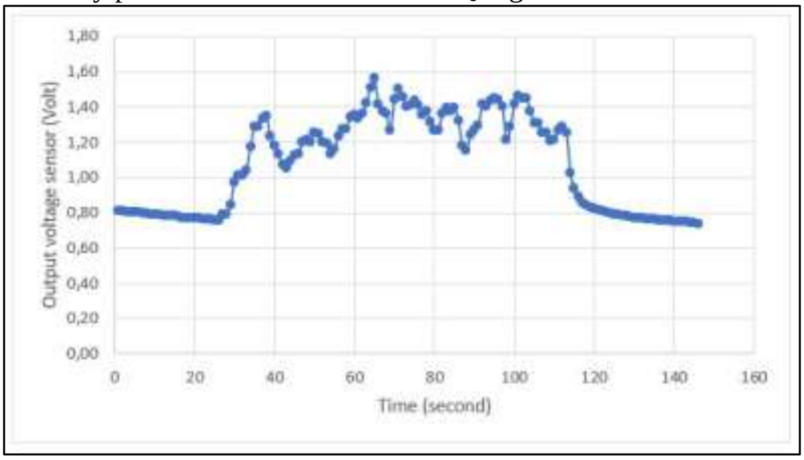

Figure 7. MQ-2 gas sensor test results

Based on the test results in Figure 7, it shows that there is a correlation between the data generated by the MQ-2 sensor and the increase in smoke concentration in the test chamber. The data generated by the sensor is in the form of sensor output voltage data. Based on the test results in a clean air environment, the measured sensor output is 0.8 volts in the time range of 0-9 seconds. Then when exposure to combustion smoke occurs, the sensor output gradually responds to changes in

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environmental conditions, indicated by an increase in the output voltage value to reach 1.6 volts. These data indicate a proportional sensor response to the increase in gas concentration in the environment. Furthermore, the test results in the recovery stage show a decrease in the sensor output voltage value proportional to the decrease in gas concentration in the environment. These test results indicate that the MQ-2 sensor has a good response to changes in gas concentration in the environment (test chamber) so that the MQ-2 sensor can be used in a fire detection system.

4.4. MLX90614 Infrared Temperature Sensor Testing Result

The purpose of testing the characteristics of the infrared temperature sensor (MLX90614) is to assess the sensor's response to temperature changes occurring in the room and to detect sudden temperature changes in the room. The testing procedure was carried out by measuring the sensor's output value before and after combustion in the test chamber. The test results are presented in Figure 8.

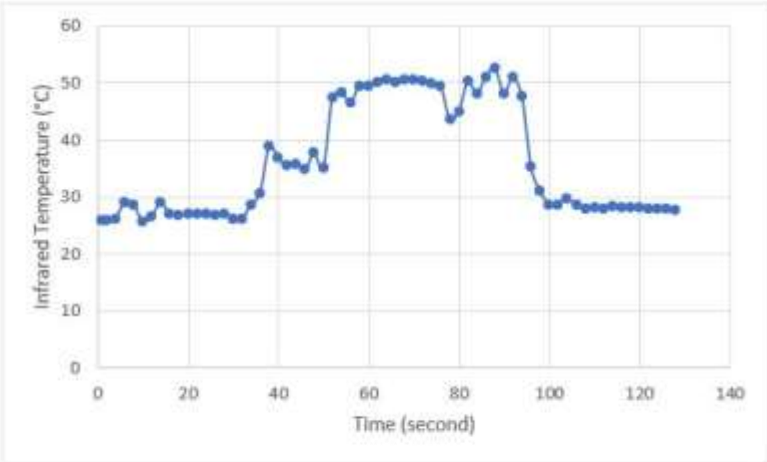

Figure 8. Test result graph of MLX90614 non-contact temperature sensor

Based on the data in Figure 8, it shows that the initial condition before the fire burned in the room, the average recorded room temperature was 28°C. After the fire source was lit, the sensor had a fast response to detect changes in temperature in the room, by recording a temperature reading that increased to 40°C within 5 seconds. This response to reading changes in temperature values indicates that the MLX90614 sensor can be used to detect fires.

4.5. Naive Bayes Algorithm Testing Result

The naive Bayes algorithm test aims to evaluate the model's performance and accuracy in classifying potential fires based on real-time sensor data. Input data for the naive Bayes algorithm are obtained from ambient temperature, infrared temperature, and indoor gas concentration. These three parameters serve as predictor variables in the early fire detection system. The testing procedure was performed by comparing the model's classification results with a verified reference dataset, allowing for identification of the model's prediction accuracy and error levels. Further analysis also included evaluating the system's responsiveness in handling real-time sensor data. The test results of the Naive Bayes algorithm are presented in Table 8.

Table 8. Real-time naive bayes algorithm test results

No	Input			Output	
	Room temperature (°C)	Non-Contact Infrared Temperature (°C)	Indoor smoke (ADC)	Naïve Bayes classification results	Description
1	29,2	28,97	164	Safe	Success
2	29,3	29,25	160	Safe	Success
3	29,3	29,29	158	Safe	Success
4	29,3	30,51	161	Safe	Success
5	29,3	30,63	161	Safe	Success

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6	29,4	32,75	173	Safe	Success
7	29,4	36,49	186	Safe	Success
8	29,4	41,35	194	Safe	Success
9	29,4	39,77	207	Safe	Success
10	29,5	37,49	211	Safe	Success
11	29,5	37,69	236	Safe	Success
12	29,6	34,81	247	Safe	Success
13	29,7	47,73	263	Safe	Success
14	29,7	43,03	254	Safe	Success
15	29,8	42,77	240	Safe	Success
16	30	44,95	253	Safe	Success
17	30,2	51,69	272	Danger	Success
18	30,4	61,47	276	Danger	Success
19	30,4	83,95	273	Danger	Success
20	30,5	76,91	257	Safe	Success
21	30,7	73,95	241	Safe	Success
22	31,1	76,25	145	Safe	Success
23	31,4	62,07	255	Safe	Success
24	31,8	46,37	257	Safe	Success
25	32,3	46,51	278	Danger	Success
26	33	64,05	287	Danger	Success
27	33,5	44,41	260	Danger	Success
28	34,3	51,09	237	Danger	Success
29	34,6	48,81	220	Danger	Success
30	34,8	37,53	267	Alert	Failed

The performance testing of the Naïve Bayes algorithm was performed on 30 data points acquired in real-time from the sensors, as detailed in Table 8. The value ranges for the input parameters were an ambient temperature (29–34°C), a non-contact infrared-based object temperature (29–83°C), and a smoke reading (158–287 in ADC values). This data was subsequently processed and classified into four levels of fire risk status: Safe, Caution, Danger, and Critical. The algorithm issued its first warning at the 'Danger' status upon detecting a combination of a relatively low ambient temperature (30.2°C), a high infrared temperature (51.69°C), and a high smoke density (an ADC value of 272).

Figure 9. Testing results of the naive bayes algorithm

4.6. Fuzzy Logic Algorithm Testing Result

This study conducted an evaluation of a fuzzy logic algorithm with a dual objective: (1) to assess its performance and reliability in classifying fire potential based on real-time sensor data, and (2) to position it as a comparative method against the previously analyzed Naïve Bayes algorithm. The input data was obtained from three predictor variables: ambient temperature, non-contact infrared

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temperature, and smoke concentration level. The algorithm subsequently generated a crisp numerical output on a scale of 1–40, which was then converted into four levels of fire risk status with the following intervals: Safe (1-10), Caution (11-20), Danger (21-30), and Critical (31-40). The comprehensive results of this testing process are presented in Table 9.

Table 9. Real-time fuzzy logic algorithm test results

Time (Second)	INPUT			Fuzzy Output	Classification Result
	Room Temperature (°C)	Infrared Temperature (°C)	Indoor smoke (ADC)		
1	24,9	23,71	120	10	Safe
10	24,9	26,41	116	10	Safe
20	25	26,03	113	10	Safe
30	25	24,59	110	10	Safe
40	25,1	23,87	208	10	Safe
50	25,4	44,65	227	13	Alert
60	25,9	37,13	166	10	Safe
70	26,4	41,81	142	10	Safe
80	26,9	35,99	129	10	Safe
90	27,4	37,59	120	10	Safe
100	27,8	35,29	115	10	Safe
110	28,3	33,25	111	10	Safe
120	28,7	35,39	108	10	Safe
130	29,3	37,95	106	10	Safe
140	30,4	39,49	104	10	Safe
150	31,4	40,17	102	10	Safe
160	32,6	40,61	101	10	Safe
170	33,7	40,17	100	13	Alert
180	34,6	40,83	98	17	Alert
190	35,2	40,53	97	22	Danger
200	35,7	39,51	95	26	Danger
210	36,1	42,41	251	35	Very Danger
220	36,4	42,39	245	36	Very Danger
230	36,7	38,89	241	35	Very Danger
240	36,9	48,81	193	38	Very Danger
250	37,2	54,03	269	40	Very Danger
260	37,7	51,73	262	40	Very Danger
270	38,2	51,45	284	40	Very Danger

Based on the test results in Table 9, it shows that the applied fuzzy logic algorithm successfully classified potential fires into four main categories: Safe, Alert, Dangerous, and Very Dangerous. Data collection was carried out systematically with recording intervals of every 10 seconds to ensure adequate accuracy. The input parameters used in this testing had the following value ranges: ambient temperature ranged from 24–38°C, the temperature of the object measured by the non-contact infrared sensor was within the range of 23–54°C, and the smoke sensor readings represented in ADC values ranged from 95–284. Specifically, the system successfully identified and detected an 'Very Danger' condition when a combination of several critical parameters occurred, namely when the ambient temperature reached a high value (36.1°C), the temperature recorded by the infrared sensor was also at a high level (42.41°C), and the smoke sensor detected a moderate concentration of particles, as indicated by an ADC value of 251. From 30 experimental data points, the fuzzy logic algorithm produced an accuracy of 100%.

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Figure 10. Testing results of the fuzzy logic algorithm

4.7. Comparative Analysis of Naive Bayes and Fuzzy Logic Methods

Based on the test results, a comparative analysis can be conducted on the performance of the Naive Bayes and Fuzzy Logic algorithms within the fire risk potential classification system, as shown in Table 10.

Table 10. Comparative Analysis of Naive Bayes and Fuzzy Logic

Aspect of Comparison	Naive Bayes Algorithm	Fuzzy Logic Algorithm
Working Principle	Based on statistical probability. Assumes independence between input variables.	Based on linguistic logic that mimics human reasoning. Uses fuzzy set theory and degree of membership.
Strengths	**Consistency with extreme data:** Highly reliable in classifying data where all parameters have high/extreme values (e.g., data points 17, 18, 19).	**High flexibility:** Can handle ambiguity and non- linear relationships between variables. **Contextual assessment:** Does not rely solely on a single absolute value, but evaluates the combination and degree of contribution of each parameter. **Finer output resolution:** Provides more informative danger level gradation (scale of 1-40).
Weaknesses / Limitations	**Rigidity:** Inflexible in handling variations of non-extreme parameters proportionally. **Cannot handle ambiguity:** Unable to manage transitional states or when input variables give contradictory indications (e.g., data point 30).	(Based on the text, weaknesses of Fuzzy Logic are not explicitly mentioned. The implication is that this algorithm is more complex in designing rules and membership functions).
Performance	**Success:** Data points 17, 18, 19 (high IR temperature + high smoke) correctly classified as **'Danger'**. **Failure:** Data point 30 (moderate ambient temp, high smoke, but moderate IR temp) classified as **'Alert'**, when it should be dangerous. This shows an inability to handle cases where not all parameters are extreme.	**Success:** At the 190-second mark, the system detected a **'Danger'** status (fuzzy value 22) even though not all parameters were at maximum (ambient & IR temps fairly high, but smoke level low). This shows an ability to capture sensor interaction dynamics, where an increase in two key parameters can compensate for a third parameter not yet critical.

Ability to Handle Uncertainty	Weak. Operates on precise data and less capable of modeling uncertainty or fuzziness in sensor data.	Excellent. Specifically designed to handle uncertainty and fuzziness using degrees of membership.
Suitability for Fire Early Warning Systems	Suitable for clear and extreme threat scenarios, providing high consistency under such conditions.	**More Superior and Robust.** Suitable for applications requiring sensitivity to a wide range of complex and not always extreme threat scenarios. The results better reflect real-world conditions.
Output Form	Discrete/categorical classification (e.g., 'Alert', 'Danger'). Tends to be binary.	Continuous numerical value (scale 1-40) that can be mapped to danger levels, providing more detailed gradation.
Overall Conclusion	A reliable algorithm for extreme data, but rigid and prone to misclassification in transitional conditions or with non- uniform parameters.	Has significant advantages in terms of flexibility, ability to handle sensor data uncertainty, and providing more representative output. Yields more robust and reliable results for fire early warning systems.


Figure 11. Real-time testing of Naive Bayes algorithms and fuzzy logic

5 Conclusion

The designed fire potential detection system has been successfully implemented and tested using the Naive Bayes and Fuzzy Logic algorithms. The sensors used (DHT22, MQ-2, and MLX90614) have successfully collected data for environmental temperature, infrared temperature, and indoor smoke concentration parameters in real-time for the fire detection system. From 30 experimental data points, the Naive Bayes algorithm produced 96% accuracy, while the Fuzzy Logic algorithm produced 100% accuracy. A comparative analysis conducted on the two algorithms concluded that the Naive Bayes algorithm showed high consistency in classifying fire potentials when the sensors detected extreme indoor conditions and was less sensitive when the sensor data was less uniform. Meanwhile, the Fuzzy Logic algorithm showed advantages in handling non-uniform data, resulting in a better classification of fire potentials because it reflects actual conditions through an inference mechanism that mimics human reasoning. Therefore, although both algorithms are feasible to use, Fuzzy Logic provides more robust and reliable performance for fire early warning systems that require sensitivity to various complex and dynamic threat scenarios.

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