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LPG Safety Monitoring System Using Artificial Neural Network with Back Propagation Method Based on The Internet of Things (IoT)

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Abstract

This study aims to create an Artificial Neural Network (ANN) to determine the results of LPG gas monitoring based on gas leakage levels, smoke levels, fires, and ambient temperatures and apply Internet of Things technology in the monitoring system. Variations in the number of nodes in the hidden layer indicate that the ANN performance will be maximal, with seven nodes in the hidden layer with an accuracy value of 99.63%, a precision of 100%, and a loss function of 0.423%. The microcontroller used is NodeMCU ESP32S, with input from the MQ6 sensor to detect LPG gas leaks, an infrared sensor to detect flames, an MQ-2 sensor to detect smoke, and a DHT-22 sensor to measure the ambient temperature. The resulting system output is a monitoring display using the Blynk platform, fans and Buzzers controlling, and WhatsApp notifications. The system will turn on the fan when the detected LPG level exceeds 250 ppm.

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Abstrak

Penelitian ini bertujuan untuk membuat Jaringan Saraf Tiruan (JST) untuk menentukan hasil monitoring gas LPG berdasakan kadar kebocoran gas, kadar asap, api, dan suhu sekitar, serta untuk menerapkan teknologi internet of things dalam sistem monitoring. Variasi jumlah node pada lapisan tersembunyi menunjukkan bahwa kinerja JST akan maksimal dengan 7 node pada lapisan tersembunyi dengan nilai akurasi sebesar 99,63%, presisi sebesar 100%, dan loss function sebesar 0,423%. Mikrokontroler yang digunakan adalah NodeMCU ESP32S, dengan masukan dari sensor MQ-6 untuk mendeteksi kebocoran gas LPG, sensor infrared untuk mendeteksi api, sensor MQ-2 untuk mendeteksi asap, dan sensor DHT-22 untuk mengukur suhu sekitar. Keluaran sistem yang dihasilkan berupa tampilan monitoring menggunakan platform Blynk, pengontrolan kipas dan Buzzer, serta notifikasi menggunakan WhatsApp. Sistem akan menghidupkan kipas ketika kadar LPG yang terdeteksi melebihi 250 ppm.

1. Introduction

The role of Liquefied Petroleum Gas (LPG) is currently significant in human life, both at home and in the industry. However, LPG gas can cause considerable losses if we are not careful, primarily if there has been an unknown leak from the LPG gas cylinder or the storage area (Putra et al., 2021). This gaseous fuel has a negative effect, especially when it evaporates in the free air and forms a layer due to condensation. The coating formed is flammable, so it is very hazardous if it builds up in a closed room and potentially causes a fire (Puspaningrum et al., 2020).

One of the efforts to prevent fires is to provide a device that works as a gas leak detector in LPG cylinders before a fire occurs (Amirah et al., 2021). With the installation of a detection system, the user will know if there has been a gas leakage in the gas cylinder. The detection system is an automatically integrated security system that can provide information on the state of an event or condition so we can use it for housing, offices, or agencies that need it (Berliani & Saragih, 2021).

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One of the developing technologies is the Internet of Things (IoT). IoT is a network of devices using the internet that has a concept to expand the benefits of being constantly connected to the internet connection (Kurniawan, 2021). Because we can reach and control the internet remotely, the internet will become the main link in interaction, while humans are only device supervisors (Weber & Weber, 2009). For example, we can attach an electronic device to a sensor that is always active and connected to the internet (Maidoni & Elfizon, 2020).

Concerning the LPG gas leak detection system, researched LPG gas leak detection using an Arduino detector with the Mamdani fuzzy logic algorithm, which in this study produced an LPG gas leak detector using an MQ-2 sensor and a fire sensor that is connected directly to the SMS Gateway. Meanwhile (Dwitama et al., 2021) researched the design of a gas leak monitoring prototype using the MQ-6 sensor based on NodeMCU 8266. This study resulted in an LPG gas leak monitoring device that connects directly to Telegram as a medium of information for users. Another study was conducted by (Dewi et al., 2021) on Household Gas Leak Detection Tools based on the Internet of Things.

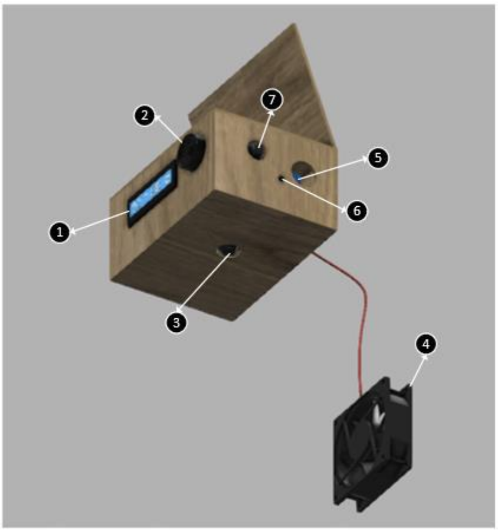
This study uses the MQ-2 sensor as an LPG gas detection sensor and NodeMCU V3 as a microcontroller module that can be connected directly to the Internet. It will create an artificial neural network that can classify the monitoring results of LPG gas cylinders based on several parameters in the surrounding environment obtained as input from the sensors. The Artificial Neural Network method is backpropagation, programmed using Python 3.9 software.

2. Methods

The tools and materials used in this study include MQ-6, MQ-2, DHT-22, infrared sensors, LCD I2C, NodeMCU ESP32S, buzzer, relay, connecting cable, resistor, fan, and 12 V adapters. This study consisted of several stages, including design and manufacturing tools, sensor testing, artificial neural network programming, IoT systems configuration, data retrieval, and analysis of results.

2.1. Design and Manufacture of Monitoring System Tools

This study will create an LPG gas monitoring tool consisting of one LPG gas sensor and one smoke sensor, temperature sensor, fire sensor, fan, buzzer, NodeMCU ESP32S, relay, and LCD. **Figure 1** shows the outside of the monitoring system device in this study and what is inside the monitoring device in **Figure 2**.



Description:

1. LCD I2C;	6. Infrared sensor;
2. Buzzer;	7. Sensor MQ-2;
3. MQ-6 sensor;	8. Relay;
4. Fan;	9. NodeMCU ESP32S.
5. DHT-22;	

Figure 1. Monitoring system design (outside)

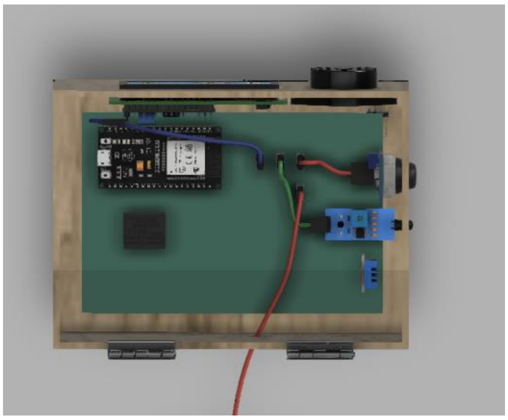


Figure 2. Monitoring system design (inside)

The monitoring system block diagram in this study can be seen in **Figure 3**.

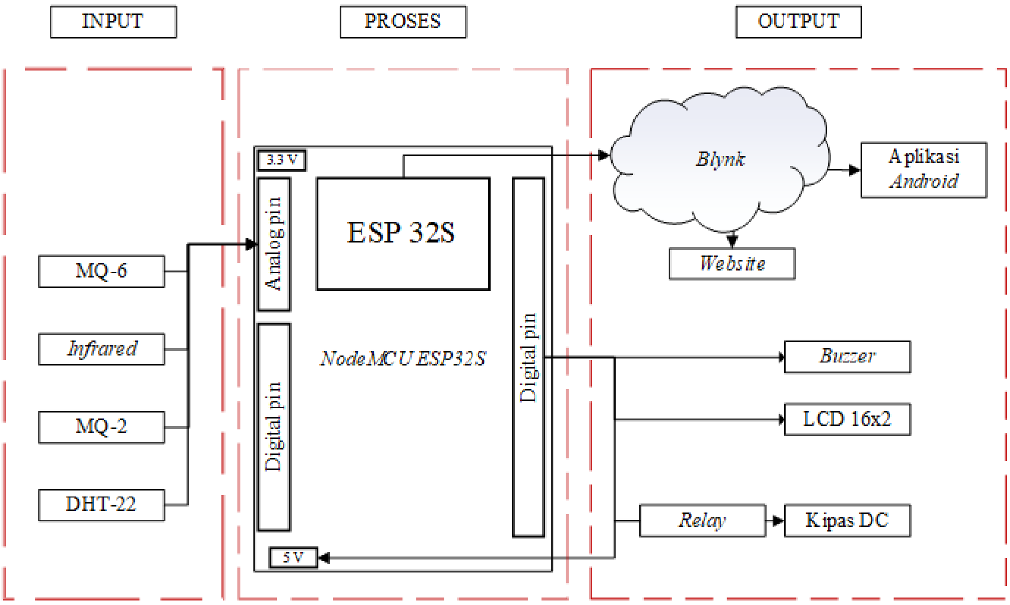


Figure 3. Monitoring system block diagram

Based on **Figure 3**, the signal processing begins when the system receives the measurement results of several physical parameters as input from the sensors. Then, the input signal is processed by the NodeMCU ESP32S microcontroller. This signal-processing process converts analog signals sent by each sensor to the NodeMCU ESP32S into digital data. Then, the 12-bit analog-to-digital converter on the NodeMCU ESP32s converts the analog signals into digital signals. Finally, LCD and Blynk display the processed signal results as monitoring results. The signal processing result will activate the relay and buzzer based on fixed set points.

2.2 Artificial Neural Network Programming

In this study, the ANN was programmed using the backpropagation method using the Python 3.9 programming language. The artificial neural network used in this study uses four input nodes in the input layer and three output nodes in the output layer. In the hidden layer, the activation function used in this ANN model is sigmoid, while in the output layer, the activation function used is the softmax function with a learning rate of 0.01.

The selection of the softmax activation function for nodes in the output layer is due to the problem that the ANN model is trying to solve in this study: multiclass classification. The softmax activation function keeps the total output value of each node equal to 1 and limits each node's output value at intervals of 0-1 (Kim, 2017). Because the softmax activation function also considers each node's output value, the softmax activation function is the right choice for multiclass classification problems (Tagliaferri et al., 2019).

In the hidden layer, the number of nodes varies to obtain an Artificial Neural Network (ANN) model with maximum accuracy. The number of nodes in the hidden layer used in this study can be seen in **Table 1**.

Table 1. Nodes in the hidden layer

Model	Nodes in the hidden layer
JST-1	$N_h = n = 4$
JST-2	$N_h = N_o = 3$
JST-3	$N_h = n + N_o = 7$

The performance of each ANN model used in this study will be calculated based on the loss function value and several other parameters mentioned in **Equations 1** to **3**.

$$AC = \frac{TP + TN}{TP + FP + TN + FN} \times 100\% \tag{1}$$

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

$$Loss = \frac{1}{2N}\sum_{i=1}^{N}(d_i - y_i)^2 \times 100\% \tag{3}$$

Description:
Loss = error;
d_i = the output from dataset/target;
y_i = the output from the JST model;
TP = the cases when the actual class of data point was 1, and the predicted is also 1;
TN = the cases when the actual class of the data point was 0, and the predicted is also 0;
FP = the cases when the actual class of data point was 0, and the predicted is also 1;
FN = the cases when the actual class of the data point was 1, and the predicted is also 0;
AC = Accuracy;
PR = Precision.
(Tutorialspoint, 2016, Rosebrock, 2017).

2.3 IoT System Design

In this study, the IoT system uses the Blynk platform. We created this system so that users can monitor processes via the internet network through a website or Android application. **Figure 4** shows the display of the IoT system in this study.

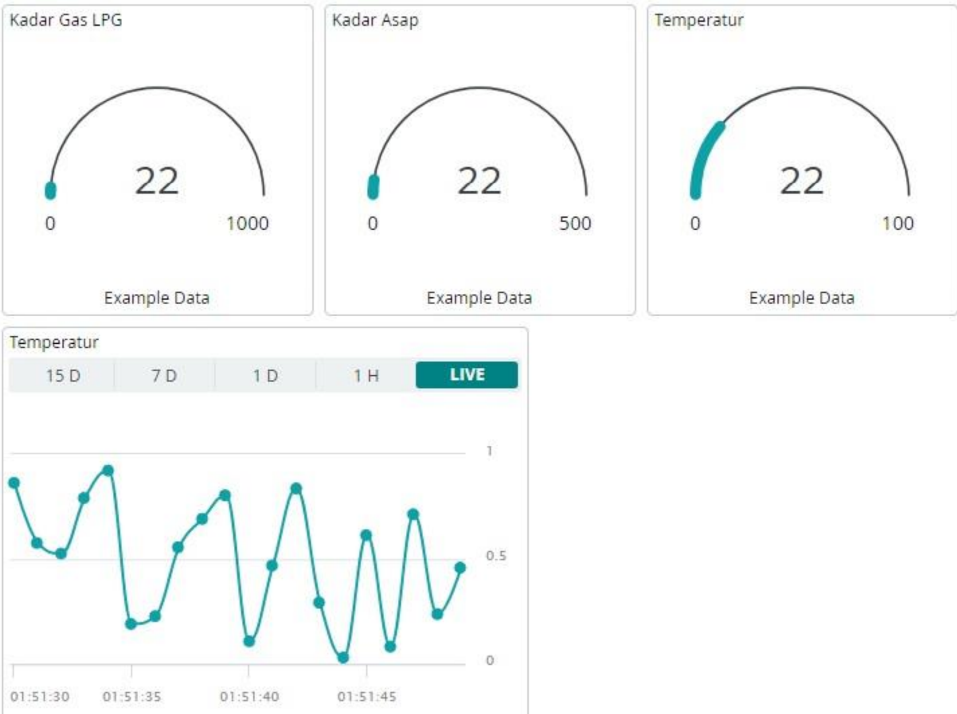


Figure 4. IoT dashboard display

2.4 Monitoring System Test

Monitoring system testing aims to determine whether all components can work properly and whether the ANN model can classify the monitoring results of LPG gas cylinders based on several physical parameters obtained from sensors.

The trained neural network classifies the monitoring result into three conditions (safe, warning, and dangerous). The safe condition happens when the MQ-6 sensor detects less than 250 ppm of LPG, the infrared sensor detects no flames nearby, the MQ-2 sensor detects less than 25 ppm of smoke, and the DHT-22 sensor measures the temperature below 60 C. The warning condition happens when the MQ-2 sensor detects more than 25 ppm of smoke, or the DHT-22 sensor measures the temperature above 60 C. The dangerous condition happens when the MQ-6 sensor detects more than 250 ppm of LPG, or the infrared sensor detects any flames nearby.

3. Results and Discussions

3.1 Realization of Monitoring Tools

The realization of the monitoring system tool in this study can be seen in **Figure 5**. The monitoring tool uses several components, such as an LPG gas sensor and an MQ-6 sensor. Then, there is a temperature sensor using a DHT-22 sensor. Then, there is a fire sensor using an infrared sensor and a smoke sensor using an MQ-2 sensor. In addition, there is also a 12 V adapter that works as a voltage source, then an I2C LCD, which displays monitoring results based on input from each sensor, and a buzzer and DC fan that will activate based on some set point.

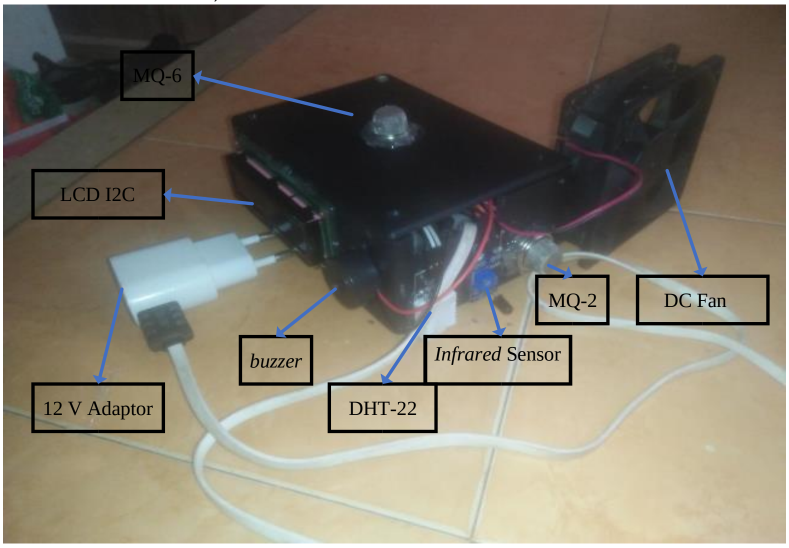


Figure 5. Monitoring system device realization (outside)

3.2 The Results of Gas Sensor Testing

This study uses two gas sensors, namely the MQ-6 and MQ-2 sensors. The MQ-6 sensor detects LPG gas leaks, while the MQ-2 sensor detects smoke around LPG gas cylinders.

3.2.1 MQ-6 Sensor Testing

In the MQ-6 sensor test, the LPG gas used for testing comes from the contents of a gas lighter with the same content as LPG gas cylinders. This test aims to determine the relationship between the distance of gas injection and the sensor readings. The results of the MQ-6 sensor test can be seen in **Table 2**.

Table 2. MQ-6 Sensor Testing Result

Distance (cm)	V_{out} (V)	ΔV_{out} (%)
2	2.3	4.00
3	2.2	4.35
4	2.07	5.91
5	2.1	7.14
Average		5.35

Based on **Table 2**, it can be seen that the sensor output voltage reading is influenced by the sensor distance to the gas source to be detected. The farther the distance between the gas and the sensor, the smaller the output voltage produced (Dwitama et al., 2021). Overall, the response of the MQ-6 sensor has shown appropriate results, with an average percentage change in voltage of 5.35% for every 1 cm increase in distance. However, there is a response discrepancy, where the sensor voltage value at a distance of 5 cm is greater than the sensor voltage at a distance of 4 cm, although the difference is only 0.03 V.

3.2.2 MQ-2 Sensor Testing

In the MQ-2 sensor testing, smoke comes from combustion in a closed container. The sensor is tested by varying the distance of gas injection with the sensor. This test aims to determine the relationship between the distance of gas injection and the sensor readings. The results of the MQ-2 sensor test can be seen in **Table 3**.

Table 3. MQ-2 Sensor Testing Results

Distance (cm)	V_{out} (V)	ΔV_{out} (%)
2	2.81	
3	2.49	11.39
4	2.15	13.65
5	2.12	1.4
Average		8.81

Table 3 shows that the sensor output voltage reading is influenced by the sensor distance to the gas source to be detected. The farther the distance between the gas and the sensor, the smaller the output voltage produced (Dwitama et al., 2021). Overall, the MQ-2 sensor's response has shown appropriate results, with an average percentage change in voltage of 8.81% for every 1 cm increase in distance.

3.3 DHT-22 Temperature Sensor Testing

DHT-22 temperature sensor testing compares the sensor readings with the temperature readings from an ideal tool. The standard tool used is the HTC-2. There are two stages in the DHT-22 sensor testing, namely, the initial sensor testing and the final sensor testing stage. Initial testing of the sensor is carried out by reading the results of temperature measurements from the sensor and HTC-2 and then fitting the results into a graph to find the linear equation. The linear equation is then used to calibrate the DHT-22 sensor. The final test of the sensor is done by reading the temperature measurement results from the calibrated sensor. The results of the initial testing of the DHT-22 sensor can be seen in **Figure 6**.

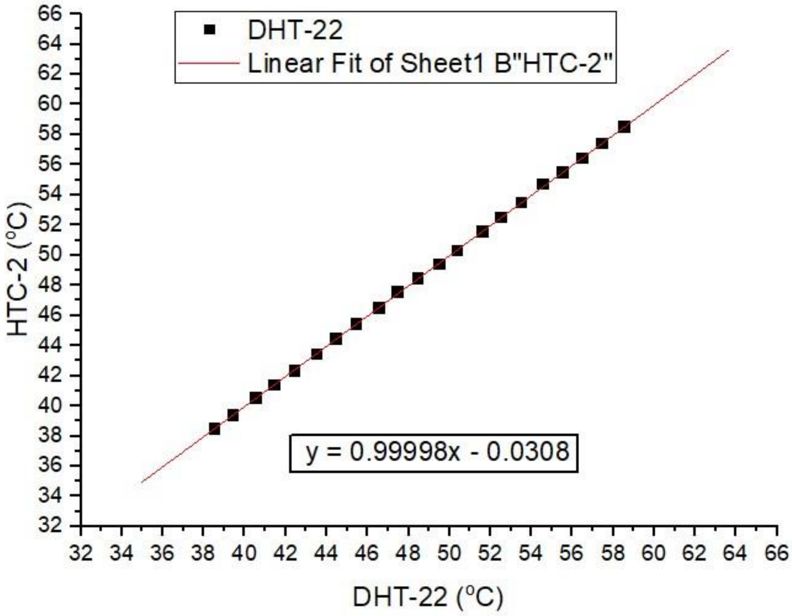


Figure 6 DHT-22 initial testing sensor graph

Figure 6 shows a graph of the DHT-22 sensor's initial test results before being calibrated. The fitting curve between the sensor's temperature and HTC-2's temperature measurements produces a regression equation.

$$y = 0{,}99998x - 0.0308 \tag{4}$$

with x is the DHT-22 sensor reading.

Equation 4 is entered into the Arduino program to calibrate the DHT-22 sensor. Table 4 shows the results of the DHT-22 sensor test after the calibration process.

Table 4. DHT-22 sensor reading after the calibration process

No	DHT-22 (°C)	HTC-2 (°C)	Accuracy (%)
1	39.64	39.60	99.90
2	40.14	40.10	99.90
3	40.74	40.70	99.90
4	41.34	41.30	99.91
5	41.84	41.80	99.91
6	42.34	42.30	99.91
7	42.84	42.80	99.91
8	43.14	43.10	99.91
9	43.54	43.50	99.91
10	44.14	44.10	99.91
11	44.44	44.40	99.91
12	44.64	44.60	99.91
13	44.84	44.80	99.91
14	45.24	45.20	99.91
15	45.34	45.30	99.91
16	46.04	46.00	99.92
17	48.14	48.10	99.92
18	50.94	50.90	99.92
19	54.74	54.70	99.93
20	58.94	58.90	99.93
21	63.64	63.60	99.94
	Average		99.91

Table 4 shows that the temperature measurement accuracy of the DHT-22 sensor has increased after the calibration process, and the measurement results are getting closer to those from HTC-2. **Table 4** also shows that the DHT-22 sensor's average accuracy is 99.9%.

3.4 Infrared Sensor Testing

Infrared sensor testing aims to test the sensor's sensitivity to changes in distance with fire. Sensor testing uses a candlelit as a source of fire, with a test based on the distance between the candle and the infrared sensor ranging from 10 cm to 100 cm, with an increase of 10 cm. The infrared sensor test results can be seen in **Table 5**.

Table 5. The results of infrared sensor testing

No	**Distance (cm)**	**V_{out} (V)**
1	10	0.02
2	20	0.06
3	30	0.09
4	40	0.12
5	50	0.64
6	60	0.77
7	70	1.20
8	80	1.60
9	90	1.91
10	100	2.04

Infrared sensors have the characteristics of a high output voltage when there is no fire and a low output when there is a fire with a low wavelength (Sumarto, 2017). It means that the farther the sensor is from the fire source, the higher the output voltage will be. The results shown in Table 5 show appropriate results where the sensor output voltage increases as the distance between the sensor and the ignition source increases. The sensor output voltage with the smallest value occurs at a distance of 10 cm, and the highest output voltage occurs at a distance of 100 cm.

3.5 The Results of Artificial Neural Network (ANN) Programming

There are two stages in the creation of ANN in this research, namely the programming and training stages and then the application stage to the monitoring system tool. The ANN programming and training phase uses the Python 3.9 programming language. This process aims to enhance the accuracy of the ANN model by recognizing the data patterns contained in the dataset to produce a more accurate output. The ANN training process is carried out until the output value of the ANN can approach the output value of the dataset, and the resulting error is at a tolerable value. **Table 6** compares the ANN models' accuracy, precision, and loss.

Table 6. The comparisons of accuracy, precision, and loss of the ANN models

ANN parameters (%)	Number of nodes in the hidden layer				
	4 nodes	3 nodes	7 nodes	8 nodes	9 nodes
Accuracy	98.52	98.50	99.63	99.25	97.78
Precision	97.92	97.78	100	98.92	96.97
Loss	1.018	1.108	0.423	0.72	0.777

Table 6 shows that increasing the number of nodes in the hidden layer to 8 and 9 reduces ANN performance. This is because the ANN architecture with 8 and 9 nodes in the hidden layer is too complex and prone to overfitting. Overfitting occurs when the ANN model pays too much attention to the details in the training data so that it not only captures the existing data patterns but also noise (Guido & Muller, 2017).

3.6 LPG Gas Monitoring Using Blynk

In the research, the IoT platform used is Blynk. Blynk is an application service that controls the microcontroller from the internet network (Prayitno et al., 2017). The use of Blynk is to make the monitoring process more accessible so that users can monitor the safety of LPG gas cylinders in real-time by utilizing an internet connection to find out the security conditions of LPG gas cylinders wherever and whenever. Blynk platform consists of a web dashboard and a mobile dashboard. The web dashboard is used for the website-based monitoring process, while the mobile dashboard is used for the Android application-based monitoring process. The appearance of the web and mobile dashboards made in this study can be seen in **Figure 7**.

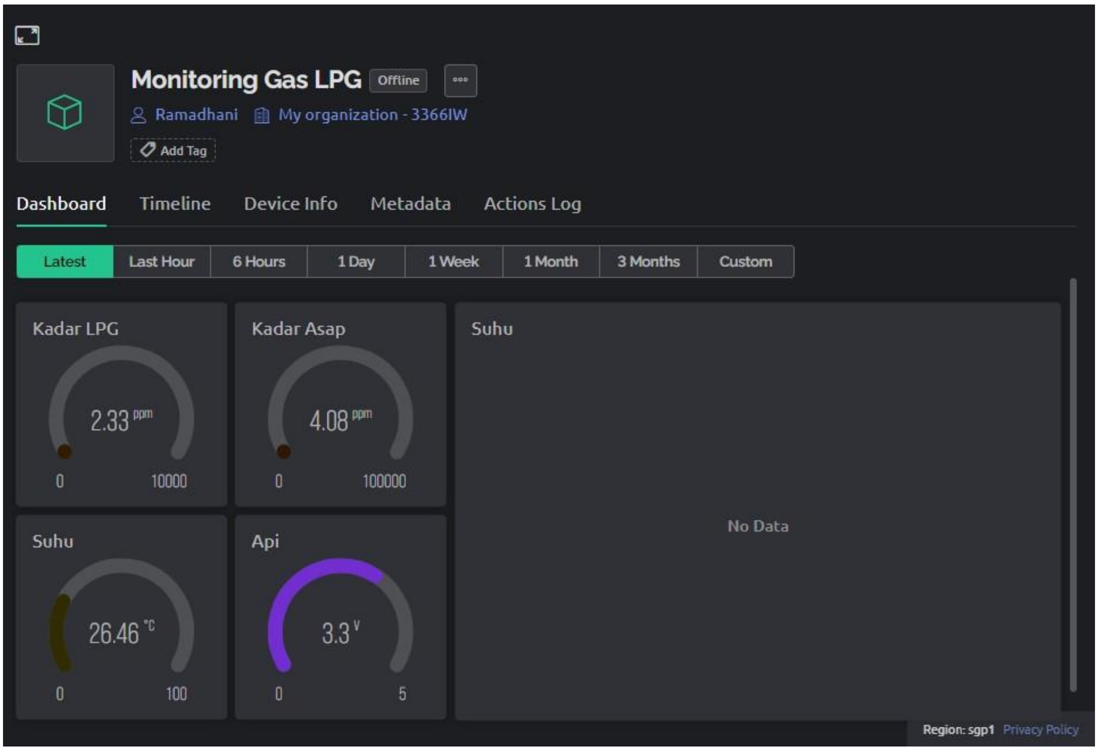


Figure 7. Web and mobile dashboards display

On the Blynk platform, there are limitations for notifications and warnings to users if the results of LPG monitoring indicate a dangerous or alert condition. Therefore, this study uses WhatsApp Bot to make user notifications in the event of a dangerous or alert condition, for example, an LPG leak or a fire has been detected, and so on. This study uses the WhatsApp Bot from the Twilio platform with the ThingESP platform. **Figure 8** shows an example of the notification.

Figure 8. WhatsApp Notifications

Figure 8 shows the received WhatsApp notification if the device detects a fire around the LPG cylinder. The results imply that the monitoring system using Blynk can work well and be implemented into the LPG safety monitoring system.

4. Conclusions

Based on the results of research and data analysis that has been carried out, it can be concluded that an artificial neural network to determine the results of LPG gas monitoring based on gas leakage levels, smoke levels, fires, and room temperature has been successfully created with an average accuracy of 99.63%, the average precision is 100%, and the average error (loss function) is 0.423%.

5. Bibliography

Amirah, Intan, I., Salman, & Arifin, S. R. (2021). Sistem Deteksi Dan Pengaman Kebocoran Gas Pada Kompor Bebasis Sms Gateway. *Prosiding Seminar Ilmiah Sistem Informasi dan Teknologi Informasi*, *X*(2), 144–153.

Berliani, D., & Saragih, Y. (2021). Pemanfaatan 4G LTE Dalam Implementasi NodeMCU ESP8266 Pada Sistem Pendeteksi Kebocoran Gas LPG. *Journal of Electrical Technology*, *1099*, 1–6.

Dewi, A. K., Wardhana, A. S., Pratama, A., & Nugraha, W. A. (2021). Alat Deteksi Kebocoran Gas Rumah Tangga Berbasis Internet of Things. *Jurnal Hilirisasi Technology Pengabdian Masyarakat*, *2*(2), 56–65.

Dwitama, A. P., Janardana, I. G. N., & Wijaya, I. wayan A. (2021). Rancang Bangun Prototipe Pemantau Kebocoran Gas Menggunakan Sensor MQ-6 Berbasis NodeMCU 8266. *Jurnal SPEKTRUM*, *8*(1), 9–14.

Guido, S., & Muller, A. C. (2017). *Introduction to Machine Learning with Python: A Guide for Data Scientists*. O'REILLY. Sebastopol.

Hakim, L., & Yonatan, V. (2017). Deteksi Kebocoran gas LPG menggunakan Detektor Arduino dengan. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi*, *1*(2), 114–121.

Kim, P. (2017). *Matlab Deep Learning With Machine Learning, Neural Networks and Artificial Intelligence*. Apress. Seoul.

Kurniawan, A. (2021). *Beginning Arduino Nano 33 IoT Step-By-Step Internet of Things Projects*. Apress. Depok.

Maidoni, I., & Elfizon. (2020). Perancangan Sistem Keamanan Ruangan Akibat Kebocoran Gas Berbasis Internet of Things (IoT). *Jurnal Teknik Elektro Indonesia*, *1*(2), 124–128.

Prayitno, W. A., Muttaqin, A., & Syauqy, D. (2017). Sistem Monitoring Suhu , Kelembaban , dan Pengendali Penyiraman Tanaman Hidroponik menggunakan Blynk Android. *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *1*(4), 292–297.

Rosebrock, A. (2017). *Deep Learning For Computer Vision With Python*. PYIMAGESEARCH, New York.

Sumarto. (2017). *Sistem Peringatan Dini Deteksi Dan Pemadam Kebakaran Berbasis Raspberry Pi*. Skripsi, Surabaya: Fakultas Teknologi Elektro Institut Teknologi Sepuluh Nopember.

Tagliaferri, L., Morales, M., Birbeck, E., & Wan, A. (2019). *Python Machine Learning Projects*. DigitalOcean. New York.

Tutorialspoint. (2016). *Artificial Intelligence with Python*. Tutorials Point.

Weber, R. H., & Weber, R. (2009). *Internet of Things Legal Perspectives*. Springer. Zurich.