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Fire fighter robot with deep learning and machine vision

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Abstract The deep learning algorithms and robotics have emerged in each and every field of human life. Most of the recent innovations in image recognition are dependent on deep learning technology. In this manuscript, we present an intelligent robot that uses this deep learning to detect and classify fire. We have used a combination of Alexnet to detect fire and Imagenet for detecting the type of fire. We found out that the classification accuracy of fire detection goes up to 98.25 %. and classification accuracy of firetype classification was around 92 %. We believe that there is a lot of scope to improve the accuracy in firetype classification but could be a good starting point to design robots as per the class of fire with machine vision.

Keywords Fire Fighting Robot · Deep Learning · FFR

1 Introduction

Fire Fighting Robot (FFR) autonomously performs a fire extinguishing operation. FFR can be used as an alternative or supportive mechanism for human firefighters. FFR can save the life of human firefighters and can reduce the risk of accidents. Extinguishing a fire is an exhausting process as the number of fire accidents is increasing day by day e. g. recent bushfires in Australia. FFR scans for a fire around a particular radius and moves towards it autonomously once the fire is detected. The bot stops at a safe distance from the fire using the sensor. The nature extinguishing process is performed depending upon the type and class of the fire. As there is a wide variety of research going on in this area, so many types of robots are already designed as a prototype by engineers and some of them are being used for fire fighting.

The fire fighting robot proposed is controlled by a fully programmable microcontroller. The proposed robot comprises of 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 day time. There is a facility to send an SMS if the fire is not extinguished and extinguisher tank level goes below a certain level. Figure 1 shows operational block diagram.The fire is detected by PI camera, using open cv image processing and CNN (Alextnet [1, 2] and Imagenet [3,4]). 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 fire fighting robot. The battery powers up the entire circuitry. GSM module sends the SMS to 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.

2 Literature review

The main aim of this section is to offer a brief understanding of what technologies many people already used to make firefighting robots[5,6]. As there is a wide variety of research going on in the fire fighting robot area, there are many types of robots already designed and prototype by engineers[7,8], and some of them are even actually being used for fire fighting. Robots like Ther-

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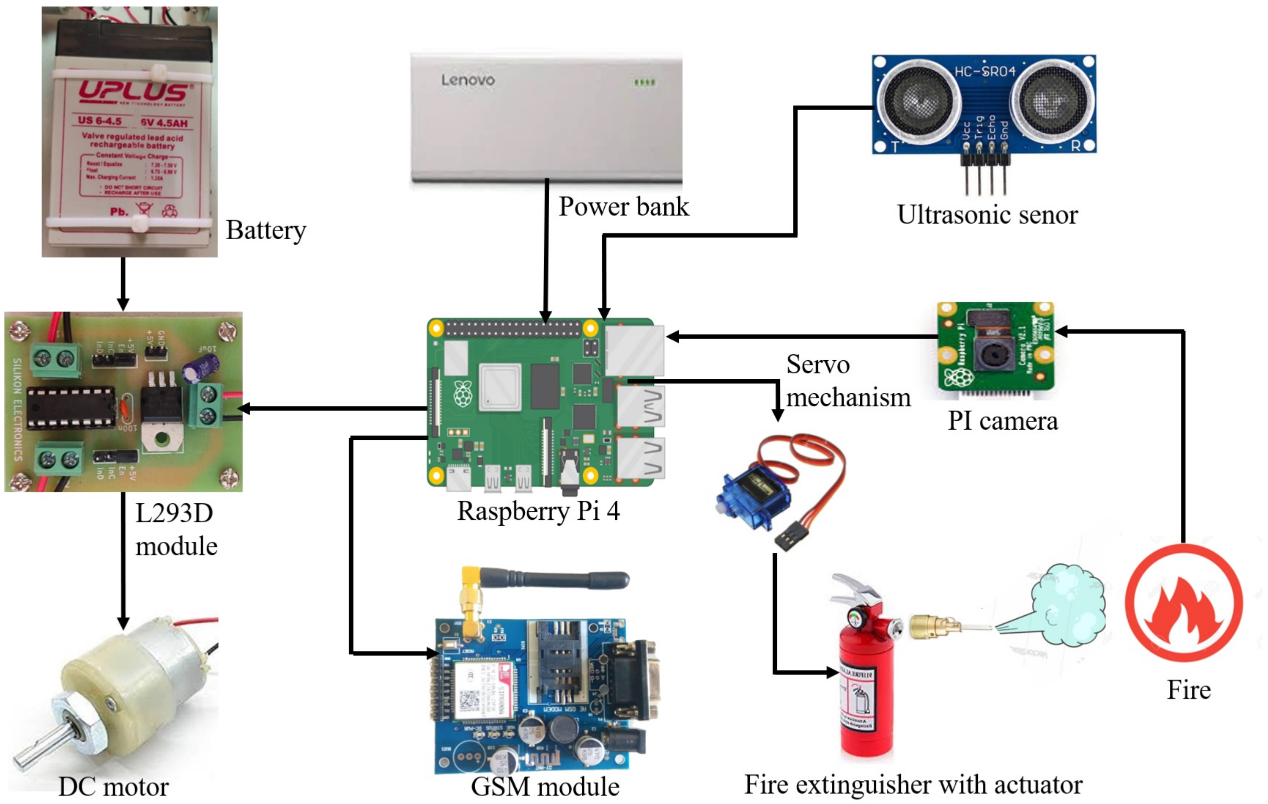

Fig. 1 Operational block diagram of fire fighting robot. The fire is detected by PI camera, using open cv image processing and CNN. The power bank provides extra current to raspberry pi and acts as a power backup in case of power failure of the main battery. The ultrasonic sensor is used to measure the distance from the fire. The L293D module drives the dc motors required for the movement of the fire fighting robot. The battery powers up the entire circuitry. GSM module sends the SMS to 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.

mite RS1-T4 (1250 GPM) [9] are built by U.S. army. It is very small in scale but can produce a thrust of 600 gallons per minute during fire fighting. The thermite [10] is powered remotely and can be operated from up to a quarter-mile (400m) away. It also has robotic arm (fig. 2 (a)) and camera attachment[11,12]. Another version of Thermite RS3-T1 (2500 GPM) [9], which is improved version of the RS1-T4 thermite. Every feature is improved and it also includes a plow assembly [13] and a positive pressure ventilation [14,15] (PPV) roller hose (fig. 2 (c)). THOR/SAFFiR [16] is an autonomous firefighting robot used to protect the ships from fire due to leaked fuel. SAFFiR operated with a small drone to detect fires, using infrared sensors and cameras. The big downside is robot speed and hence the U. S. Navy is working to develop more advanced sensors for SAFFiR to boost its speed, intelligence, and communication capabilities [17]. Turbine Aided Firefighting Machine (TAF 20) [18] was developed in Australia (fig. 2 (b)). It was a fire fighting robot that can be remotely operated and can clear away hazards and clear smoke from burning buildings. It can also spray 60 up to meters of water or foam and 90 meters of blast water. It can be controlled remotely up to 500 meters away and sent to situations where it is too risky for firefighters to breathe. Fire Ox [19] fire fighting robot has support for features like situational awareness, navigation of GPS, and GSM communications [20]. It can carry 250 gallons and work at night with IR cameras, optional battery charging stations. The MVF-5 robot [21] can be operated remotely but provides great reliability. It uses GPS-INS (Global position system-Initial Navigation system), the video system consists of six high resolution and waterproof cameras. One of the cameras is a thermal camera [22] which allows the MVF-5 to operate under reduced visibility conditions.

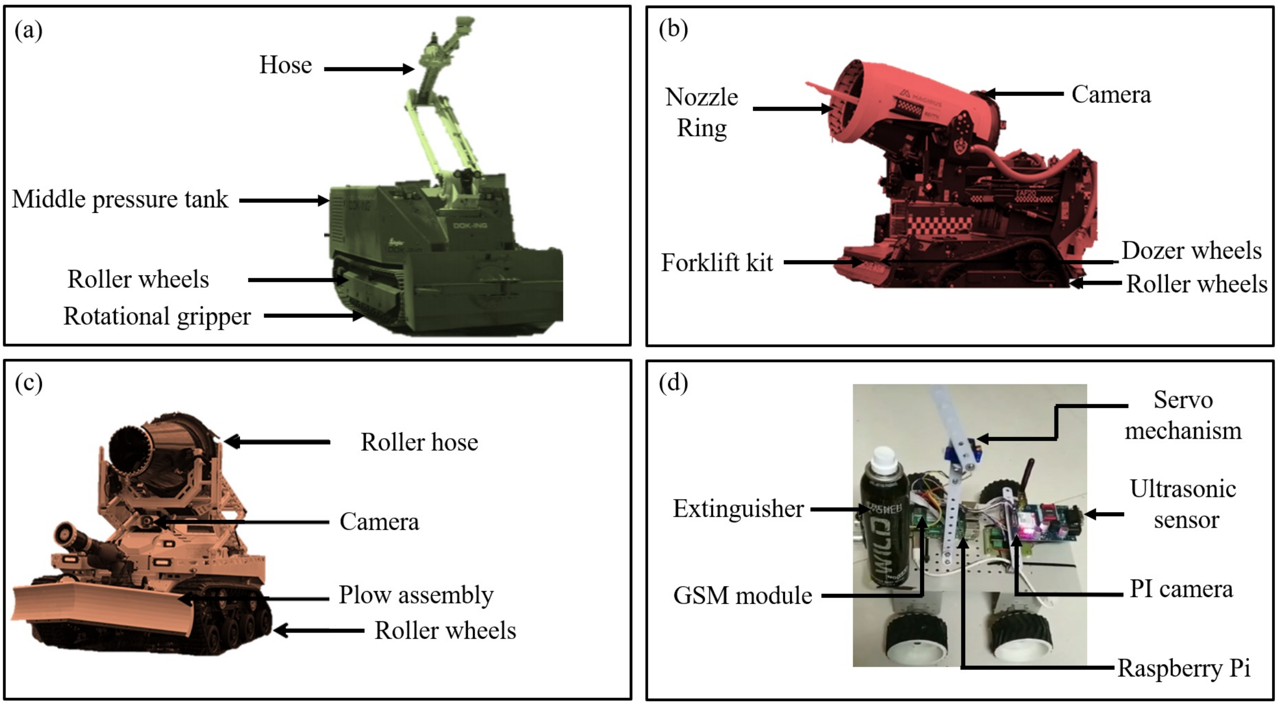

Fig. 2 Fire fighting bots reported in literature along with our fire fighting bot. (a) A fire fighting robot with adjustable Hose and a pressure tank. (b) A robot with a nozzle ring and a special wheel arrangement called Dozer or Roller wheels. (c) A robot with a roller hose with a Plow assembly in the front to pick up all the obstacles between fire and firefighter. (d) Our robot, that has a servomechanism, ultrasonic sensor, Pi camera, and Raspberry pi. We have currently used a sample spray extinguisher mechanism along with and a GSM module

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

Table 1 Result evalution of firetype classification

3 Methodology

3.1 Hardware details

The firefighting bot (fig. 2) (d) consists of an ultrasonic distance sensor, 5 Megapixel Pi-camera, GSM module, Motor driver, and Servo motor based fire extinguishing mechanism attached to Raspberry-pi microcontroller. The technology we are using is an image processing and CNN networks (Alexnet and Imagenet) for classification. Assembly production pathway is as per figure 3.Figure 3 (a) shows the initial mounting of the components on the front side of the chassis and backside of the chassis. Frontside consisted of Raspberry pi and the motor driver module backside consisted of a battery and motors. Figure 3 (b) shows the complete assembly of the fire fighting robot with GSM module, Pi-Camera, ultrasonic sensor, fire extinguisher with servo mechanism. Figure 3 (c) 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 around the fire is been dipected in red. The code compilation is done on python IDE software called Thonny editor. Figure 3 (d) shows the GSM module interfaced with the raspberry pi and panel on right shows the message received by the human firefighter regarding mismatching of class with respect to fire extinguisher mounted.

3.2 Working

The robot initially moves and searches for the fire, if there is a fire in the path it moves on then the robot

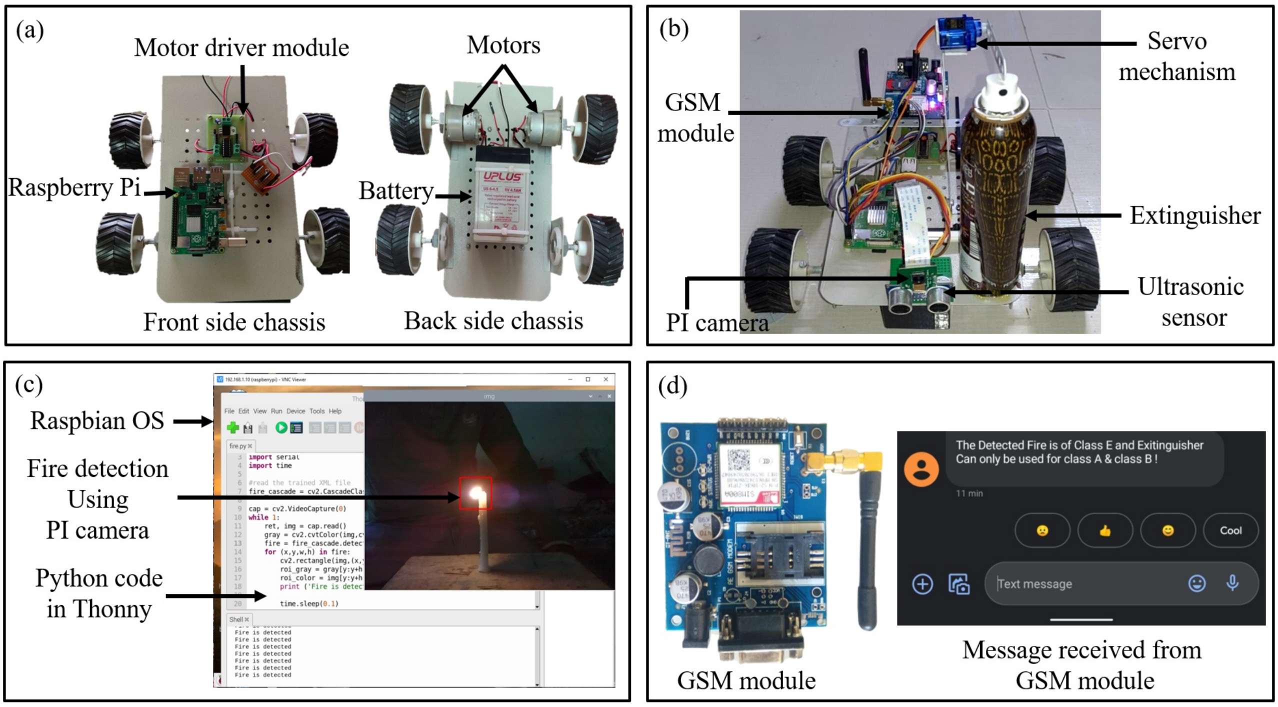

Fig. 3 Production pathway of fire fighting bot. (a) The initial mounting of the components on the front side of the chassis and backside of the chassis. Frontside consisted of Raspberry pi and the motor driver module backside consisted of a battery and motors. (b) The complete assembly of the fire fighting robot with GSM module, Pi-Camera, ultrasonic sensor, fire extinguisher with servo mechanism. (c) The code running in Raspberry pi 4 on raspbian OS with Pi camera detection algorithm, binary classification output, and also the region of interest around the fire is been dipected in red. The code compilation is done on python IDE software called Thonny editor. (d) The GSM module interfaced with the raspberry pi and panel on right shows the message received by the human firefighter regarding mismatching of class with respect to fire extinguisher mounted.

will process the image and detect the type of fire, and then Extinguish the fire.

3.3 Fire detection

Initially, the Fire Fighting Robot is brought to the floor by the firefighter and simultaneously, turns on the robot by placing it in a room where the fire is ignited. The robot then calculates the average distance by observing the wall boundaries and corners of the particular room. Once the dynamic distance mapping is done, the robot then tries to move towards the center and performs a 360-degree rotation to check the fire in the area. Once the checking is done the robot then moves towards another room performing the same searching task again. The edges were extracted from the image using a canny edge detector. To find the center of the room robot tries to bring the equidistance between the edges. If the fire is not found after searching in multiple rooms the bot returns to its starting position using the robot sets alerts to the firefighter using the GSM module that " No fire is detected ". To detect the fire in a particular room, the robot performs the binary classification using transfer learned derived network from Alexnet. This binary classifying CNN has 25 layers the same as traditional Alexnet. Figure 5 (a) shows the signal flow diagram of the AlexNet. The input image is passed to the 2d convolution layer, ReLU, and cross normalization with max-pooling 4 times. A fully connected network, ReLU, and a dropped layer is applied twice, and finally, the softmax and classification layer is applied. If the binary classification outputs positive i.e. if the fire is detected then the robot starts performing the secondary image processing Algorithm.

3.4 Firetype classification

In the secondary image processing algorithm, we had generated a deep neural network that consisted of a training 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 lab at Thane, India (Ninad‘s Research Lab). To determine the class and type of the fire software flow diagram is as shown in figure 4, we used image

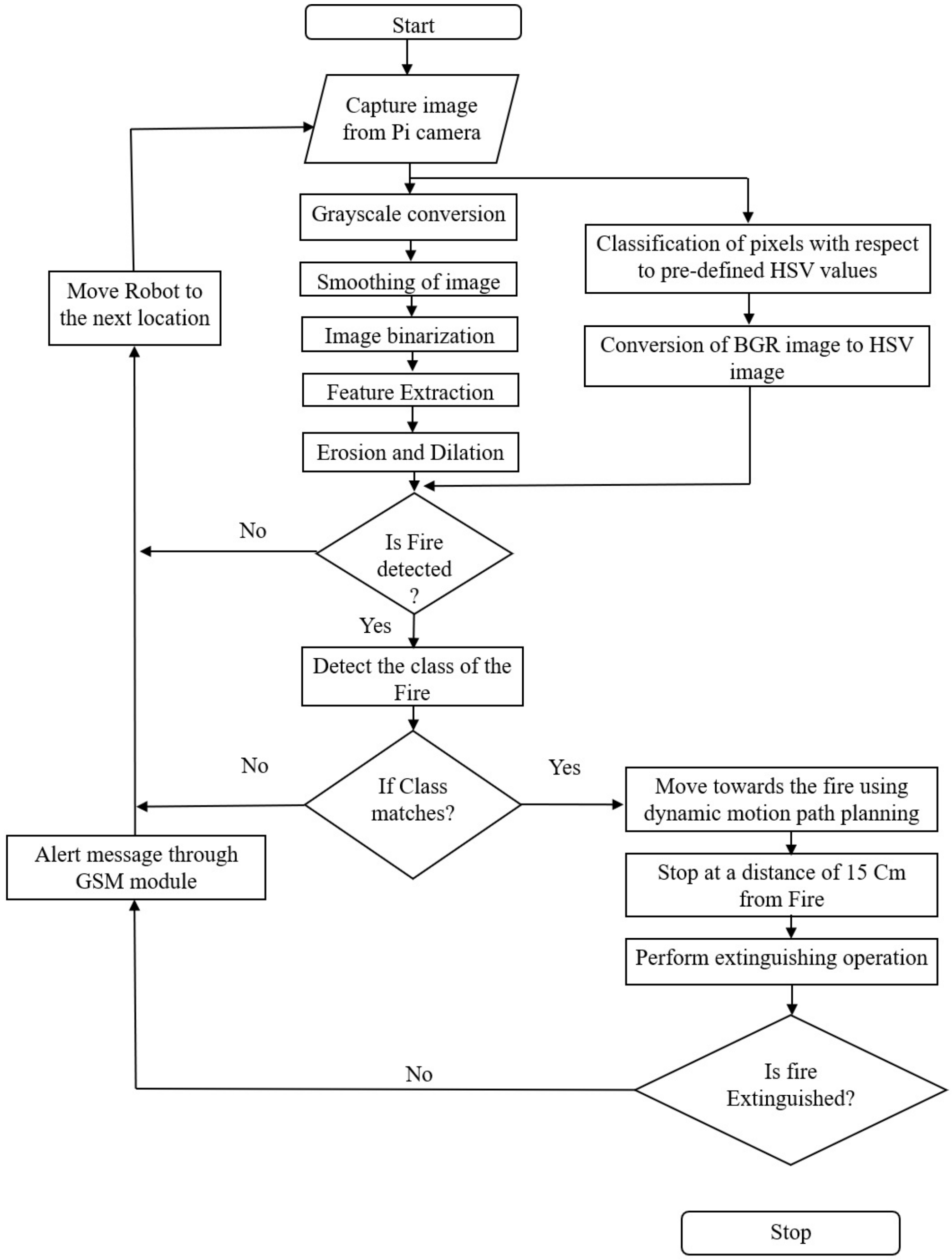

Fig. 4 Software algorithm flow chart for deep learning fire fighting robot. Initially the color image is captured and is converted into HSV format for feature extraction. Simultaneously the original image is converted into grayscale and smoothened using Gaussian Filter. Further the Smoothened image is binarized and morphological operations 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 towards 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 towards the next possible fire location.

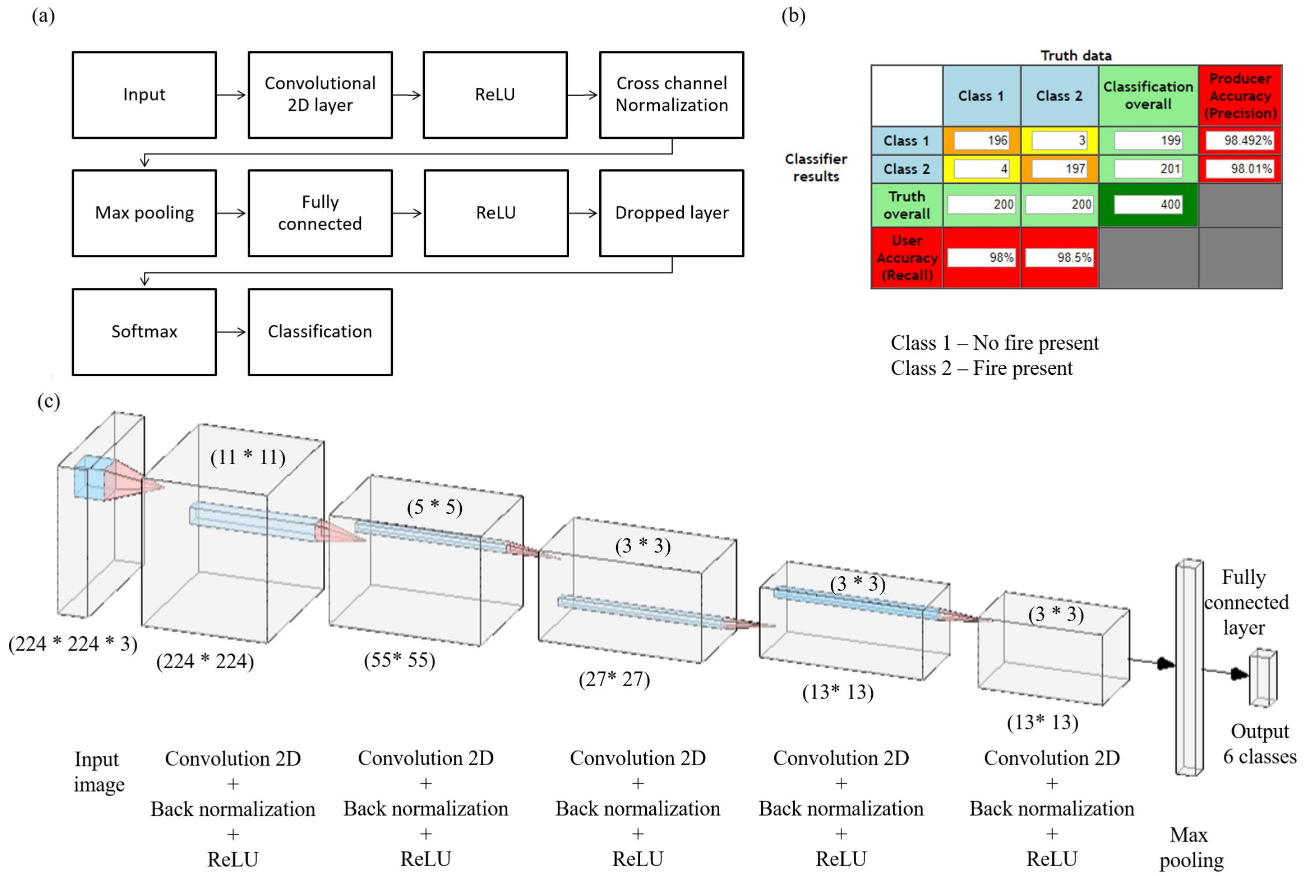

Fig. 5 (a) The signal flow diagram of the AlexNet (Standard 25 layer network). The input image is passed to the 2d convolution layer, ReLU, and cross normalization with max-pooling multiple times. A fully connected network, ReLU, and a dropped layer is applied twice, and finally, the softmax and classification layer is applied. (b) A confusion matrix for fire detection algorithm. Total 200 images of each type were given to binary classifier testing and 98.25 % overall accuracy was achieved. (c)The firetype classifier network which is a modified version of Imagenet with transfer learning. It has a total of 5 convolution layers consisting of 2d convolution, back normalization, and max-pooling units. The size of convolution layers are (254*254), (55*55), (27*27), (13*13), (13*13) respectively. Finally output is given to max-pooling and fully connected layer. The input image size is (224*224*3) color image. If ROI of the cropped image is smaller than the input image, the image is resized accordingly.

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 smoothened by applying the Gaussian filter and thus a clear image is obtained. The image binarization was then performed using Otsu's algorithm. The fire pixels are then extracted from the image and with the help of erosion and dilation techniques. The original image is then also parallelly converted from BGR format to HSV format depending upon the predefined HSV ranges. Finally both HSV and binary are used to extract the binary classification of Fire or No fire. If the fire detected is cross-verified then features are passed to imagenet and thus the class of the Fire is determined. Once the class of fire and type of extinguisher are verified then the extinguishing process is initialized or SMS sent to human firefighter about the class mismatch. figure 5 (c) shows the firetype classifier network which is a modified version of Imagenet with transfer learning. It has a total of 5 convolution layers consisting of 2d convolution, back normalization, and max-pooling units. The size of convolution layers are (254*254), (55*55), (27*27), (13*13), (13*13) respectively. Finally output is given to max-pooling and fully connected layer. The input image size is (224*224*3) color image. If ROI of the cropped image is smaller than the input image, the image is resized accordingly.

3.5 Fire extinguishing process

If the detected class of fire matches the extinguisher type installed on to the robot, then the only robot then moves towards the fire area by keeping the fire area at the center of the frame of pi CAM. The extinguishing process begins once the ultrasonic distance sensor and

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%

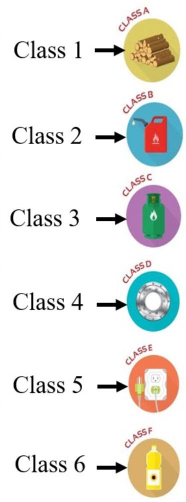

Fig. 6 Confusion matrix for the classification of firetype classifier using imagenet. 100 images of each class i.e. 600 images from six different types of fire, were given as testing images to tunned Imagenet network. Maximum accuracy obtained was from class 5/E i.e. electrical type of fire, and minimum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

image processing techniques confirm the arrival of the robot and safe extinguishable distance i. e. 15 cm from the fire. The servo mechanism attached to the robot is released according to the timer attached and estimated water quantity required for fire extinguishing. If the water quantity is below the low level then the robot sends an alert message to the firefighter “Fire not extinguished returning to the starting position ”. The robot then moves to its original starting point by performing a reverse mapping technique (e.g. 15 seconds clockwise moved robot now will rotate the same motor for 15 seconds anticlockwise.)

4 Results and discussion

Fire detection was tested using the Alexnet. Figure 5 (b) shows a confusion matrix for fire detection algorithm. Total 200 images of each type were given to binary classifier testing and 98.25 % overall accuracy was achieved.

As shown in fig. 6, the classification accuracy of the firetype classifier has reached up to overall accuracy of 91.83 %. There are 6 desired classes and corresponding 6 predicted classes in the confusion matrix. 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. It was expected because, most of the images in class B fire, were closely resembling with class C, D, and E. Accuracy of classifying flammable liquids was difficult because of large color variations also. On the other hand Class F fire which belongs to Electrical fire has a distinct background and texture with black smoke makes 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 efficiency of 91.83 %. There were 100 images selected randomly from validation images folders from all types of classes. As seen in table 1 the maximum True Positive(TP) count of fire class type could go up to 97/100. 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 fire fighting robots. Since ours was the prototype hence the size was very compact, compared to others, except for MVF5. Though the speed of the proposed autonomous bot was the slowest, the main reason behind it is real-time image processing using deep learning takes time for computation on Raspberry Pi and hence reduces the speed. The only two battery-powered robots were SAFFIR and our proposed system, which is a major advantage. The most important advantage of our bot is autonomous nature and the second best thing is the price, which is just 200 USD. Though most of the commercial robots are from the USA, ours will be the first one from India. The working of the robot is shown in the supplementary video 1. The following improvements are possible in the proposed bot. We had only one layer of protection but the indoor fire fighting robot should have 5 layers. Ag coating, Aluminum board, Non-flammable

	Size (L*W*H)	Speed (km/hr)	Power source	Control	Weight (kg)	Price	Origin
Thermite RS1-T4 [9]	(188*89*144)	20	Diesel Engine	Radio control	744	$98000	US
Thermite RS1-T1 [10]	–	–	Diesel Engine	Remote control	–	–	US
SAFFIR [16]	1.77m	–	Battery	–	63	$1000000	US
TAF20 [18]	–	–	–	Remote control	–	$310,000	Germany
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

Table 2 Comparison between different fire fighting robots

material, air barrier, and Insulation board. As the layers added, the main drawback is that the material is heavy, and also the weight of the fire extinguisher increases the weight of the entire machine. FFR can have LiDAR or a Radar sensor. Under zero visibility, as in the case of fire smoke, even for many electronic sensors, it is very difficult to detect fire, so IR vision can be used to acquire 3-D scene information. FFR can have a flame sensor as well.

5 Conclusions

We had implemented a Fire fighting 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. For transfer learning purposes, we preferred using high-end computers, and to run a live image processing with pre-trained networks Raspberry pi 4 was capable enough. We assume that this could be the starting point of innovative deep learning technologies in the field of fire fighting and similar applications where human life can be saved.

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Compliance with Ethical Standards

Conflicts of interest

Authors declare that they have no conflict of interest.

Involvement of human participant and animals

This article does not contain any studies with animals or Humans performed by any of the authors. All the necessary permissions were obtained from the Institute Ethical Committee and concerned authorities.

Information about informed consent

Informed consent was not required as there were no participant

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