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Intelligent System for Internet of Things-Based Building Fire Safety with Naive Bayes Algorithm

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ABSTRACT

Population growth is increasing every year. Population growth causes an increase in population density in a country. The largest population density is in urban areas. Fires in a city with a high population density will potentially cause greater damage. Material and non-material losses due to fire can be caused by not functioning maximally early warning systems, especially fire detection. In addition, other factors, such as system errors in detecting fires, can potentially cause fires. This research aims to build an intelligent system that can minimize building fire detection errors to reduce user material losses. The intelligent system can classify fire potential into four classifications, namely ”very dangerous,” ”dangerous,” ”alert,” and ”safe.” The method used in this research is Research and Development (R&D) with artificial intelligence using the Naïve Bayes method, which has been integrated with the Internet of Things (IoT). This research shows that the Naïve Bayes algorithm can be used to classify fire potential, proven by the overall system testing accuracy of 93.33% with an error of 6.77%.

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1. INTRODUCTION

Population growth is increasing every year. Based on world population growth data [1], in 1960, it amounted to 303 million people, while in 2000, the world's population amounted to 6.1 billion people, and the population data in 2022 is as many as 8 billion people. Population growth causes an increase in population density in a country. The largest population density is in urban areas. The population density in a city will potentially cause greater damage in the event of a fire. Some data on fire incidents worldwide show large numbers, such as fire data from 2014-2018. The highest number of fire incidents occurred in India, with an annual average of 1.6 million fires, followed by America with 1,324,700 fires, Bangladesh with 18,266 fires, Russia with 142,576 fires, Japan with 39,864 fires and Indonesia with 2,501 fires [2, 3]. Economic losses in property caused by fires from 2007 to 2011 amounted to 1.4 billion dollars, and the increase from 2012 to 2016 amounted to 1.7 billion [4]. These material losses can be caused by early warning systems not functioning maximally, especially fire detectors, and other factors can be caused by system errors in detecting the type of fire that can potentially cause a fire.

Several types of fire detection systems are implemented in homes, office buildings, industrial buildings, and other buildings, such as smoke detection [5], temperature [6], flames [7], and gas [8]. Fire detection tools have been widely used and widely circulated in the market. Fire detection tools that have been circulating focus on one type of fire parameter, such as the presence of fire, smoke, increased temperature, or gas leakage. These tools have the disadvantage of not being able to classify the type of fire with several parameters that can potentially cause a fire. Errors in fire detection can activate the fire extinguishing system automatically, causing material losses. Efforts to improve accuracy and minimize fire detection errors require a fast and precise way to detect fires.

Previous research by Lule et al. (2020) explained the IoT-based fuzzy prediction model for early fire detection, but testing in this study is still at the simulation level with MATLAB, so in real applications, it has not been tested [9]. Other research by Shi and Songlin (2020) is only able to detect one type of fire parameter, such as cigarette smoke, by utilizing a Thermal Camera to detect temperature and also using the Fuzzy logic method to analyze the intensity of the flame [10, 11]. Furthermore, other research with robots focuses on evaluating sensing capabilities based on image processing from thermal sensor imaging. The utilization of robots in fire monitoring and detection can function properly, but robots can only be used when a fire has occurred and is not preventive [12–15].

Based on the problems and developments of previous research, this research developed a prototype of a building fire safety system that can classify the potential occurrence of building fires using multiple sensors with artificial intelligence using the Nave Bayes method and fire monitoring using the Internet of Things technology. The IoT developed in this prototype is monitoring and sensor notification using the Telegram application. The Telegram Bot application has been programmed to monitor sensor data, fire potential data from the Nave Bayes method, and fire notifications in real-time. At the same time, the Nave Bayes algorithm is used as an intelligent system that can classify the potential fire occurrence in the building. The Naive Bayes algorithm was chosen because it is very well used for microcontroller-based intelligent systems. NodeMCU ESP32 microcontrollers do not have large storage for large training data processes [16], so they need intelligent system algorithms that are lightweight and fast in making decisions. This research aims to develop an intelligent system that can minimize building fire detection errors to reduce material losses for users. The intelligent system can classify fire potential into four classifications, namely "very dangerous," "dangerous," "alert," and "safe." This classification is intended so that the system can take preventive action if it detects potential fires, with the classification of "dangerous" and "very dangerous." With the intelligent building fire safety system, this research is expected to reduce the potential for fire if implemented directly in the building to reduce material losses from users.

2. RESEARCH METHOD

This study manufactures hardware and software systems using the Research and Development (R&D) method with the design stages as shown in Figure 1.

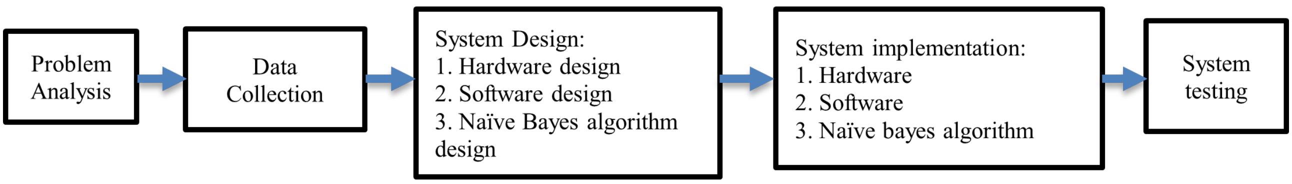

Figure 1. Research and Development design method

2.1. Data Collection

Data collection is carried out in two stages. The first stage is conducting literature studies from scientific articles and books. The literature study includes microcontroller-based fire fighting systems, sensors and actuators used in potential fire detection systems, and specifications of these sensors and actuators. The second stage is to make observations by conducting interviews with the fire department related to the tools built. The tool developed is at the prototype stage, which hopes to be developed into a large-scale tool that can be installed in buildings. The results of data collection can be shown in Table 1.

Table 1. Components used in building fire safety systems

No	Component name	Total	Description
1	NodeMCU ESP32	1 pcs	As a control center, data processing, sending data to mobile apps
2	DHT22	1 pcs	As a temperature sensor used to measure the ambient temperature around the sensor
3	MLX9064	1 pcs	As a non-contact infrared temperature sensor used to measure the temperature of objects in the form of fire
4	MQ-2	1 pcs	As a gas sensor used to measure the concentration of gas in the form of smoke in the sensor environment
5	Flame sensor	2 pcs	As a fire sensor that detects whether there is a fire or not.
6	LCD 16x2 and I2C LCD	1 pcs	Which is used to display the sensor value
7	Relay 5 volt	1 pcs	Which is used as an electronic switch and connected to a DC motor
8	DC Water Pump 12volt	1 pcs	Which is used to extinguish the fire
9	Box	1 pcs	As a protector of the electronic components used
10	Cable	1 set	Which is used to connect each electronic component used

2.2. Building Fire Safety System Design

The building fire safety system consists of two systems. The first system is hardware with a Nave Bayes algorithm that functions to classify the potential of building fires into four classifications, namely "Safe," "Alert," "Dangerous," and "Very Dangerous." The Nave Bayes algorithm can classify potential building fires based on input from temperature sensors (DHT22), smoke sensors (MQ-2), flame sensors, and infrared temperature sensors (GY-906-BCC). The control center of the system uses a node MCU ESP32 microcontroller. The second system is a sensor notification design using Telegram. Telegram monitors the sensor value and the percentage value of each potential fire classification. The design of the building's fire safety system can be shown in Figure 2. In this design, the node MCU ESP32 has been integrated with the ESP32 WiFi module so that the system can connect to the internet via a WiFi Router.

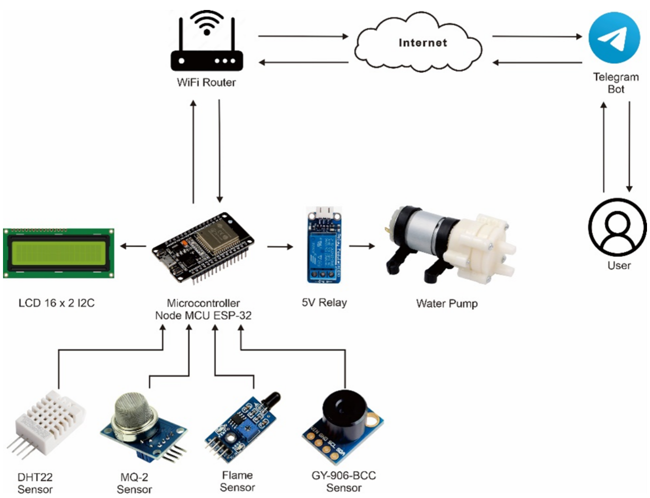

Figure 2. Block diagram of building fire safety system

2.3. Hardware Design

In the hardware design stage, the wiring and schematic circuit of the building fire safety system are carried out. Wiring describes how each electronic component can be connected using cables so that each sensor, actuator, and microcontroller component can send, receive, and process data. Wiring also makes it easier when the system is implemented. The circuit schematic serves to create a printed circuit board (PCB) main board on the building's fire safety system. The results of the hardware wiring are shown in Figure 3, and the system circuit schematic is shown in Figure 4.

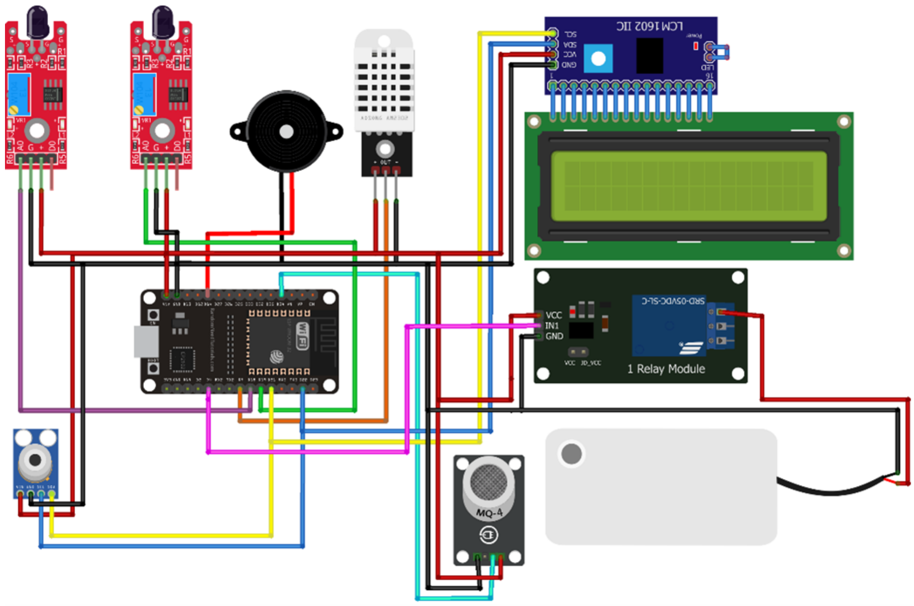

Figure 3. Building fire safety system hardware wiring

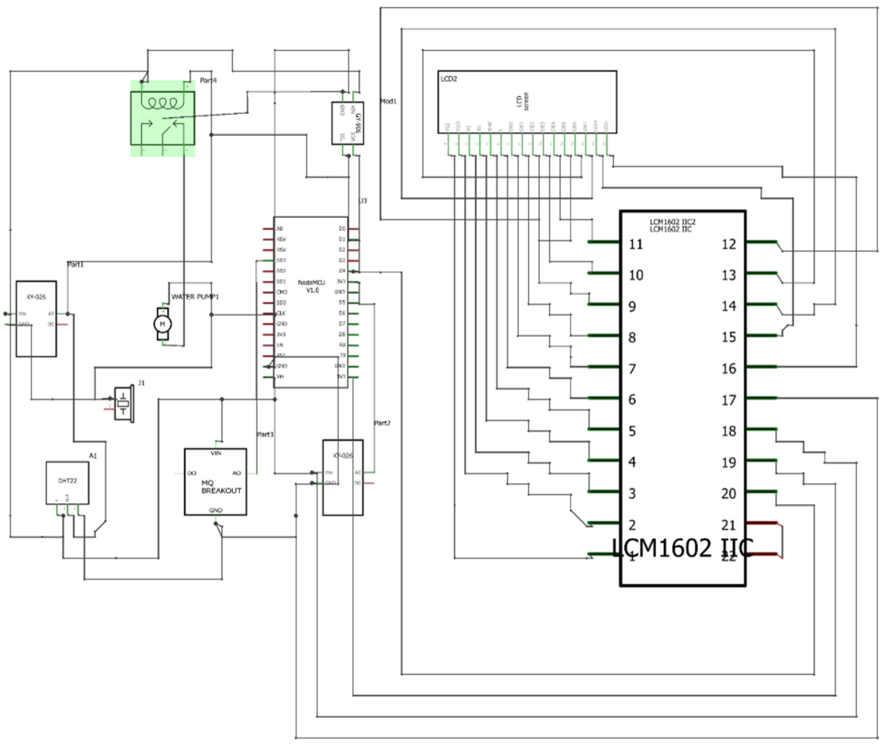

Figure 4. Schematic circuit of building fire safety system

2.4. Software Design

The software design aims to illustrate every step of the instructions that will be made in the form of a source code to run the building fire safety system tool. The system flowchart can be shown in Figure 5. The flowchart begins by initializing each sensor, namely the fire, temperature, smoke, and non-contact infrared temperature sensors. After that, the sensor will collect data from the microcontroller. If the sensor is detected, the Nave Bayes algorithm is activated, and if not, it will return to collecting data. If the Nave Bayes algorithm produces a higher percentage of ”danger” and ”very dangerous” classifications than other classifications, the alarm and motor pump will be activated. In addition, the system will send the data to a telegram as a notification to the user.

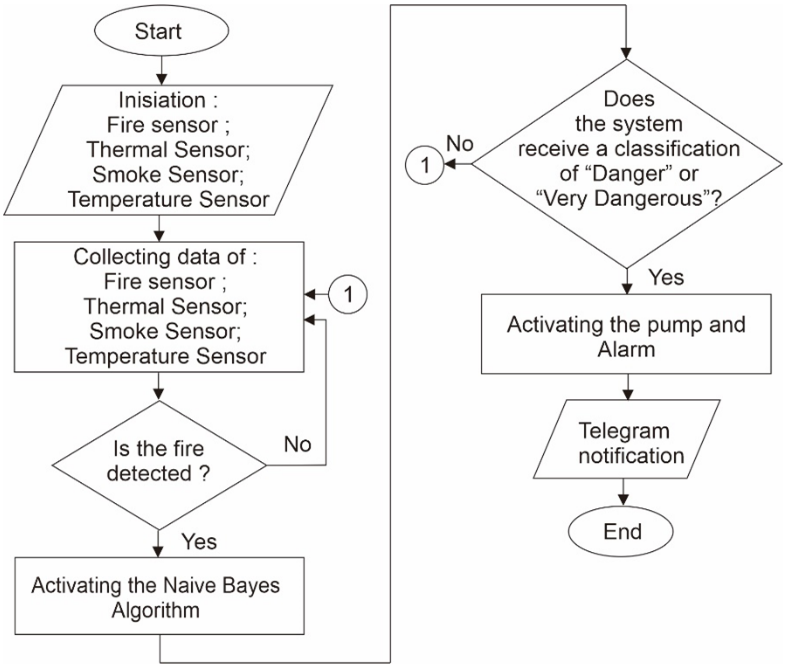

Figure 5. Flowchart of building fire safety system software

2.5. Naïve Bayes Algorithm Design

Naïve Bayes is a classification method using probability and statistical methods proposed by British scientist Thomas Bayes. The Nave Bayes algorithm predicts future probabilities based on previous experience, known as Bayes' Theorem. The main feature of the Naïve Bayes Classifier is the very strong assumption (naïve) of the independence of each condition or event. The Naive Bayes Classifier works very well compared to other classifier models. This is proven in the journal Xhemali, Daniela, Chris J. Hinde, and Roger G. Stone. ”Naïve Bayes vs. decision trees vs. neural networks in the classification of training web pages.” (2009) said that ”Naïve Bayes Classifier has better accuracy than other classifier models.” The advantage of using this method is that it only requires a small amount of training data to determine the parameter estimates needed in the classification process. Because it is assumed to be an independent variable, only the variance of a variable within a class is needed to determine classification, not the entire covariance matrix, as the stages of the Naïve Bayes algorithm process are.

1. Data Selection
   This stage is the data selection stage. Four attributes are used for data selection in the selection process: room temperature, indoor smoke, indoor fire, and fire object temperature.
2. Pre-processing
   This stage is the stage of data cleaning if there is empty data, inconsistent data, and data mismatches.
3. Transformation Data
   At this stage, the numeric data type generated by the sensor will be transformed into a nominal data type. The results of data transformation can be shown in Table 2.

Table 2. Data Transformation

Attribute	Nominal Data	Numerical Data
Room temperature	High Temperature	>38
	Medium Temperature	32-38
	Low Temperature	<32
Smoke in the Room	Dense Smoke	>2000
	Medium Smoke	800 - 2000
	Low Smoke	<800
Fire in the Room	Fire	1
	No Fire	0
Fire Object Temperature	High Temperature	>45
	Medium Temperature	41-45
	Low Temperature	<41

4. Naïve Bayes Algorithm Implementation
   At this stage, the Nave Bayes algorithm is used to classify the potential occurrence of building fires into four classifications, namely "Safe," "Alert," "Dangerous," and "Very Dangerous." The implementation of the Nave Bayes algorithm starts from taking training data. The training data used in this study can be shown in Table 3. The determining variables used as training data to classify the potential occurrence of building fires are as follows: Room temperature is divided into three classifications, namely low temperature, medium temperature, and high temperature. Fire point temperature is divided into three classifications: low, medium, and high. Smoke in the room is divided into three classifications: low smoke, medium smoke, and dense smoke. Fire in the room is divided into two classifications; namely, there is a fire, and there is no fire.

Table 3. Data Training

No	Object Temperature (MLX9064)	Room Temperature (DHT22)	Smoke (MQ-2)	Flame Sensor	Room Condition
1	High Temperature	High Temperature	Dense Smoke	Fire	Very Dangerous
2	High Temperature	High Temperature	Dense Smoke	No Fire	Very Dangerous
3	High Temperature	High Temperature	Medium Smoke	Fire	Very Dangerous
4	High Temperature	High Temperature	Medium Smoke	No Fire	Dangerous
5	High Temperature	High Temperature	Low Smoke	Fire	Very Dangerous
..	...	...	...	...	...
35	High Temperature	High Temperature	Low Smoke	Fire	Safe
36	High Temperature	High Temperature	Low Smoke	No Fire	Safe

   Based on the training data in Table 3, the amount of training data on the intelligent building fire safety system is 36 data. The amount of training data is because the nodeMCU ESP32 microcontroller has a relatively large amount of work, such as connecting to telegrams and mobile applications. The training data determines the room's condition based on the sensor's value. The training data is used to calculate the probability of classes and attributes. The Naïve Bayes algorithm can be started with the steps:
   a. Calculating the number of classes/labels ($P(C_i)$)
      The number of classes can be calculated based on the training data used. This study has four classes: very dangerous, dangerous, alert, and safe. The amount of data for the very dangerous classification is four, for the hazard classification is seven, for the alert classification is eleven, and for the safe classification is fourteen. The probability data for each class can be shown in Table 4.

Table 4. Calculating the number of classes

Overall Probability		
Room Condition	Amount	Probability
Very Dangerous	4	0,11111
Dangerous	7	0,19444
Alert	11	0,30556
Safe	14	0,38889

b. Calculating the probability ($P(X|C_i)$) of occurrence of each value for each attribute
In addition to calculating the probability of each class, it is also necessary to calculate the probability of each attribute used. The probability of the room temperature sensor attribute can be shown in Table 5, the probability of the infrared temperature sensor attribute to measure object temperature can be shown in Table 6, and the smoke sensor attribute can be shown in Table 7. In contrast, the fire sensor attribute can be shown in Table 8.

Table 5. Probability of room condition temperature

Room Condition Temperature (DHT22)	Very Dangerous	Dangerous	Alert	Safe
High Temperature	0,666666667	0,333333333	0	0
Medium Temperature	0	0,333333333	0,5	0,166666667
Low Temperature	0	0,055555556	0,277777778	0,666666667

Table 6. Probability of object temperature

Object Temperature (MLX906)	Very Dangerous	Dangerous	Alert	Safe
High Temperature	0,222222222	0,388888889	0,388888889	0
Medium Temperature	0	0	0,333333333	0,666666667
Low Temperature	0	0	0	1

Table 7. Probability of smoke in the room

Smoke in the Room (MQ-2)	Very Dangerous	Dangerous	Alert	Safe
Dense Smoke	0,166666667	0,25	0,25	0,333333333
Medium Smoke	0,083333333	0,166666667	0,416666667	0,333333333
Low Smoke	0,083333333	0,166666667	0,25	0,5

Table 8. Probability of fire in the room

Fire on the Room	Very Dangerous	Dangerous	Alert	Safe
Fire	0,166666667	0,222222222	0,222222222	0,388888889
No Fire	0,055555556	0,166666667	0,388888889	0,388888889

c. Multiplying $P(C_i) * P(X|C_i)$
d. Comparing each class's results

3. RESULT AND ANALYSIS

3.1. Hardware Design Results

The hardware in this research consists of sensors, microcontrollers, and actuators. The sensors used are a temperature sensor (DHT22), smoke sensor (MQ-2), flame sensor, and IR temperature sensor (MLX906). The microcontroller used is nodeMCU ESP-32. In contrast, the actuator used is a pump motor. To display sensor values using a 162 LCD. The prototype is equipped with an alarm in the form of a buzzer. The hardware has been assembled into a prototype and functioned properly. The results of the hardware design can be shown in Figure 6.

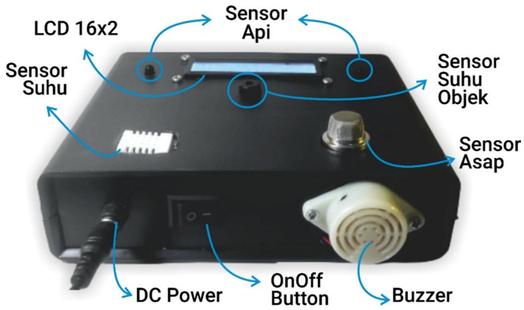

Figure 6. Building fire safety system hardware

3.2. Temperature Sensor Testing (DHT22)

The temperature sensor test aims to determine the sensor's accuracy in measuring the temperature in the sensor environment. The test procedure is that the temperature around the sensor will be increased by lighting a fire around the sensor. The sensor measurement results will be compared with a thermometer circulating in the market. The difference in temperature measurements will be obtained from the results of this comparison so that the error and sensor accuracy values can be calculated from this data. The sensor test results are shown in Table 9.

Table 9. Temperature sensor test result data

No	Time (second)	Digital Thermometer (oC)	DHT22 Sensor (oC)	Difference (oC)	Error (%)
1	1	28,5	29	0,5	1,754
2	5	28,6	29,1	0,5	1,748
3	10	28,7	29,1	0,4	1,394
4	15	28,8	29,2	0,4	1,389
5	20	28,8	29,2	0,4	1,389
6	25	29	29,3	0,3	1,034
7	30	29	29,3	0,3	1,034
8	35	29	29,4	0,4	1,379
9	40	29,1	29,5	0,4	1,375
10	45	29,1	29,5	0,4	1,375
...	...	...	...	...	...
41	200	30,5	31,6	1,1	3,607
42	205	30,5	31,6	1,1	3,607
43	210	30,5	31,7	1,2	3,934
44	215	30,5	31,7	1,2	3,934
45	220	30,5	31,7	1,2	3,934
46	225	30,6	31,8	1,2	3,922
47	230	30,6	31,8	1,2	3,922
48	235	30,6	31,9	1,3	4,248
49	240	30,6	31,9	1,3	4,248
50	245	30,7	32	1,3	4,235
51	250	30,7	32	1,3	4,235
52	255	30,7	32,1	1,4	4,560
		Average		0,754	2,509

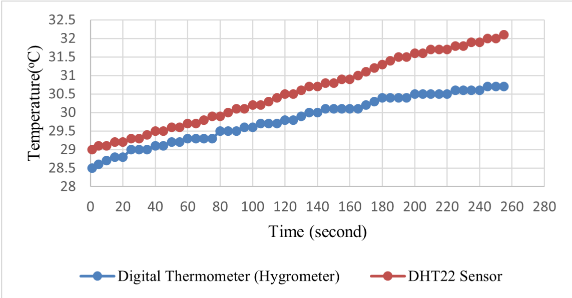

Figure 7. Temperature testing graph

Based on the test results of the DHT22 sensor compared to a digital thermometer, the average temperature measurement difference is 0.754C, and the average error produced by the sensor is 2.509%. The temperature measurement accuracy by the DHT22 sensor is 97.491%. The accuracy results prove that the sensor can work well and can be used to measure room temperature during a fire. Figure 7 compares the DHT22 temperature sensor and a digital thermometer. The result of the comparison is that the DHT22 sensor can follow the temperature changes of the digital thermometer.

3.3. Smoke Sensor Testing (MQ-2)

Smoke sensor testing using the MQ-2 sensor aims to determine changes in sensor values to the gas concentration in the sensor environment. The test procedure is that the smoke concentration in the sensor environment will be increased by burning paper, which produces more gas (smoke) concentration. The sensor measurement results are in the form of Analog Digital Converter (ADC) values, which will then be converted into voltage values with units of volts and gas concentration values in units of PPM (parts per million). The sensor test results are shown in Table 9.

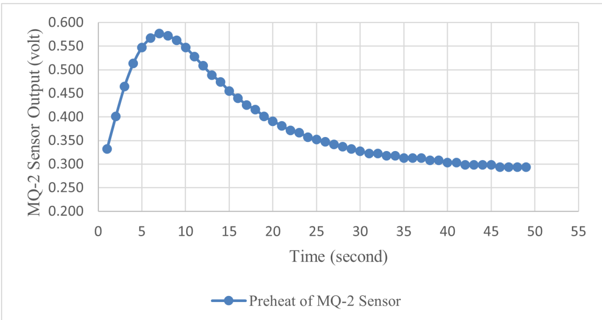

Figure 8. Preheat of a gas sensor (MQ-2)

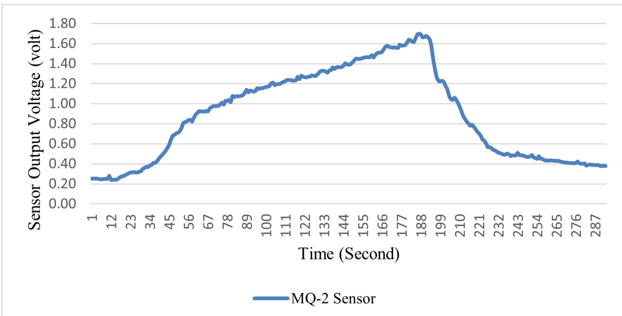

Figure 9. MQ-2 gas sensor test results on smoke

Figure 8 shows the results of the internal heating test of the MQ-2 gas sensor. The sensor requires internal heating when used. From the test results, the MQ-2 gas sensor takes about 50 seconds to reach a stable output value. So that sensor data will be taken as input to the system when the sensor has done internal heating for 50 seconds. Based on the test results of Figure 9, the output of the sensor when it is in an environment with clean air is 0.25 volts. When combustion is carried out and begins to produce smoke, the sensor output value slowly rises linearly to a value of 1.6 volts, after which the smoke in the sensor environment begins to be reduced so that the sensor output value slowly decreases and begins to stabilize again.

3.4. Non-Contact Temperature Sensor Testing (MLX9064)

Non-contact temperature sensor testing aims to determine the output value of the sensor when there is a fire around the sensor. The MLX9064 sensor testing procedure measures the temperature produced by the fire and then changes the distance between the sensor and the fire. The test results will be analyzed for changes in temperature value against the distance of the fire to the MLX9064 sensor. The sensor test results are shown in Figure 10.

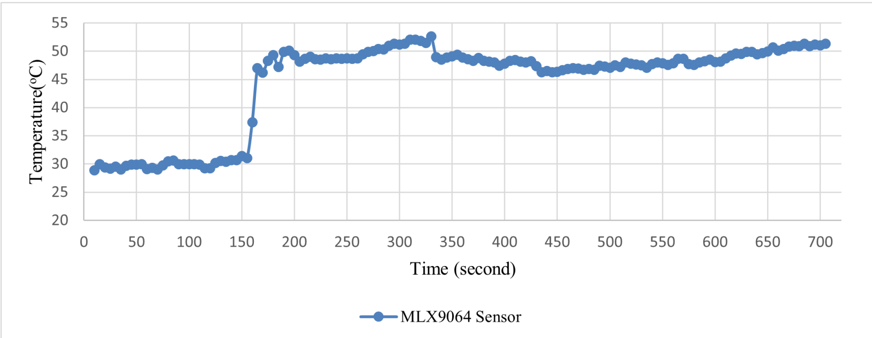

Figure 10. Effects of selecting different switching under dynamic condition

Based on the test results in Figure 10, the sensor is very sensitive if there is a change in temperature in the sensor environment. Before the fire was lit around the sensor, the temperature measured by the sensor had an average of 29.79C. Sensor measurement data is taken every 5-second increments. When the fire was lit, five seconds later, the temperature measured by the sensor increased to 46.95C, while the average sensor measurement when the fire was lit was 48.83C. The difference between the MLX9064 sensor and the DHT22 sensor is that the MLX9064 sensor has a fast response when measuring temperature changes. In contrast, the DHT22 sensor tends to be slow in measuring temperature changes. Based on the test results that have been carried out, the MLX9064 sensor can be used to detect changes in temperature due to fire.

3.5. UVTron Testing

UVTron testing aims to determine the performance of the sensor against fire. The test procedure carried out is that a fire will be lit at a distance of three meters, and the sensor output value will be observed whether it is high or low. Based on the results of sensor testing, the UVTron fire sensor has successfully detected a fire and has a high value if it detects a fire. The test data can be shown in Table 10.

Table 10. UVTron sensor test results

No	Environmental Conditions Around the Sensor	Description
1	Fire	High sensor output value
2	No Fire	Low sensor output value

3.6. Naïve Bayes Testing

Testing the Naïve Bayes algorithm aims to determine the accuracy in classifying potential building fires using the Naïve Bayes method.

Table 11. Results of Naïve Bayes testing

No	Sensor Monitoring				Nave Bayes Classification (%)				IoT Communication Network	
	Room Temperature Sensor (DHT22) (C)	Object Temperature Sensor (GY904) C	Smoke Sensor (MQ-2)	Flame Sensor (UV Tron)	Safe	Alert	Dangerous	Very Dangerous	Telegram Notification	Data transmission to Android App
1	32,50	31,57	726	0,0	2,62	1,85	1,36	1	Safe	Safe
2	33,10	32,47	637	0,0	2,62	1,85	1,36	1	Safe	Safe
3	33,30	32,77	635	0,0	2,62	1,85	1,36	1	Safe	Safe
4	33,20	32,56	641	0,0	2,62	1,85	1,36	1	Safe	Safe
5	36,30	38,55	1220	1,0	2,08	2,41	1,36	1	Alert	Alert
6	36,70	36,63	1297	1,0	2,08	2,41	1,36	1	Alert	Alert
7	36,70	35,15	1232	1	2,08	2,41	1,36	1	Alert	Alert
8	36,40	34,61	1200	1	1,54	2,27	1,36	1	Alert	Alert
9	36,10	34,53	1185	0	2,62	1,85	1,36	1	Safe	Safe
10	35,90	34,45	1188	0	2,62	1,85	1,36	1	Safe	Safe
11	35,60	34,17	1168	0	2,62	1,85	1,36	1	Safe	Safe
12	35,40	61,09	1456	1	1	1	1	1	Safe	Safe
13	35,60	62,06	1484	1	1	1	1	1,02	Very Dangerous	Very Dangerous
14	35,70	64,03	1503	1	1	1	1	1,03	Very Dangerous	Very Dangerous
15	35,90	63,97	1512	1	1	1	1	1,03	Very Dangerous	Very Dangerous

Based on Table 11, there are 15 data points taken during direct testing. There are four sensors used as input from sensors, namely, room temperature sensor (DHT22), object temperature sensor (GY904), smoke sensor (MQ-2), and fire sensor (UVTron). Based on the sensor data, the Nave Bayes algorithm produces four classifications: safe, alert, dangerous, and very dangerous. The classifications will be compared to get the highest percentage value used as the output of the Nave Bayes algorithm. Of the 15 experimental data results, one data fails to make a classification, namely in the 12th data. So, the system's overall accuracy based on the test results is 93.33%, with an error of 6.77%. Based on research conducted by [9, 10], this research has strengthened previous research by using more sensors to make the parameters for determining fire potential more accurate. The test was carried out in the room we built, as shown in Figure 11.

Figure 11. Testing the overall building fire safety system in the test room

4. CONCLUSION

Based on the results of the tests that have been carried out, the intelligent building fire safety system has been successfully built. Based on the test results of the DHT22 sensor compared to a digital thermometer, the average temperature measurement difference is 0.754C, and the average error produced by the sensor is 2.509%. The temperature measurement accuracy by the DHT22 sensor is

97.491%. While testing, the MQ-2 gas sensor takes about 50 seconds to reach a stable output value. So that sensor data will be taken as input to the system when the sensor has done internal heating for 50 seconds. Based on the test results, it shows the sensor's output when it is in an environment with clean air which is 0.25 volts. When combustion is carried out and begins to produce smoke, the sensor output value slowly rises linearly to a value of 1.6 volts, after which the smoke in the sensor environment begins to be reduced so that the sensor output value slowly decreases and begins to stabilize again. The test results of the MLX GY9064 sensor show that the sensor is very sensitive if there is a change in temperature in the sensor environment. Before the fire was lit, the temperature measured by the sensor had an average of 29.79C. When the fire was lit, five seconds later, the temperature measured by the sensor increased to 46.95C, while the average sensor measurement when the fire was lit was 48.83C. The UVTron test results show that when there is a fire, the sensor is high, while when the sensor is not detected, the sensor is low. Meanwhile, based on testing the entire system, the accuracy is 93.33%. Based on the system's overall accuracy, the intelligent building fire safety system has successfully classified the potential of building fires.

5. ACKNOWLEDGEMENTS

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6. DECLARATIONS

AUTHOR CONTIBUTION

The first author coordinated the researchers in creating the building fire safety system. The second author is responsible for building a fire safety system, testing sensors, and the whole system, making Nave Bayes algorithms, and connecting tools built with Telegram applications. The third author is in charge of making applications based on Android applications.

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COMPETING INTEREST

The authors declare no conflict of interest.

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