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Prototype smart integrated fire detection based on deep learning YOLO v8 and IoT (internet of things) to improve early fire detection

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Abstract

The high incidence of fires in Indonesia in 2018-2023 is 5,336 fire incidents have caused many deaths and enormous material losses. This system is designed to identify early signs of fire through object detection and sensor technology, which is integrated with the Blynk IoT platform for real-time sensor monitoring and Telegram for instant notifications to users. The waterfall prototype method was designed through observation, system design, program code creation, tool testing, and tool implementation. This research uses Deep Learning YOLOv8 technology and IoT using ESP 32 as a microcontroller. Based on the training datasets, it produces precision=0.95872; recall=0.91; mAP50=0.97; mAP50-95 =0.66. The system uses the integration of a multisensor KY-026 flame sensor, DHT 22 temperature and humidity sensor, and MQ-2 sensors can detect CO, LPG, and smoke gas. All these multisensors can be monitored on Blynk IoT and Telegrambot in real time.

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INTRODUCTION

Globalization, especially in the industrial sector, has had a major impact on society, in improving economic well-being (Harahap et al., 2023). The connectivity and expansion of global markets have led to increased production capacity, technological advances, and the creation of many jobs. This economic rise has facilitated a higher standard of living and the growth of society as a whole (Choe et al., 2017). However, rapid industrial advances driven by globalization also pose considerable risks. The complexity and scale of modern industrial operations increase the fire potential (Siraj et al., 2023). These incidents can be caused by inadequate safety protocols and human error. The impact of such accidents is enormous, often resulting in significant material losses, production disruptions, and even deaths (Van et al., 2023).

Fires pose a major threat due to the presence of flammable materials and high-temperature processes in industrial operations (Gaur et al., 2020). They can occur anywhere, from residential areas to commercial sectors. Fires typically arise when heat, fuel, and oxygen are present, as per the fire triangle theory (Mohammed et al., 2023). Moreover, fires are classified into three segments: A (non-metal solids like paper and plastic), B (flammable liquids and gases), and C (high-voltage

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electrical installations). While fire is beneficial, uncontrolled fires can cause severe damage (Ghali et al., 2023).

Data from the Indonesian National Police show a significant rise in fires from September 2018 to July 2023, with a peak in June 2023. Most fires in 2023 occurred in Central Java, followed by East Java and Bali, predominantly in residential areas (Media, 2023). The increase in fire incidents indicates the need for more effective preventive measures. One of the precautions is to apply sophisticated sensors and monitoring technology available to each building so that it can help firefighters get information quickly so it can be handled properly (Muhammad et al., 2018). Implementing these advanced preventive measures is expected to reduce the level of fires in Indonesia as well as significantly improve fire safety, reduce casualties, and minimize material losses.

Fire detection is one of the technologies that is currently being developed in line with rapid technological developments followed by developments in the field of Artificial Intelligence (Liu, 2023). Implementation of artificial intelligence in Integrated Smart Fire Detection based on the Internet of Things (IoT) has a revolutionary potential to improve response and fire detection efficiency. AI plays a key role in analyzing data received from IoT sensors, thus enabling quick and accurate decision-making (Rodriguez et al., 2023). With the adoption of AI, fire Detection systems can learn and evolve from the data received, enhancing their ability to detect fires and reduce detection errors (Mukhopadhyay et al., 2021).

Recent research focuses on integrating sensor technology with IoT and AI to improve fire detection. This system uses temperature DHT 22 sensor, gas sensor MQ-2, and flame sensors KY-026 connected to an ESP-32 microcontroller, enhanced with object detection through video processing YOLO v8. AI plays a crucial role in analyzing sensor data, enabling quick and accurate responses. The integration of AI and IoT promises to revolutionize fire detection and extend its applications to security monitoring and fire safety management. This research aims to develop a real-time and predictive fire detection system, contributing to developing more efficient fire management plans and improved safety and quality.

METHOD

To create a prototype of intelligent fire detection, we first focused on making hardware that uses ESP-32 as the primary device and sensors such as DHT-22, flame sensor KY-026, and gas sensor MQ-2. Also, in machine learning, the YOLO v8 algorithm detects fires more accurately, which is the methodology used.

System Design

This design describes intelligent integrated fire detection. Figure 1 is a diagram of the system design process.

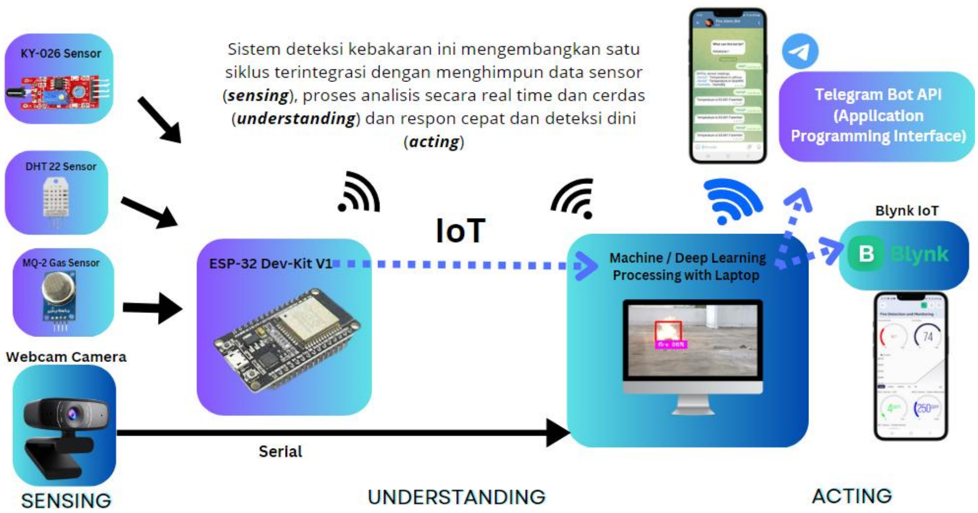

Figure 1. Design of the system.

Figure 1 shows the integrated intelligent fire detection system has two large parts, the left side of which is the input generated by the MQ-2, DHT 22, and KY-026 flame sensors that have been integrated using ESP 32, where data will be sent via the cloud to the telegram and Blynk IoT. On telegraph applications, users can access the values of the DHT sensor in real-time implementation and obtain detection notifications autonomously and also with the telegram platform, users can monitor when there is fire detection through video object detection technology. On the Blynk IoT application, users can access temperature, humidity, LPG gas, CO gas, and smoke data in real-time processing.

The other parameter uses a camera sensor equipped to detect fire using video processing technology and the YOLOv8 deep learning algorithm. Then, with autonomous detection, the system will send the image data in real-time via a telegram when the confidence of the image exceeds the set threshold. All these parameters are integrated and will be processed using computing so that when the program detects indications of fire and gas, it will produce a notification and alarm output for fire prevention.

Hardware Design

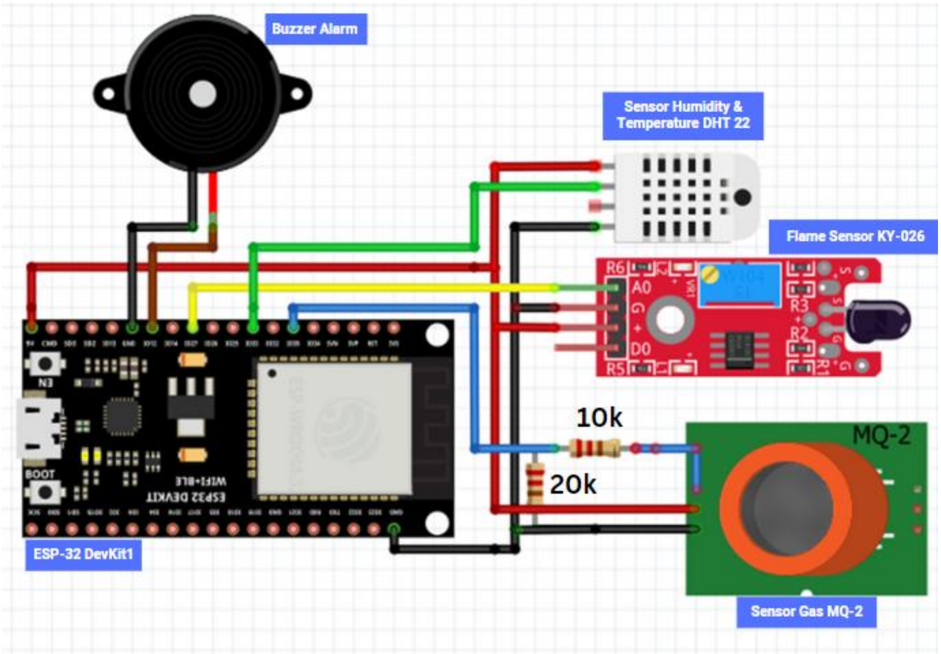

Figure 2. Schematic of the circuit

Figure 2 shows how the schematic integration of the sensors and ESP 32 microcontroller has been designed using fritzing applications. A schematic design can be found in Figure 2 where the sensor input from the MQ-2, the flame sensor, and the temperature sensor DHT 22 will be integrated, the data from the sensor will be processed by the ESP-32, and the system will send notifications to the user via IoT technology to the telegram and Blynk-IoT Real-time, so user can monitor anywhere and anytime. The system is equipped with an actuator in the form of a buzzer so that when the sensor value has exceeded the threshold, it will generate an alarm sound.

Prototyping of Smart Fire Detection

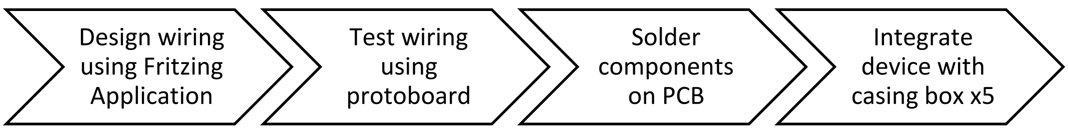

Figure 3. Step Prototyping Hardware of Smart Fire Detection.

Figure 3 shows the stages of the prototype of smart fire detection, starting from the design to the system integration. The tool design phase begins with designing prototypes for the fritzing application. Such software can make it easier for researchers to give a preliminary overview before implementing the tool physically. The next stage of the IoT system is implemented using the breadboard by installing each sensor, cable, and microcontroller ESP 32 DevKit-1 component into a network system that can be tested before performing the soldering of the network. The breadboard mounting is handy for the initial test of electronic networks because its properties can be altered by damaging the packaging and installation of components.

The next step is to connect the electronic components on top of the dot matrix PCB board using solder lead wire to make the system network more robust, reliable, and durable and have a more potent electrical connection.

Integration of IoT system with Blynk IoT platform

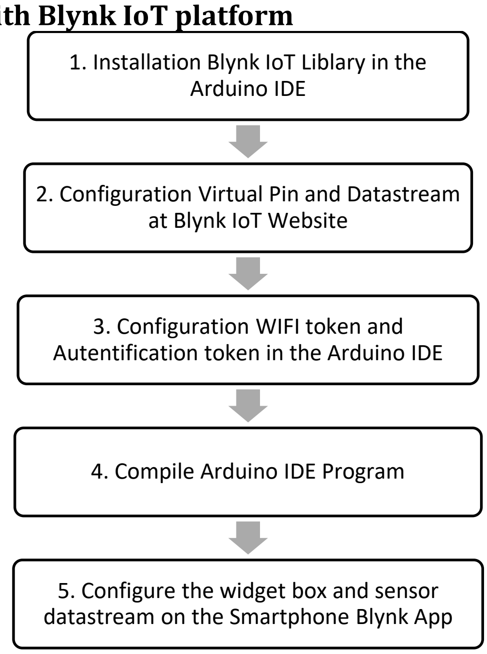

Figure 4. Integration of IoT system with Blynk IoT Flow Chart

Figure 4 shows the stages for integrating the hardware system with the Blynk IoT system. In Figure 4, there are five steps, the first is to install the Blynk IoT library on the Arduino IDE program. The second step is to configure the Blynk IoT system on the Blynk IoT website so that any sensor can be configured to be displayed and then token authentication will be obtained so that it can be connected to the program. The last step is to configure the widget box and data stream on your smartphone in the Blynk IoT app so you can set the widget box to be used to monitor sensor detection results.

Integration IoT system with TelegramBot

The study used a bot telegram as a platform to warn users early when a sensor value crosses the threshold and monitor the sensor value through chat. Figure 5 shows the steps to integrate the sensor readings on the ESP32 DevKit-1 with a bot telegram. Integrating the sensor with the bot telegrams begins with configuring the telegram application using the BotFather, which produces a customizable bot. Then, I installed the UniversalTelegramBot library onto the Arduino IDE and added the token bot telegram and the chat ID obtained. Furthermore, each sensor on the Arduino IDE can set thresholds so that when the threshold is exceeded, it will send a message to the bot's telegram.

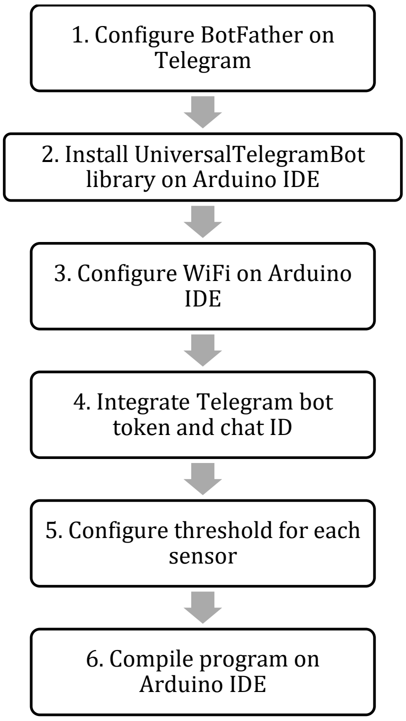

Figure 5. Integration of IoT system with Blynk IoT Flow Chart

Machine Learning Model

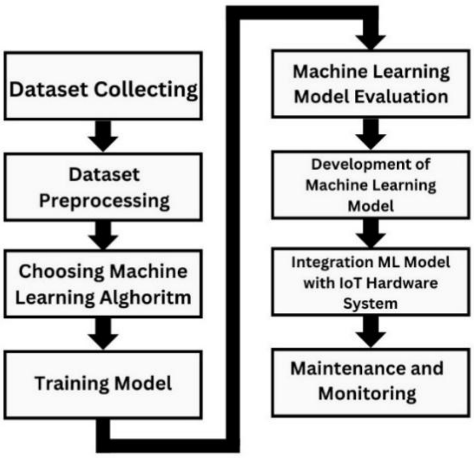

Figure 6. Deep Learning System Modeling Flow Diagram

Figure 6 gives an overview of how Step by Step to create a fire detection algorithm using YOLOv8 deep learning technology. The first step is the intelligent fire detection system prototype using YOLOv8 started with collecting images and video datasets containing fire and non-fire from various sources. These were labeled using tools like LabelImg and processed with platforms like Roboflow. After that, the Yolov8 object detection model was selected for its speed and accuracy and then trained on the data set using Google Collab with 100 epochs. The system was then developed to process live video streams and detect fires in real time, dealing with false positives with a confidence threshold. Integration is done with alarm systems, Telegram notifications, and IoT to quickly and efficiently respond to fires. Finally, a trained model was implemented in Visual Studio Code to process video from a webcam, sending notifications if a fire was detected with confidence> 60%.

RESULTS AND DISCUSSION

Prototype of Smart Fire Detection

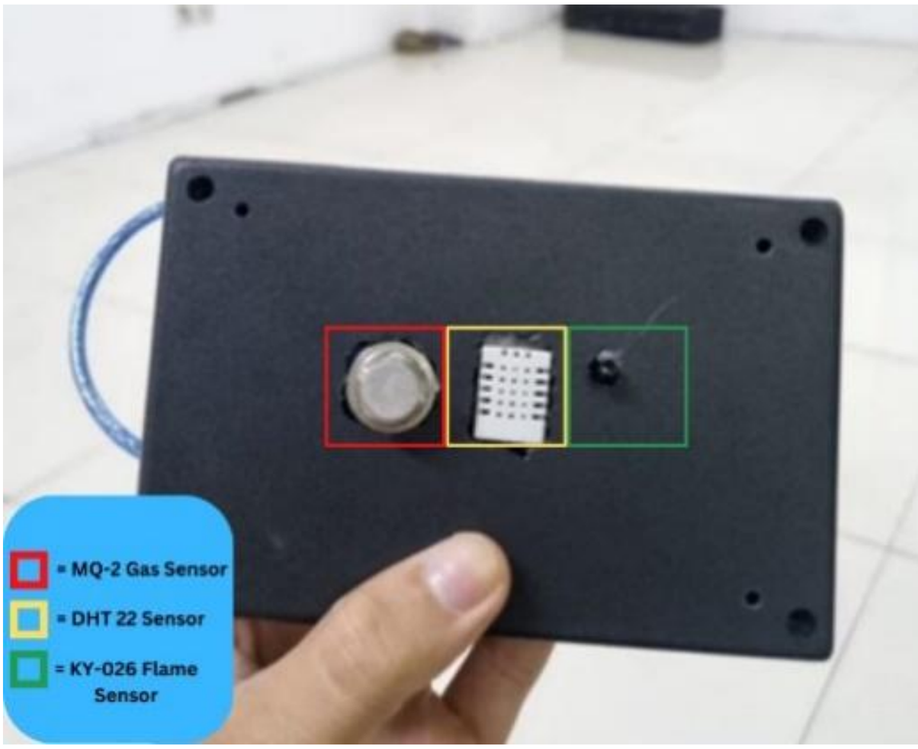

Figure 7. Prototype of Smart Fire Detection

Figure 7 shows a Prototype of Smart Fire Detection, by integrating the ESP-32 DevKit-1 with the KY-026, DHT 22, and MQ-2 sensors, all these electronic components are incorporated into the Dot Metrix PCB with soldering stages to make it more robust. The system is then inserted into the x5 case size of 14.8 x 9.7 x 5 cm. The device integration with the casing box aims to protect the sensor and microcontroller components and ensure their durability in fire conditions.

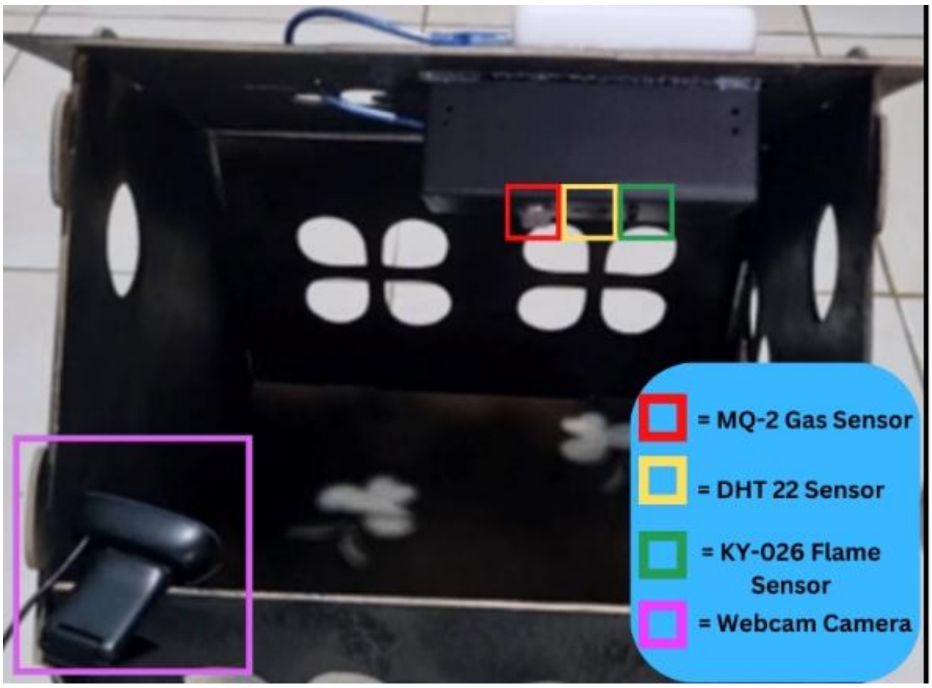

Figure 8. YOLOv8 Training Result

In Figure 8 above, the Prototype of Smart Fire Detection is an IoT hardware integrated with a webcam camera that connects to a laptop and processes video processing that has been trained using the YOLO v8 machine learning algorithm. These combinations can enhance system capabilities by complementing each other. On the IoT hardware side, the system detects fires early with the presence of DHT 22, MQ-2 gas sensors, and KY-026 flame sensors, and coupled with a fire detection system using machine learning, the combination can increase early fire alertness. So the damage caused by a massive fire can be prevented early.

Model Evaluation

In this study, the researchers designed a deep learning algorithm model YOLOv8 with a dataset of fire and flame images totaling 5,583 images. The calculation process is performed with the amount of 100 Epoch to obtain optimal accuracy. Epoch is a hyperparameter that can determine the number of deep learning algorithms to read the entire dataset by dividing it into three segments, namely 4688 images for train sets, 596 images for test sets, and 299 images for validation sets.

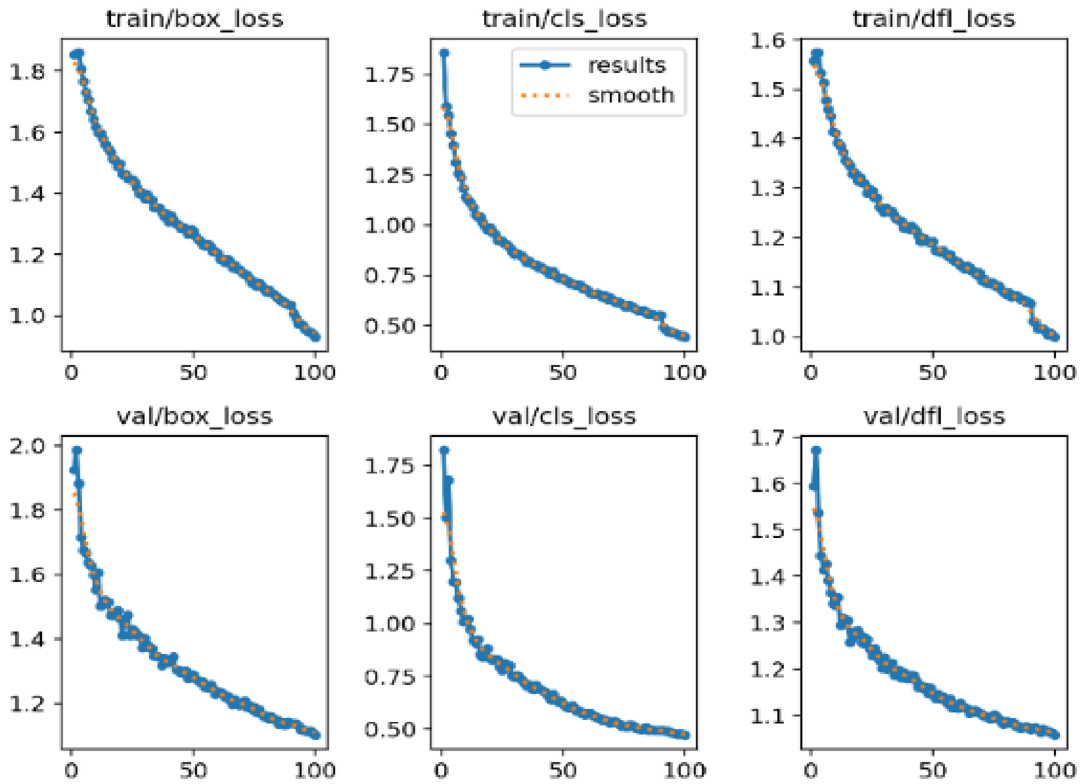

Figure 9. YOLOv8 Training Result

Figure 9 shows the train performed as many as 100 epochs and produced graphs that presented the relationships between box_loss, cls_loss, and dfl_loss with train and values. Box losses indicate both algorithms that have been created to cover the entire object that has been annotated, cls loss or classification loss suggests that the model has been made to edit the correct label/class and give the object bounding box correctly, and dfl loss or objectness loss which indicates the ability of the model to check the likelihood that the actual object is in the targeted/observed area. In the graph above, the more training is done, i.e., 100 epochs, the smaller the loss. In training model 100, the values of box_loss,cls_loss, and dfl loss have values of 0.93001, 0.44306, and 0.99916, respectively, about training, whereas box_loss, cls_losse, and Dfl loss values are 5.96e-05;5.96e05 and 5.96E-05.

Integration System with Blynk IoT and Telegram Platform

Figure 10. Blynk IoT Monitoring Interface

The Blynk IoT application can be accessed using a smartphone to improve user monitoring capabilities. On the IoT Blynk interface as Figure 10 shows, the researchers designed a 5 Gauge Chart that monitors temperature, humidity, and the concentration of LPG, CO, and smoke in the air in ppm (part per million) units. Integration with the IoT Blynk platform can improve fire surveillance and monitoring. The Blynk platform is connected to the ESP-32 microcontroller using a WiFi network to transmit data quickly and with low latency. The Blynk IoT platform displays temperature and humidity data from the DHT 22 sensor and the intensity of LPG (Liquid Petroleum Gas), CO (Carbon Monoxide), and smoke in the air.

Figure 11. TelegramBot Monitoring Interface

On the telegramBot as Figure 11 Shows, it has been integrated with the working systems of each sensor, those are the KY-026, DHT 22, and MQ-2 gas sensors, as well as camera monitoring. So, when there's an indication of a fire, the system will send a detection image to the user. Not only the camera but also the sensor detection results will also be monitored to the chat telegram as in Figure 11. Further, the flame sensor can detect the presence of a flame, then it will turn on the Alarm buzzer pin and subsequently send a warning notification message to the telegram with the message "Flame Sensor: API DETECTED!!". The MQ-2 sensor readings are segmented into three types of gases: LPG, CO, and smoke. Each output of the MQ2 gas sensor is converted to a gas value in ppm form. Each gas parameter has a threshold value to notify the telegram as shown in Figure.

Figure 12. DHT 22 Monitoring Interface on TelegramBot

Figure 12 shows how to access a DHT 22 sensor using a telegram bot, users can also monitor temperature and humidity using commands directly on the chatbot with following commands:

- /start: The program will provide guidance and navigation for the following command using the command.
- /tempF: The chatbot will use the command on the telegram to tell the sensor to send real-time temperature data of DHT 22 in Fahrenheit units.
- /tempC: Using the chatbot command, the telegram will give the command to the sensor to send the real-time temperature data of DHT 22 in Celcius units.
- /humidity: Using that command on a chatbot, the telegrams will command a sensor to transmit the DHT22's temperature and humidity data in Fahrenheit units.

with those commands, can be easier for to user to monitor the units generated by the sensor in real-time.

In Figure 13, the deep learning system can send a detection image to the user via a bot telegram, which also contains an explanation of how much confidence has been gained. Moreover, the alarm will be automatically lit when a deep learning model detects a flame with a confidence level > 60%. The confidence figure is used as a threshold because based on research conducted by Yunsov in 2024, it states that In the context of object detection using machine learning, accuracy levels above 60% can be said to be accurate. After all, high reliability and precision ensures that models are reliable in identifying objects consistently, reducing false positive and false negative errors that can have significant consequences, especially in critical applications such as forest fire detection or security surveillance. Moreover, models with accurations over 60% tend to be more efficient and effective in their use, ensuring that resources are used optimally. So, when the system detects a fire image that exceeds the threshold, then the system will capture the image, save it to the system, and send it to a bot telegraph with the confidence accuracy obtained.

Figure 13. Fire Detection Monitoring Interface on TelegramBot

CONCLUSION

Fire detection using real-time video processing technology based on the deep learning algorithm YOLO v8 has a training mAP (mean average precision) of 96% and based on the training datasets, it produces precision=0.95872; recall=0.91; mAP50=0.97; mAP50-95 =0.66. so, it can detect the fire accurately and send the detection results to the telegram. The integrated smart fire detection system with IoT and deep learning YOLO v8 can detect changes in flame sensor parameters, temperature, humidity, and gas. The system will respond to those changes by sending real-time notifications through the Blynk IoT mobile app and the telegram bot. With this integrated system, it is expected to be a solution to reduce the incidence of fires with early detection and prevention, so when there is a direct fire can be overcome.

In future research, deep learning algorithms such as the YOLOv9 and YOLOv10 algorithms can be used to increase accuracy. Moreover, it can improve the specifications of the flame sensor, gas sensor, and temperature sensor used so that more accurate results can be obtained. Furthermore, a higher-resolution camera equipped with a thermal sensor can also be used to monitor the fire more accurately.

AUTHOR CONTRIBUTIONS

M.A.F.: Conceptualization, methodology, data curation, formal analysis, & writing – original manuscript. I.A.D.: Conceptualization, supervision, validation, & writing – review & editing. H.A.D.R.: Supervision, resources, & writing – review & editing. M.A.V.L.: Methodology, data curation, & visualization. S.W.P.: Formal analysis, software, & validation.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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