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ORIGINAL ARTICLE

Firefighting robot with deep learning and machine vision

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Abstract
While extinguishing the fire, firefighters find it difficult to reach certain areas due to narrow spaces or debris blocking the way. In urban cities and industrial areas, there is a constant need to have firefighters ready in case of emergencies. This can lead to a shortage of manpower. Thus, the firefighting robot can act as assisting support for firefighters and will also lower down the risk of their life. Even though many firefighter robots have been developed currently to overcome this problem, these robots are expensive and difficult to maintain. We propose an intelligent robot that uses deep learning to not only detect and classify fire but also extinguish the detected fire based on its class. The proposed firefighter robot is cheaper, autonomous, and easier to maintain. We have used a combination of AlexNet to detect fire and ImageNet for detecting the type of fire. We achieved a classification accuracy of fire detection up to 98.25%, and the classification accuracy of fire-type classification was around 92%. The firefighter robot can be deployed in places that are hard to reach for the firefighters and thereby reduce the burden on firefighters.

Keywords Firefighter robot · Deep learning · FFR

1 Introduction

Extinguishing a fire is an exhausting process as the number of fire accidents is increasing day by day, e.g., recent bushfires in Australia. The job of firefighters has become hectic and dangerous to their life. As there is a wide variety of research going on in this area, so many types of robots are already developed as a prototype by engineers and some of them are being used for fire fighting. Firefighting robot (FFR) autonomously performs a fire extinguishing operation. Although these prototypes are serving their best as alternative support, they are costly and harder to maintain. A lot of the robots in the reported literature use specialized components which are not easily available, hence, the production cost of those robots is higher. One of the robots developed uses a drone to detect and identify fires for the robot [1], thereby increasing the production cost. Some robots in the reported literature carry around water in their storage to extinguish the fire, here the water storage component has to be built such that no water leaks into the electronics [2]; hence, such robots require regular maintenance. Since there are already many firefighting robots deployed and are currently being used as support, we have proposed a cheaper and autonomous alternative that will ease out the burden of firefighters. The proposed system is built using everyday electronic components such as Raspberry Pi, Pi camera, etc., and hence, the production cost is limited. To extinguish fires the proposed system uses a standard mini-extinguisher, and hence, there is no risk of any kind of leakage and no need for constant maintenance. Also, the extinguisher can be easily replaced once it is empty.

FFR can save the life of human firefighters and can reduce the risk of accidents. The firefighting robot proposed is controlled by a fully programmable microcontroller. The proposed robot comprises a 5 MegaPixel camera, ultrasonic distance meter, and GSM module. The infrared camera provides a vision to the robot at night as well as during the daytime. There is a facility to send an SMS if the fire is not extinguished and the extinguisher tank level goes below a certain level. FFR scans for a fire around a particular radius and moves toward it autonomously once the fire is detected. The nature of the extinguishing process depends on the type and class of the fire.

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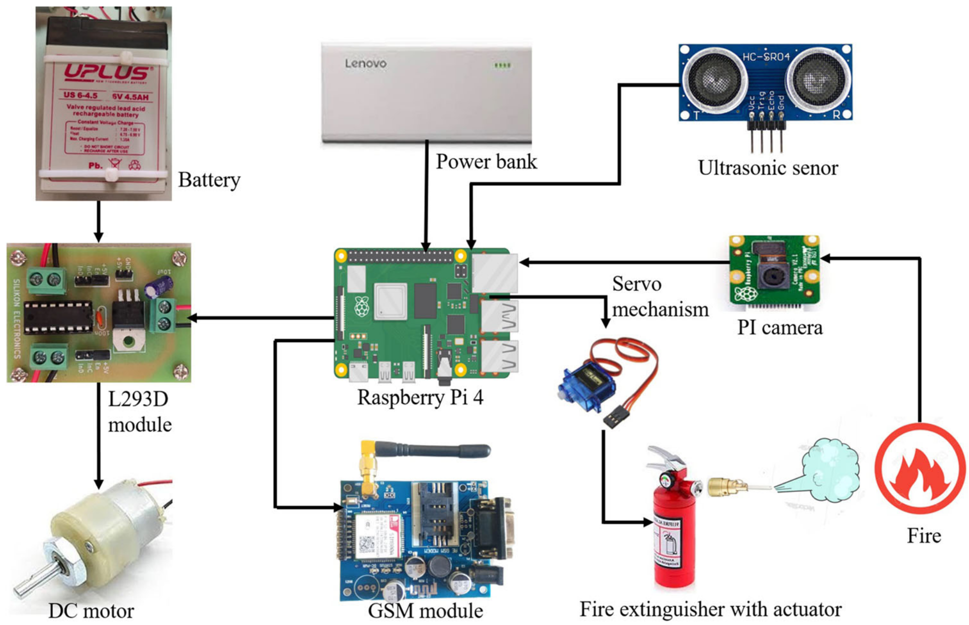


Fig. 1 Operational block diagram of firefighting robot. The fire is detected by Raspberry Pi camera, using OpenCV image processing and CNN. The power bank provides extra current to Raspberry Pi and acts as a power backup in case of power failure of the main battery. The ultrasonic sensor is used to measure the distance from the fire. The L293D module drives the DC motors required for the movement of the firefighting robot. The battery powers up the entire circuitry. GSM module sends the SMS to the firefighter in case of emergency or incapability of the robot to extinguish the fire. On detection of fire, it is extinguished by the servo-operated fire extinguisher

Figure 1 shows operational block diagram. The fire is detected by Pi camera, using OpenCV image processing and convolution neural network (CNN) (AlexNet [3, 4] and ImageNet [5, 6]). The power bank provides extra current to Raspberry Pi and acts as a power backup in case of power failure of the main battery. The ultrasonic sensor is used to measure the distance from the fire. The L293D module drives the dc motors required for the movement of the firefighting robot. The battery powers up the entire circuitry. GSM module sends the SMS to fire fighter in case of emergency or incapability of the robot to extinguish the fire. On detection of fire, it is extinguished by the servo-operated fire extinguisher.

The proposed firefighting robot has a simple designed approach compared to the other available fire extinguishing devices, [7]. The robot is compact and is developed in a way to reduce the maintenance cost and for the easy mounting of an alternate CO2 tank. For an accurate fire detection and extinguishing process, the robot has a slow movement compared to the other robots [6, 8] so that the pre-processing of the image frame can be done simultaneously. Compared to the other firefighter robots available the proposed firefighting robot is autonomous and has a fire detection accuracy of 98.25%. The proposed system is a cheaper FFR that requires less maintenance than any of the other robots in the reported literature. The proposed system is also autonomous; hence, it does not require a skilled person to operate it (Fig. 2).

2 Literature review

The main aim of this section is to offer a brief understanding of what technologies have been used to make FFRs [9, 10]. The existing methods have used different technologies to develop FFRs, and some of these have also been deployed [8, 11]. Liu et al. [2] have surveyed robots like Thermite RS1-T4 (1250 GPM) which were built by the U.S. army. It is quite small in size but can produce a thrust of 600 gallons per minute during firefighting. Another version of Thermite RS3-T1 (2500 GPM) has been included in the survey, which is an improved version of the RS1-T4 Thermite. A different version of the Thermite robot has been developed by Aliff et al. [12] that can be powered remotely and operated from up to a quarter-mile (400 m) away. FFRs consisting of robotic arms along with a camera attachment as shown in Fig. 3a have been developed by Hussien et al. [13] and Chang et al. [14]. As shown in Fig. 3b, FFR consisting of improved features such as a plow assembly [7] and a positive pressure ventilation (PPV) roller hose [15, 16] has been developed. Shipboard Autonomous FireFighting Robot (SAFFiR) developed by Lahr et al. [1] is an autonomous firefighting robot used to protect the ships from fire caused due to leakage of fuel. SAFFiR is operated with a small drone to detect fires using infrared sensors and cameras. The major downside is the slow speed of the robot and hence the U. S. Navy is working to develop more advanced sensors for

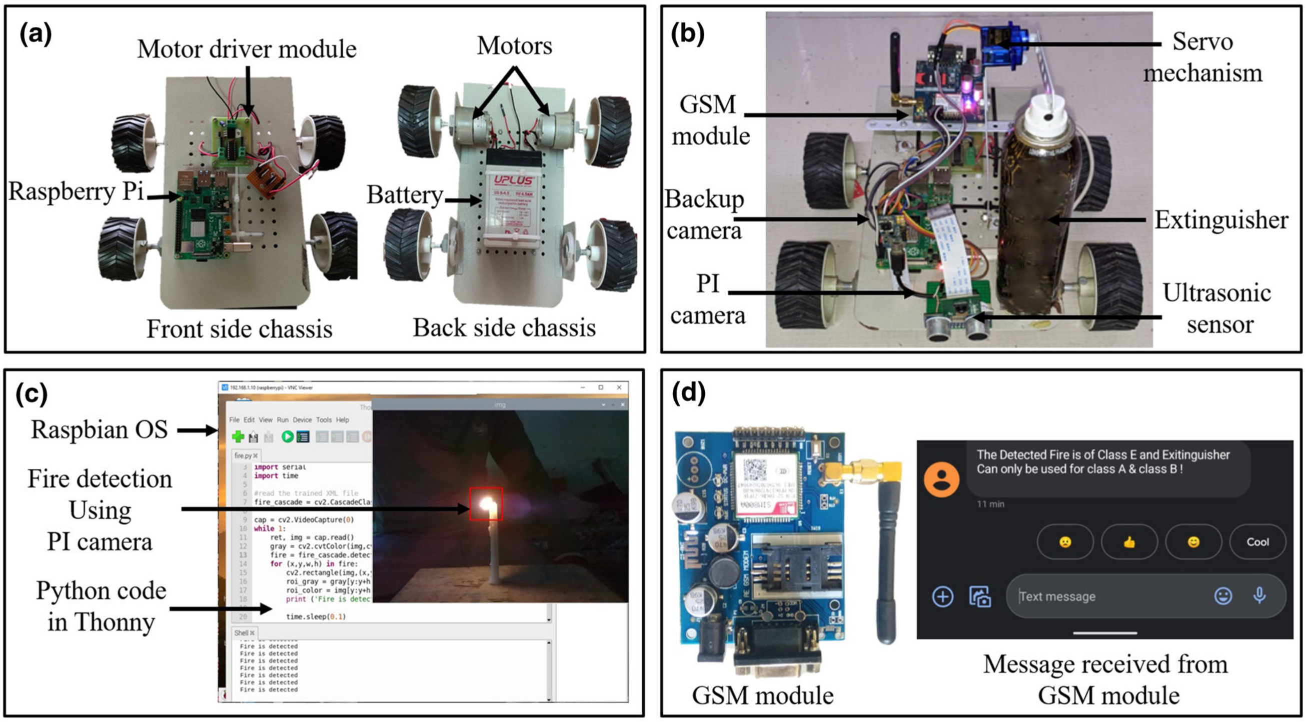


Fig. 2 Production pathway of firefighting robot. **a** The initial mounting of the components on the front side of the chassis and backside of the chassis. The front side consists of Raspberry Pi and the motor driver module, while the backside consists of a battery and motors. **b** The complete assembly of the firefighting robot with GSM module, Pi-Camera, ultrasonic sensor, fire extinguisher with servo mechanism. There is a backup camera attached in case the primary camera fails. **c** The code running in Raspberry Pi 4 on Raspbian OS. The code contains the Pi camera detection algorithm. The binary classification output along with the region of interest around the fire is shown in the image. The code compilation is done on python IDE software called Thonny editor. **d** The GSM module interfaced with the Raspberry Pi. The panel on the right shows the message received by the human firefighter regarding mismatching of class concerning the fire extinguisher mounted

SAFFiR to boost its speed, intelligence, and communication capabilities [17]. Fire Ox is an FFR surveyed by Abad et al. [18], it has support for features like situational awareness, navigation using Global Positioning System (GPS), and Global System for Mobile Communications (GSM) communications. It can carry 250 gallons and work at night with IR cameras, optional battery charging stations. The use of GPS for navigation was demonstrated by Velagic et al. [19] in their proposed robot. The MVF-5 robot developed by Župančić et al. [20] can be operated remotely but provides great reliability. It uses Global Position System-Initial Navigation System (GPS-INS), the video system consists of six high-resolution and waterproof cameras. Few FFRs also consist of a nozzle ring to dispense water and consist of a unique wheel arrangement called Dozer wheels, as shown in Fig. 3c.

Each of the available FFRs reported in the literature is unique in its way and has its mechanism of detecting fire and extinguishing it. Most of the robots use water for the fire extinguishing process, whereas the proposed system uses CO2. The proposed FFR as shown in Fig. 3d is cheaper and more compact compared to the available robots and can be easily deployed. It also has a secondary camera attached to it and consists of a secondary power source in case of any power failure. Due to its compact nature and size, it can be easily used on a small-scale area and can easily extinguish the matching fire class.

3 Methodology

3.1 Hardware details

The proposed FFR (Fig. 3d) consisted of an ultrasonic distance sensor, 5-megapixel Pi-camera, GSM module, motor driver, and servo motor-based fire extinguishing mechanism attached to Raspberry-pi micro-controller. We have used image processing and CNN networks (AlexNet and ImageNet) for classification. The proposed FFR has a battery life of 4.5 hours when powered by a 300 mAh battery.

Assembly production pathway is as per Fig. 2. Figure 2a shows the initial mounting of the components on the front side and the backside of the chassis. The front side

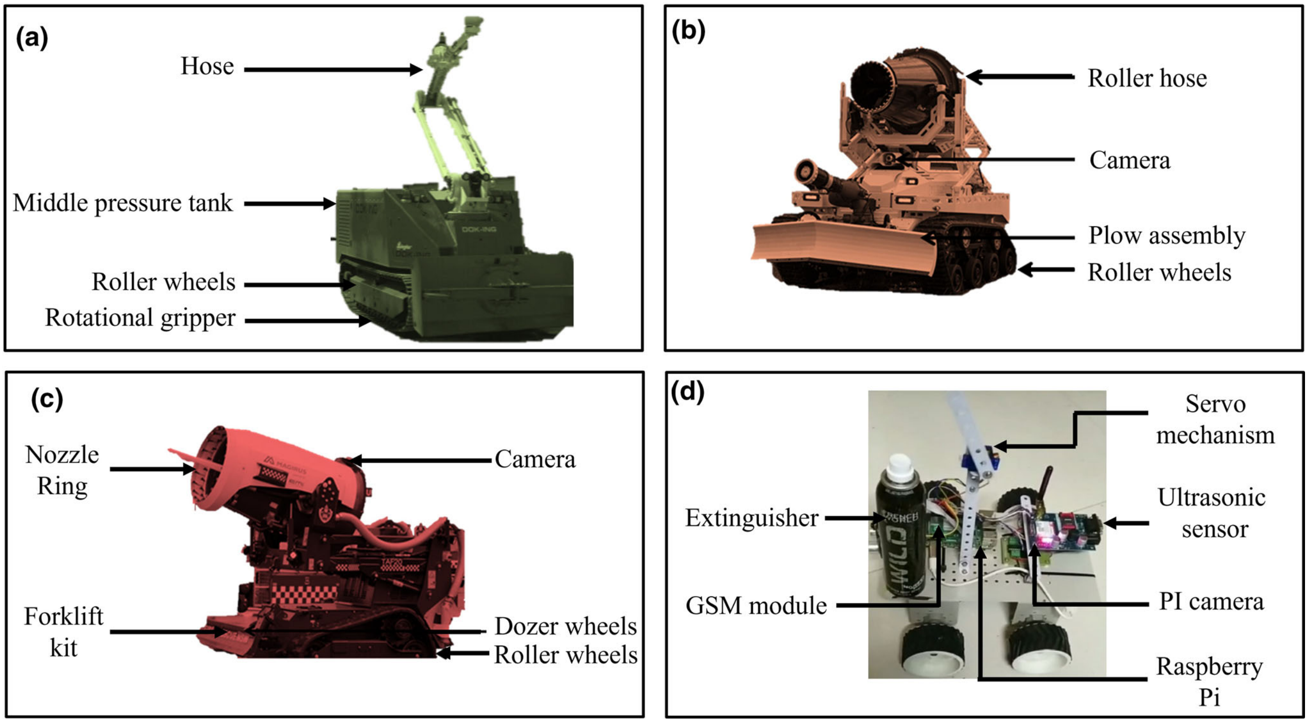
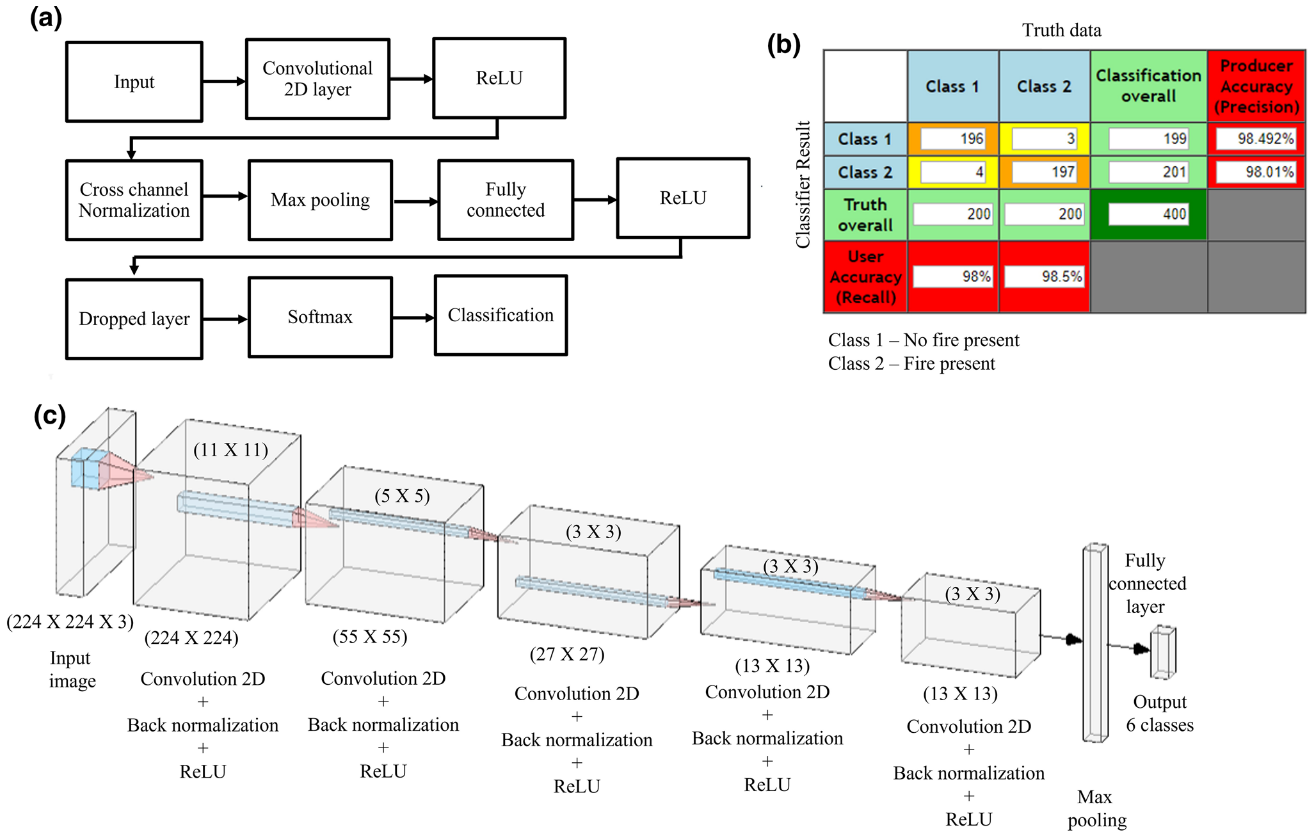


Fig. 3 Firefighting robots are reported in the literature along with our proposed firefighting robot. **a** An FFR with an adjustable hose and a pressure tank. **b** A robot consisting of a roller hose with a plow assembly in the front to pick up all the obstacles between fire and firefighter. **c** A robot with a nozzle ring and a special wheel arrangement called Dozer or roller wheels. **d** The proposed FFR consisting of a servomechanism, ultrasonic sensor, Pi camera, and Raspberry Pi. We have currently used a sample spray extinguisher mechanism along with and a GSM module

consisted of Raspberry Pi 4 and the motor driver module's backside consisted of a battery and motors. Figure 2b shows the complete assembly of the firefighting robot with GSM module, Pi-Camera, ultrasonic sensor, and fire extinguisher with servo mechanism. Figure 2c shows the code running in Raspberry Pi 4 on Raspbian OS with Pi camera detection algorithm, binary classification output, and also, the region of interest (ROI) around the fire has been depicted in red. The code compilation was done on python IDE software called Thonny editor. Figure 2d shows the GSM module interfaced with the Raspberry Pi and the panel on the right shows the message received by the human firefighter regarding the mismatching of class with respect to fire extinguisher mounted.

3.2 Fire detection

Initially, the firefighting robot was placed at the suspected area by the firefighter. Then, the firefighting robot was turned on to search the room where the fire was ignited. The robot then calculated the average distance by observing the wall boundaries and corners of the particular room. Once the dynamic distance mapping was done, the robot then tried to move toward the center and performed a 360-degree rotation to check the fire in the area. Once the checking was done, the robot then moved toward another room and performed the same searching task again. The edges were extracted from the image using a canny edge detector. To find the center of the room, the robot tried to bring equal distance in between the edges. If the fire was not found after searching in multiple rooms, the robot returned to its starting position. The robot sent an alert to the firefighter using the GSM module that "No fire is detected." To detect the fire in a particular room, the robot performed the binary classification with the help of a network derived using transfer learning from AlexNet. This binary classifying CNN had 25 layers the same as the traditional AlexNet. Figure 4a shows the signal flow diagram of AlexNet. The input image was passed through the 2D convolution layer, ReLU, and cross-normalization with the max-pooling layer. This process was repeated five times. A fully connected network, ReLU, and a dropped layer were applied twice. Finally, the softmax and classification layer was applied. If the output of the binary classification was positive, it indicated that fire was detected. Hence, the robot would start performing the secondary image processing algorithm.



	Class 1	Class 2	Classification overall	Producer Accuracy (Precision)
Class 1	196	3	199	98.492%
Class 2	4	197	201	98.01%
Truth overall	200	200	400	
User Accuracy (Recall)	98%	98.5%		

Fig. 4 **a** The signal flow diagram of the AlexNet (standard 25 layer network). The input image is passed multiple times through the 2D convolution layer, rectified Linear Unit (ReLU), and cross-normalization with max-pooling layer. A fully connected network, ReLU, and a dropped layer are applied twice. Finally, the softmax and classification layer is applied. **b** A confusion matrix for fire detection algorithm. A total of 200 images of each type were given to the binary classifier for testing, and overall accuracy of 98.25% was achieved. **c** The fire-type classifier network is a modified version of ImageNet with transfer learning. It has a total of five convolution layers consisting of 2D convolution, back normalization, and max-pooling units. An RGB image of dimensions 224 × 224 pixels is given to the network as an input. The size of convolution layers is 224 × 224, 55 × 55, 27 × 27, 13 × 13, 13 × 13, respectively. Finally, the output is given to max-pooling and fully connected layer. If the ROI of the cropped image is smaller than the input image, the image is resized accordingly

3.3 Fire-type classification

In the secondary image processing algorithm, we had generated a deep neural network that consisted of a trained transfer learning model from ImageNet. The training model was trained using 100 positive fire images and 100 images with no fire. Files used for transfer learning for ImageNet were obtained from the local research laboratory at Thane, India (Ninad‘s Research Lab).

Figure 4c shows the fire-type classifier network which was a modified version of ImageNet with transfer learning. It had a total of five convolution layers consisting of 2D convolution, back normalization, and max-pooling units. The size of convolution layers was 224 × 224, 55 × 55, 27 × 27, 13 × 13, and 13 × 13, respectively. Finally, the output was given to max-pooling and fully connected layer. The size of the input RGB image was 224×224 pixels. If the ROI of the cropped image was smaller than the input image, the image was resized accordingly.

To determine the class and type of fire, the software flow diagram is as shown in Fig. 5. We used image cropping and pre-processing techniques. The image obtained from the camera feed was resized and then converted into a grayscale format. After performing the grayscale conversion, the image was smoothed by applying the Gaussian filter, and thus, a clear image was obtained. The image binarization was then performed using Otsu’s algorithm. The fire pixels were then extracted from the image with the help of erosion and dilation techniques. The original image was then also parallelly converted from BGR format to HSV format depending upon the predefined HSV ranges. Finally, both HSV and binary images were used to extract the binary classification of ‘Fire’ or ‘No fire’. If the fire detected was cross-verified, the features were passed to ImageNet. Thus, the class of the fire was determined. Once the class of fire and type of extinguisher matched, the extinguishing process was initialized otherwise SMS was sent to the human firefighter about the class mismatch.

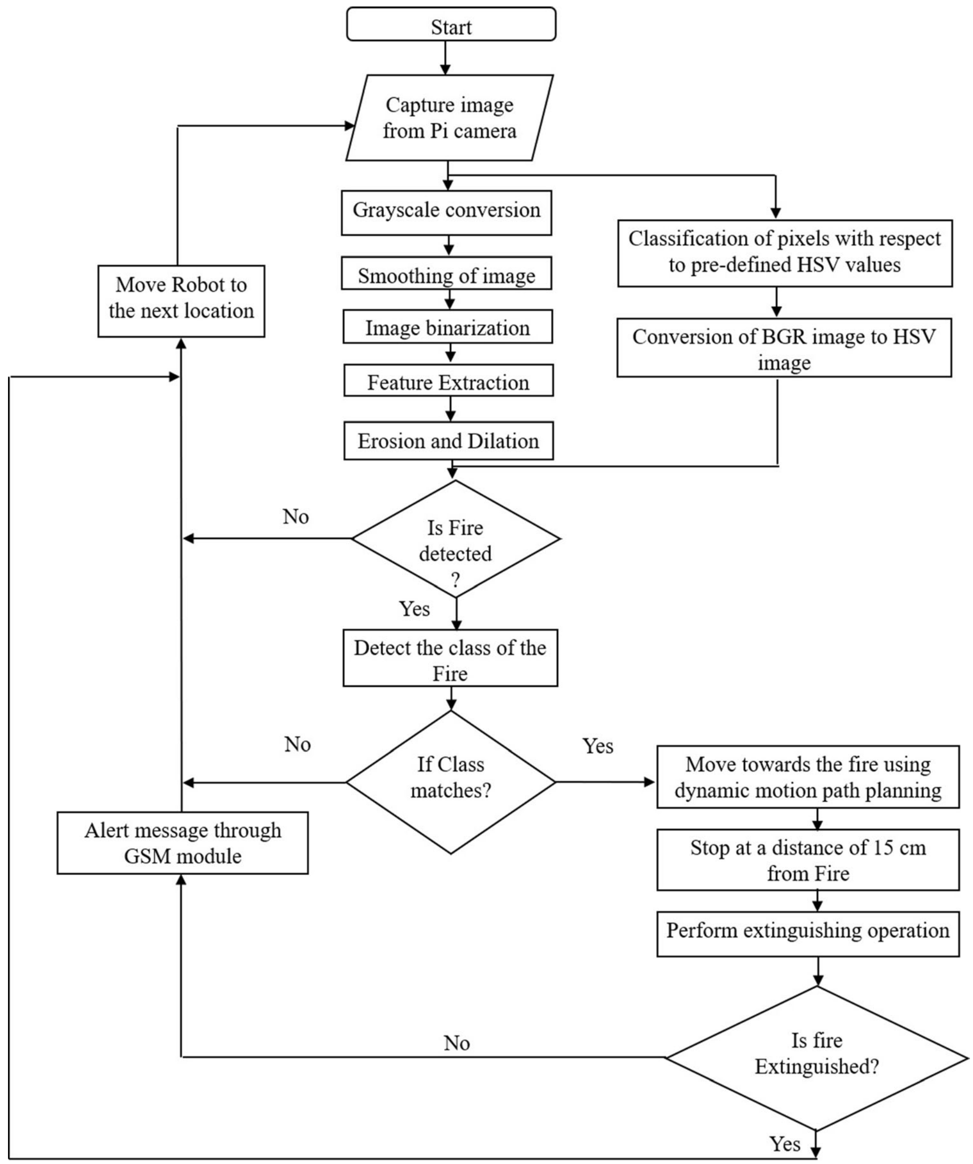


Fig. 5 Software algorithm flow chart for deep learning firefighting robot. Initially, the color image is captured and is converted into HSV format for feature extraction. Simultaneously the original image is converted into grayscale and smoothed using Gaussian Filter. Further, the smoothed image is binarized and morphological operations are performed on it. The HSV and binary features are used for fire detection. Once the fire is detected, the class of fire is obtained using ImageNet and compared with the extinguisher mounted. If the class is matched, the fire extinguisher moves toward it and extinguishes it from a safe distance of 15 cm. In case of any failure, the alert message is sent to the human firefighter and the robot moves toward the next possible fire location

3.4 Fire extinguishing process

If the detected class of fire matched the extinguisher type installed on to the robot, then only the robot moved toward the fire area by keeping the fire at the center of the frame of the Pi-camera. The extinguishing process began once the ultrasonic distance sensor and image processing techniques confirmed the arrival of the robot at a safe extinguishable distance of 15 cm from the fire. The servo mechanism attached to the robot was released according to the timer attached and the estimated water quantity required for fire extinguishing. If the water quantity was below a certain level, then the robot sent an alert message to the firefighter saying 'Fire not extinguished returning to the starting position.' The robot then moved to its original starting point by performing a reverse mapping technique. For example, if the robot would have rotated in a clockwise direction for 15 s, then the robot would rotate in the anti-clockwise direction for 15 s.

3.5 System operation

The proposed FFR can be placed in any area/room. When the system is switched on, it will mark its initial position as the starting position. Then, it will start searching for the fire, by positioning itself at the center of a room and rotating 360°. If a fire is not detected the system will move onto the next room and repeat the procedure until the entire area is checked. If no fire is detected in the entire area, then the system will return to its starting position. If a fire is detected in one of the rooms, then the type of fire will be checked using ImageNET. If the detected fire type and the fire type of the installed extinguisher match, then the extinguisher is used to put out the fire. If the two fire types do not match the system informs the firefighter by sending an SMS, that the system cannot extinguish the fire.

4 Results and discussion

Fire detection was tested using the AlexNet. Figure 4b shows a confusion matrix for fire detection algorithm. A total of 200 images of each type were given to binary classifier testing, and 98.25% overall accuracy was achieved. As shown in Fig. 6, the overall classification accuracy of the fire-type classifier had reached up to 91.83%. There are 6 desired classes and corresponding 6 predicted classes in the confusion matrix. Class A fires consist of combustible solid substances, class B fires consist of combustible liquids, class C fires consist of combustible gases, while fires caused due to combustible metals come under class D. The total number of test images (of each type of fire) in each desired class was 100 and hence, we were expecting all the diagonal elements (i.e., true positive) to be 100. We got a maximum accuracy of 97 % in Class E fire, which belonged to the short circuit and electrical fire category, whereas minimum accuracy appeared in Class B fire. The minimum accuracy was expected in class B because, most of the images in class B fire were closely resembling class C, D, and E. Fires caused due to oils and fats come under class F. Achieving a high accuracy for class B was difficult because of the large color variations. On the other hands, Class E fire had a distinct background and texture with black smoke making it easy to segregate from other types of fires. As shown in Table 1, the algorithm was able to classify the image type with an overall accuracy of 91.83%.

100 images from all types of classes were selected randomly from the validation folders. As shown in Table 1, the maximum True Positive (TP) count of fire class type could go up to 97 out of 100. The maximum value of accuracy, precision, and F1 score was 98.67, 98, and 96%, respectively, and was recorded for the class F fire-type.

Table 2 shows a comparison between different FFRs. Since the proposed system was a prototype, the size was very compact compared to others, except for the MVF-5 robot [20]. However, the speed of the proposed autonomous robot was the slowest, the reason being that it performs real-time image processing using deep learning that takes time for computation on Raspberry Pi. The only two battery-powered robots were SAFFiR [1] and our proposed system, which is a major advantage. The most important advantage of our robot is its autonomous nature, and the second-best thing is the price, which is just about 200 USD. The working of the robot is shown in supplementary video 1.

The following improvements are possible in the proposed robot. We had only one layer of protection but the indoor firefighting robot should have five layers, namely AG coating, aluminum board, non-flammable material, air barrier, and insulation board. The main drawback of adding these materials is that they are heavy and they slow down the robot movement. FFRs can also have a LiDAR or a radar sensor. Under zero visibility (as is the case of fire smoke) even for many electronic sensors, it is very difficult

Desired class

Resultant class	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Classification overall	Producer Accuracy (Precision)
Class 1	89	0	1	4	2	5	101	88.119%
Class 2	5	87	1	5	0	0	98	88.776%
Class 3	3	1	93	0	1	0	98	94.898%
Class 4	0	2	5	91	0	1	99	91.919%
Class 5	1	10	0	0	97	0	108	89.815%
Class 6	2	0	0	0	0	94	96	97.917%
Truth overall	100	100	100	100	100	100	600	
User Accuracy (Recall)	89%	87%	93%	91%	97%	94%		Overall Accuracy 91.833%

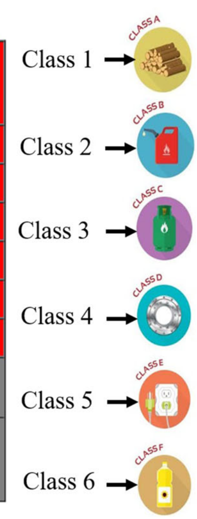


Fig. 6 Confusion matrix for the classification of the fire-type classifier using ImageNet. 100 images of each class, i.e., 600 images from six different types of fire were given as testing images to the tuned ImageNet network. Maximum accuracy obtained was from class 5/E, i.e., electrical type of fire, and minimum accuracy obtained was from class 2/B, i.e., fire due to fuels and other combustible gases. Overall accuracy was approximately 92%

Table 1 Result evaluation of fire-type classification

Class	*n* (truth)	*n* (classified)	Accuracy	Precision	Recall	F1 Score
1/A	100	101	0.9617	0.88	0.89	0.89
2/B	100	98	0.96	0.89	0.87	0.88
3/C	100	98	0.98	0.95	0.93	0.94
4/D	100	99	0.9717	0.92	0.91	0.91
5/E	100	108	0.9767	0.9	0.97	0.93
6/F	100	96	0.9867	0.98	0.94	0.96

The highest accuracy of 97% was achieved for class E types fires. Minimum accuracy was achieved for class B fires

Table 2 Comparison between different firefighting robots

	Size (L*W*H)	Speed (km/hr)	Power source	Control	Weight (kg)	Price	Origin
Thermite RS1-T4 [2]	(188*89*144)	20	Diesel Engine	Radio control	744	$98,000	US
Thermite RS1-T1 [12]	–	–	Diesel Engine	Remote control	–	–	US
SAFFIR [1]	1.77m	–	Battery	–	63	$1,000,000	US
MVF5 [21]	(38*21*21)	12	Diesel Engine	Remote control	9.2	–	Croatia
Proposed system	(20*25*45)	5	Battery	Autonomous	5.6	$200	India

All reported robots are larger in size, costly, and heavier than the proposed FFR. In comparison to the reviewed robots, only the proposed FFR is autonomous

to detect the fire, so infrared vision can be used to acquire 3-D scene information. FFRs can also have a flame sensor. The proposed firefighting robot uses wheel drive which we are planning to replace with a biped mechanism. The current fire classification accuracy can be improved by adding more images to the training dataset. We also intend to install multi-class fire extinguishers in near future. Also, flawless detection of fire will be possible if a thermal vision camera or a contactless temperature sensor such as LMX 90614 is installed.

5 Conclusion

We have implemented a firefighting robot using deep learning technology and machine vision on the Raspberry Pi 4 (4GB) platform. We found that a combination of AlexNet and ImageNet is useful for achieving an accuracy of 98.25% and 92%, respectively. High-performance computers were used for performing transfer learning. The Raspberry Pi 4 has enough computation power to perform real-time image processing with pre-trained networks. We assume that this could be the starting point of applying innovative deep learning technologies in the field of fire-fighting and similar applications where human lives can be saved. Although the proposed firefighting robot will extinguish the fire autonomously, it is limited to certain fire types. The proposed firefighting robot has high accuracy in extinguishing fire belonging to class E type and as of now, it can only be used in the household to extinguish fires caused due to electric appliances. The firefighting robot is a great alternative, but its usage is limited to its battery and the availability of CO2.

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Author contributions Conceptualization was done by Ninad Mehendale (NM). All the experiments/code executions were performed by Amit Dhiman (AD) and NM. The formal analysis was performed by AD and NM. Manuscript writing- original draft preparation was done by AD. Review and editing were done by NM. Visualization work was carried out by AD and NM.

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Declarations

Conflicts of interest Authors A. Dhiman and N. Mehendale declare that there has been no conflict of interest.

Ethics approval All authors consciously assure that the manuscript fulfills the following statements: (1) This material is the authors' own original work, which has not been previously published elsewhere. (2) The paper is not currently being considered for publication elsewhere.

(3) The paper reflects the authors'own research and analysis in a truthful and complete manner. (4) The paper properly credits the meaningful contributions of co-authors and co-researchers. (5) The results are appropriately placed in the context of prior and existing research.

Consent to participate This article does not contain any studies with animals or humans performed by any of the authors. Informed consent was not required as there were no human participants. All the necessary permissions were obtained from Institute Ethical committee and concerned authorities.

Consent for publication Authors have taken all the necessary consents for publication from participants wherever required.

code availability All the codes used in this study are provided in the supplementary material.

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