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A Smart Gas Stove with Gas Leakage Detection and Multistage Prevention System Using IoT

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***Abstract*: Today's technologies rely heavily on smart embedded systems, and IoT-based smart embedded systems are the hottest area of study. In our study, we suggest an Internet of Things-powered smart stove. Any moment, a stove mishap could occur. We are creating a two-way safety stove with a child lock mechanism and a gas leak detecting feature as a result. Through real-time video streaming, the smart stove will make an effort to assure safety and will determine age. Our primary worry is that a kid wouldn't know how to start the stove. Additionally, the stove has a gas detection alert that can give safety. We're using a Raspberry Pi and a gas detection module with a buzzer as our hardware. Additionally, we employ a deep learning architecture and a machine learning object detection method (Haar Cascade) for system execution (CNN). Our IoT-based stove provides safety both manually and remotely in an effort to stop unintended occurrences.**

***Keywords*: Age detection, Buzzer, Child lock system, Embedded system, IoT, Raspberry Pi, Machine Learning, Smart embedded system.**

1. Introduction

The internet and embedded systems are two of the most rapidly expanding fields that have the potential to alter how people go about their daily lives. Using embedded devices, a unique computing system can be built. In most cases, an embedded system performs a single operation. On the other hand, these internet-connected embedded devices can speak with other network devices. An embedded system typically does a single operation. On the other hand, these embedded devices that are linked to the internet can talk to other network devices. In this study, we present a smart embedded device, an IoT-based smart stove. Real-time age monitoring for child locks and protection from unintentional gas leaks are two ways that the stove will safeguard us. The perceptions of Bangladesh between people are the subject of our research. Both a manual and an electronic ignition will be available for the stove. In our study, we'll demonstrate a smart IoT-based system that will serve as a superior comprehension of our smart stove. The system is powered by a Raspberry Pi, a tiny computer. The Raspberry Pi can be linked to other relevant sensors, modules, and equipment. A credit-card-sized, inexpensive computer called the Raspberry Pi connects to a computer or television and operates using a regular gamepad and mouse.

It is a capable small device that empowers adventurers of all ages. It is capable of carrying out every function that a regular user would imagine a personal computer to have, notably playing high-definition video games, using the internet, and creating spreadsheets and word processing documents. The Raspberry Pi has also been used in a number of digital maker projects, including parent detectors, weather stations, and music machines.

As a safety precaution, we have suggested the child lock for our system. So that a youngster under the age of 12 cannot turn on the stove, we incorporated an age detection technique. For age detection, we are use the Raspberry Pi Camera Module, which is directly attached to the Raspberry Pi. Additionally, for the software implementation, we interacted with OpenCV (a library) python scripts with algorithms and trained datasets. The fact that Python supports both procedure-oriented and object-oriented programming is one of its fundamental strengths. Python combines enormous capability with straightforward syntax. Python contains dynamic data kinds and dynamic composing that are extraordinarily irregular in state and incorporate modules, classes, and exemptions. Interfaces are provided for a range of framework calls, libraries, and windowing frameworks.

There are two algorithms used in the age detection process. One illustration is the Haar Cascade Classifier Algorithm. A machine learning object recognition system called Haar Cascade can identify things in pictures or videos. A typical face database is used to test the system's HAAR-like properties. The prototxt file defines the layers of the neural network as well as the inputs, outputs, and functionality of each layer. The model file contains information on the trained neural network (trained model). Here, we have assembled age detection trained datasets that have been generated by a machine learning classifier. [2] Artificial intelligence (AI) is used in machine learning, which allows systems to learn from experience without being actively changed. Another algorithm that is a classification algorithm (CNN) for system execution is a deep learning architecture. Convolutional neural networks, or CNNs, are a subclass of deep neural networks used in deep learning. Each layer of a CNN monitors the output of the layer before it to produce both increased and decreased yields. Convolutional neural networks (CNN) utilize previously discovered information.

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2. Related Work

A. Age Detection

Over the years, a number of studies and journals on age detection have been released. Untung et al. [6] claim that the accessibility of computer systems has led to the development of numerous automated personal identification applications. Among the different aspects of biometrics, face verification techniques, in particular, have been a study focus. In the 1960s, researchers developed an interest in facial recognition methods, which was started by Woodrow W. Bledsoe in partnership with the US Department of Defense and Intelligence Agency, according to Marques, I. et al. [7]. In a semi-automated approach created and put into use by Bledsoe, the data needed for face recognition is first computed by a computer using some manual calculations of facial coordinates. The first age-related approach was created in 1999 by Kwon and Lobo [8]. detection relies on geometric aspects of the face that establish the ratios between different facial feature dimensions However, they are unable to identify between young adults and senior adults. These geometric traits efficiently distinguish between youngsters and adults. To accomplish accurate age group and gender categorization of unfiltered real-world faces, Viriri, S. et al. [9] proposed a novel one after another CNN approach in a subsequent research paper released in 2020. However, due to the relatively restricted data base accessibility and the impact of age progression on face verification, comparing image pairings from single faces has proven to be challenging. Techniques for face verification based on age progression haven't gotten much attention lately. This is a result of the system's limitations.

B. Haar Cascade

An algorithm for object detection using machine learning: Early in the new millennium, Cascade and features resembling Haar were released. Various facial detection techniques were already taken into consideration. A machine learning method for visual item detection that can quickly prepare images and achieve high detection rates was proven by Viola, P. et al. [10]. The scientists suggested a method for combining classifiers that are increasingly more difficult in a cascade structure, allowing background parts of the image to be instantly eliminated while concentrating more computation on promising object-like areas. In a different study, Chris et al. [11] offered a comprehensive arrangement of Haar-like features that went beyond the conventionally aligned vertically and horizontally and the 45-degree-twirled Haar-like features. The extended rotated Haar-like features, they claimed, are based on the normal Haar-like features that have been rotated using whole integer pixel rotations. Rotated integral pictures can likewise be used to calculate these rotated feature values.

C. Neural Convolutional Network

Yann LeCun introduced the first Convolutional Neural Network (CNN) strategy in 1994. This is an example of a deep learning architecture. He is regarded as a founding father of convolutional nets and is widely recognised for his work on optical character recognition and computer vision using CNN. [12] Then, numerous academic papers on deep learning and its architectures, including CNN, were published. A hybrid neural-network solution that Lawrence, S. et al. [13] introduced in 1997 beats existing approaches. The system combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network. 2015 saw the publication of yet another article on deep-CNN age and gender classification. This was proved by T. Hassner et al. [2] using deep convolutional neural networks to learn representations (CNN), On certain tasks, a considerable execution improvement can be made. They consequently suggested a straightforward convolutional net architecture that may be applied even in the absence of much learning data. D. Gas Detection: There are a tonne of works for gas detection in different articles. Various papers and magazines have covered a wide range of gas detection methodologies. A leak detection system was previously created by Heinrich et al. [14] using flexible hydrocarbon sensing cable that was put in pipelines in 1989. A straightforward electrical circuit is also a part of the system, and it can locate leaks anywhere along the sensor's length. Tanvira and co. [15] Early in 2014, a microcontroller-based gas leakage warning system was developed. In order to release the gas, the system will also turn on an exhaust fan. Many Internet of Things (IoT)-based smart home products now employ Raspberry Pi. A Raspberry Pi-based IoT-based industrial monitoring system was proposed in 2019 by Sourabh et al. [16]. They have verified that their system is capable of both gas and fire detection, and that it will send the user a GSM notification if either is found.

D. Gas Detection

For detecting gas in various articles, there are numerous works available. Various papers and magazines have covered a wide range of gas detection methodologies. A leak detection system was previously created by Heinrich et al. [14] using flexible hydrocarbon sensing cable that was put in pipelines in 1989. A straightforward electrical circuit is also a part of the system, and it can locate leaks anywhere along the sensor's length. In the beginning of 2014, Tanvira et al. [15] developed a GSM-based gas leakage alert system utilising a microcontroller. The authors claim that in addition to releasing the gas, the system will also turn on an exhaust fan. Nowadays, a lot of IoT-based smart home gadgets employ Raspberry Pi. An industrial IoT was proposed by Sourabh et al. [16]. A raspberry pi monitoring system will be utilised in 2019. They affirmed that their system can detect both gas and fire, and that it will send the user a GSM notification if either is found.

3. Proposed Methodology

A. Overall Methodological Approach

In this study, a Raspberry Pi microcomputer, a Pi camera, and other embedded system project apparatus are used to build a device. The appliance will be fixed to the stove and offer the required safety features. Additionally, as the stove is Internet of Things (IoT) based, users of internet-connected smart devices like a smartphone, tablet, or PC may view its status from anywhere.

B. System Execution Software

The version of Raspbian we're using is Raspberry Pi OS (32-bit) with desktop and suggested software. Python 3.8 is the programme used in connection with the Raspberry Pi and the IoT-based server. We also utilise Thingspeak to remotely access and keep an eye on the entire system, including the stove. We built a confidential route for our study. making use of a local area network "Gas Detection" and "Gas Monitoring" are the two fields on the channel. key (write) and interfaced it with the python programmes. We are able to remotely monitor the system as a result. Additionally, we are using the Fritzing 0.9.3b software to create the system's physical and schematic schematics. C. The Tools We're Using: For the hardware implementation, we used a Raspberry Pi 3 Model B v1.2, a MQ-2 Flammable Gas & Smoke Sensor, a Raspberry Pi Camera Module Rev 1.3 - 5MP, a TMB12A12 Electromagnetic Active buzzer 12V DC, an LED light, a 330-ohm resistor, a breadboard, and jumper wires.

The Python programming language and the UNIX operating system are both compatible with the Raspberry Pi. Several gadgets, including a buzzer, LED light, resistor, and a gas detection module, are attached to the raspberry pi's GPIO header. Additionally, the 15-pin MIPI CSI (Camera Serial Interface) connector on the Raspberry Pi accepts a direct connection from the pi camera module. is made primarily for interacting with cameras. Aerial gas leaks and smoke are discovered by the MQ-2 Gas and Smoke Detection Module. The gases H_2, LPG, CH_4, CO, alcohol, smoke, and propane are the ones it primarily finds. Due to its great sensitivity and short response time, actions can be taken as quickly as feasible. Additionally, the buzzer serves as an alarm at our office.

The buzzer will constantly beep if the gas detection module finds any gas. Furthermore, a resistor is being used to stop the LED light from reaching full voltage, and the LED light is connected to the raspberry pi GPIO header through a breadboard and jumper wires. Its colour code is orange, orange, brown, and gold D, and its resistance is 330 ohm. Procedure for Analysis: a) Physical Diagram How the hardware devices are linked to the Raspberry Pi is depicted in the physical diagram.

Figure 1 shows a direct connection between the raspberry pi camera and the CSI connector. Furthermore, the stove switch is represented by the LED light in this study. The camera will identify a person's age based on their faces if they attempt to switch on the stove. The stove will start up and the LED light will come on if the person is an adult. The LED light will remain off if a child tries to turn on the stove, but the stove will prevent the youngster from doing so. are using a 330-ohm resistor to avoid full voltage.

A straightforward electrical circuit is also a part of the system, and it can locate leaks anywhere along the sensor's length. In the beginning of 2014, Tanvira et al. [15] developed a GSM-based gas leakage alert system utilising a microcontroller. The authors claim that in addition to releasing the gas, the system will also turn on an exhaust fan. Many Internet of Things (IoT)-based smart home products now employ Raspberry Pi. An industrial IoT was proposed by Sourabh et al. [16]. A raspberry pi monitoring system will be utilised in 2019. They affirmed that their system can detect both gas and fire, and that it will send the user a GSM notification if either is found.

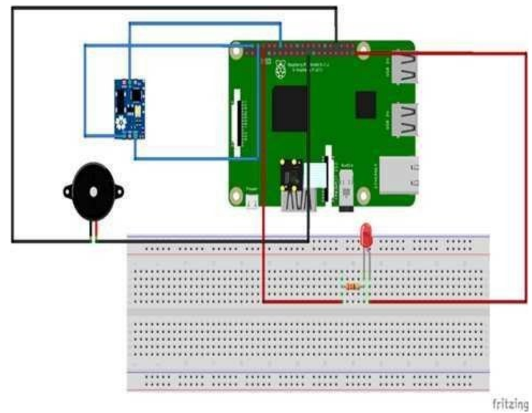

Fig. 1. Physical diagram of the system

The Gas detector module and 12V active buzzer are connected to the GPIO header via jumper wires. The gas detecting module will identify a leak if one exists, and the buzzer will promptly sound an alarm. The Raspberry Pi is additionally connected to an LED light, a resistor, a buzzer, and a gas detecting module using a breadboard and jumper wires.

C. Schematic Diagram

The CSI connector and GPIO header connections of the apparatus to the Raspberry Pi are shown in the schematic diagram. The graphic is a visual representation of the key elements or connections but not their specifics. Additionally, there are some gaps between the wiring and the real device's physical layouts. Additionally, the wiring does not quite match the physical layouts of the device.

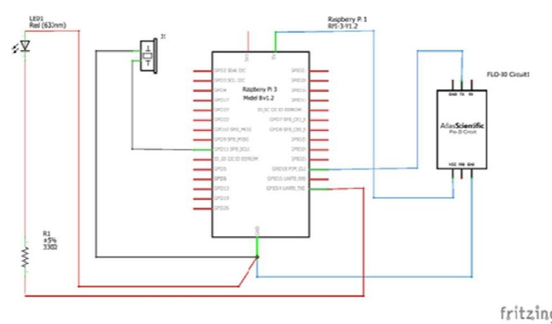

Fig. 2. Schematic diagram of the system

In figure 2, the gas detector module's DO (Digital Output) is linked to GPIO pin 18, the module's VCC is connected to the raspberry pi's 5V, and the module's GND is connected to the raspberry pi's GND. The buzzer has activated. connected to the raspberry pi's GPIO 11 pin on the positive end and the GND pin on the negative end to interface with the gas detection module. Additionally, a 330-ohm resistor is used to connect the LED's positive (anode) lead to the raspberry pi's GPIO 14 pin. Additionally, the negative (cathode) lead is linked to the ground of the Raspberry Pi. The Raspberry Pi camera module is attached directly to the Raspberry Pi's CSI connector, despite the fact that it is not depicted in the schematic diagram (which is shown in the physical diagram of the system).

4. Result and Discussion

A. Entire Hardware Setup

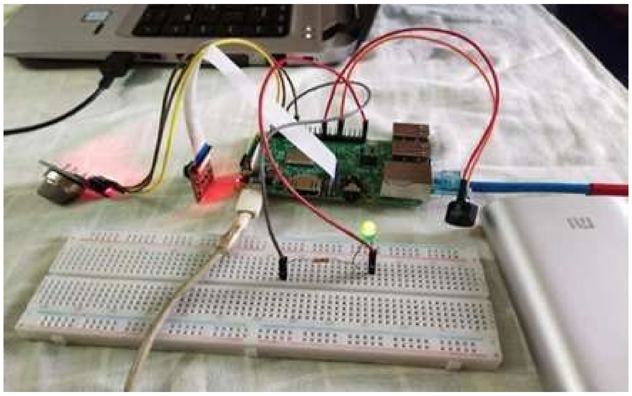

Fig. 3. Hardware setup

The raspberry pi is assigned to the devices listed below. Figure 4 depicts the trial configuration for the full system. The configuration also shows some quick data including values, the time and date on the ThingSpeak server, and a line chart of the data.

Table 1
Test condition for raspberry pi camera module and led (For age detection)

S. No.	Raspberry Pi Camera Module	LED Light
1	Child's face detected (age<12)	Remains off
2	Adult's face detected (age≥12)	Turns on

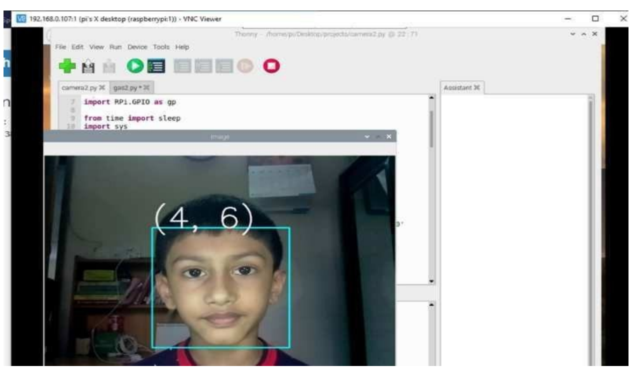

Fig. 4. Age detection output picture (child)

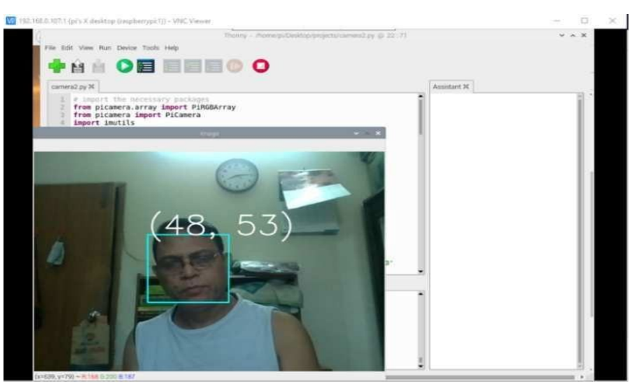

Fig. 5. Age detection output picture (adult)

In figures 4 and 5, the OpenCV Age detector is shown estimating a child's and an adult's age range using real-time facial images that were recorded while video streaming. Here, the adult is 49 years old and the youngster is 5 years old. Although age prediction accuracy is not perfect, age estimation range is quite close to perfection. Above the frame, the age range is visible.

Table 2
Test condition for gas detection module and active buzzer
(For gas leakage detection)

S. No.	Gas Detection Module	Buzzer
1	No gas detected	Off
2	Gas detected	Sound

B. Outputs for IoT (Thingspeak)

In figure 5, the Field-2 Chart has identified the ages of two people and has also shown them in line chart form. Here, one individual is an adult (age 50) while the other is a child (age 5). (child). The age value will continue to cause the line chart to rise and fall.

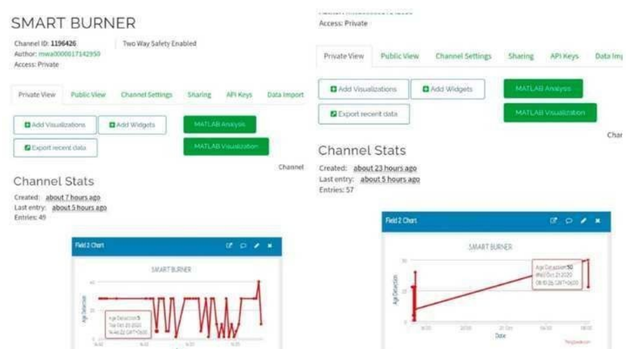

Fig. 6. Field 1's output (gas detection)

Following system execution, Field-1 Chart identified gas and represented it as a line chart form in Figure 4.5. The line stayed flat, providing the value of 0, when there was no gas detection. The value here is 1 following the gas detection, and it gradually decreases over time.

C. Benefits

The two-way safety features in our suggested smart stove include a kid lock mechanism and an alarm for an unintentional gas leak. Users can remotely monitor the stove to ensure its safety because it is IoT-capable. Deaf or mute individuals can also ensure safety by watching it from an IoT server. Blind persons can also hear the alert for an unintentional gas leak and respond appropriately.

5. Conclusion

We have proposed a combined method of both for safety measurements, despite the fact that numerous prior studies relating age detection and gas leakage detection separately have been conducted. We enabled two-way safety features, like a child lock system, in our smart stove. Our smart stove also alerts you in the event of an unintentional gas leak. Users will be able to remotely monitor the stove thanks to the IoT foundation of the smart stove we propose in this paper, helping to avoid any unintended incidents. Additionally, other nations are becoming familiar with our system. Users can remotely monitor the IoT-based smart stove's system to ensure safety GSM networks. We can add a module to our system that will enable customers to monitor the stove as well as receive email or SMS alerts when something goes wrong.

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