2023 IEEE 9th International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)

SmartFire Car: An Image Processing and Artificial Intelligence-Based Fire Detection and Extinguishing System

Indrojit Sarkar, Fazle Rabbi, Md. Ayenul Azim, Md. Ashiqul Haider Chowdhury, Maliha Ferdous and Mohammad Ali
Department of Electrical and Electronic Engineering, Bangladesh University of Engineering and Technology
Email: {indro.ij, rabbifazle38, mdayenulazim.jahin, aupurbo392000,mohammadali.kazmi61 }@gmail.com

***Abstract*—In this work, we present a novel image processing and artificial intelligence-based autonomous vehicle system for swift fire detection and suppression. The suggested approach offers a unique and economical option, especially for developing nations, to properly tackle fire-related threats in crowded residential spaces and outdoors. The algorithm used by the system, the Haar cascade, is effective in spotting fire in real-time video feeds. After detecting and determining the ideal stopping distance from the fire, the SmartFire car begins to effectively and efficiently extinguish it. To put the proposed theoretical system to the test in actual practical settings, we developed our prototype. The capacity of the SmartFire prototype to measure distances from the fire source and continue operating amid several fire sources has been used to evaluate its effectiveness. To make the system reliable and efficient, its limitations, such as the smallest fire size needed for detection, have also been examined. This work has the potential to significantly contribute to the modernization of the traditional fire-fighting system, particularly in developing countries, leading to more effective fire-handling capabilities.**

***Index Terms*—SmartFire car, Artificial Intelligence, Image Processing, Cost-effective, Haar Cascade Algorithm, Prototype**

I. Introduction

Risks from fire-related hazards pose a serious threat to people, communities, and the environment, with far-reaching negative effects. Due to the residential buildings' frightening proximity to one another and the lack of basic safety measures, fire threats are particularly dangerous in developing countries like Bangladesh, Nepal, etc. Conventional manual fire extinguishing methods are also to blame for the deaths of numerous firefighters in recent years. Wildfires have recently come to light as one of the deadliest natural disasters that have devastating effects on ecosystems, communities, and the environment.

However, traditional fire detection methods, such as smoke or flame sensors and temperature sensors, have proven unreliable, particularly in outdoor environments [1] [2]. Ren C. Luo et al. [3] introduced an adaptive sensory fusion approach for an intelligent security robot, which incorporates three sensors including smoke, flame, and temperature sensors. The purpose of this fusion methodology is to enhance the robot's ability to perceive and respond to security-related events by integrating information from different sensor modalities. Jinsong Zhu et al. [4] proposed an intelligent fire monitor based on infrared image feedback control. Also, Shang Gao et al. [5] proposed an infrared-based flame sensor and a high-pressure water pump to build a fire-fighting robot. With applications ranging from medical image analysis [6] [7] to Nanophotonics [8] and even traffic system control [9], machine learning and artificial intelligence have emerged as blessings for humanity in the 21st century. Artificial intelligence has found its way into the firefighting sector as well. Di Wu et al. [10] proposed an image processing-based approach utilizing Graph Neural Network (GNN) for multi-view fire detection. Furthermore, alternative methods such as analyzing the temporal variation of fire intensity [11], employing Gaussian-smoothed color-based detection [12], utilizing Support Vector Machine (SVM)-based fire detection [13], using Markov random fields [14] (for static image) have been explored to detect fire.

To address the limitations of conventional fire detection methods and harness the power of artificial intelligence, we present the SmartFire Car, an artificial intelligence and image processing-based fire detection and extinguishing system. Departing from conventional methods that rely on flame sensors, smoke sensors, and infrared sensors [1] [2] [4] our system leverages the power of image processing-based fire detection to enhance both safety and efficiency. The SmartFire Car not only provides a more up-to-date solution than traditional sensor-based systems, but it also has substantial cost-saving potential when compared to vision and other image-processing-based systems with comparable capabilities. Specifically designed for combating fires in vehicular-accessible regions, the SmartFire Car incorporates advanced features, including the ability to measure real-time distances from the fire. This capability allows the vehicle to detect and track moving fire sources, enabling swift identification and suppression. As a result, it enhances the firefighting capabilities of the vehicle.

II. Methodology

The proposed approach is broken down into five distinct phases, each of which is pivotal to effectively put out flames. In the first step, image processing and artificial intelligence-based methods have been used to reliably detect the fire's presence. Following this, the system calculates the precise distance between the vehicle and the fire, determining the optimal direction for the car. Once the fire is located, advanced tracking mechanisms guide the car to the fire's exact location. At this point, the system ensures the vehicle comes to a precise stop, allowing for efficient fire suppression. Finally, the water spraying mechanism is activated, effectively extinguishing the fire and concluding the firefighting process. A full overview

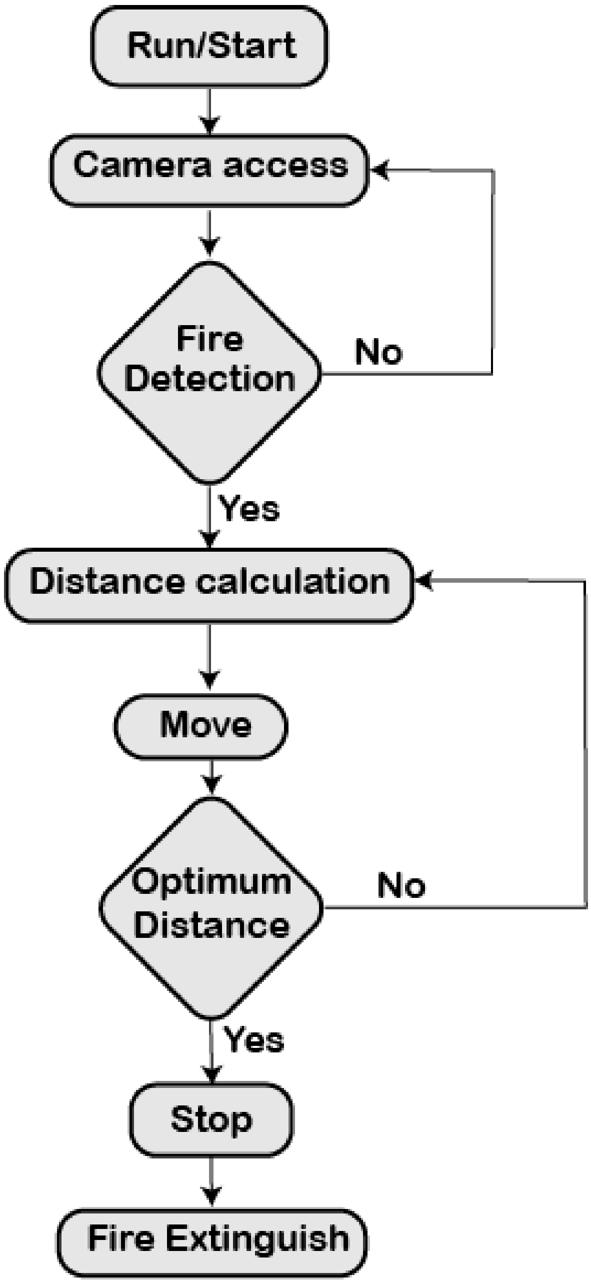

Fig. 1: Algorithm Flowchart for Fire Suppression System. The flowchart describes the sequential steps and functionality of the whole system.

of the fire detection and extinguishing system's functionality is provided by the detailed flowchart in Fig. 1, which visually illustrates the sequential procedures.

A. Haar Cascade Classifier

The Haar cascade classifier [15] [16] specifically designed for fire detection, employs a cascade structure consisting of multiple stages of classifiers. Each stage acts as a filter to sequentially evaluate regions of an input image or frame and determine if they contain a fire. The cascade structure enables efficient processing by quickly discarding non-fire regions and focusing computational resources on potential fire regions. During the training phase, a diverse dataset comprising positive examples (fire images) and negative examples (non-fire images) is used. The classifier learns to distinguish between these two classes by extracting and analyzing Haar-like rectangular features. These features capture local image variations and are computed at different scales and positions within the image. In the detection phase, a sliding window is applied to the input image or frame, and each region within the window undergoes evaluation by the cascade of classifiers. The classifiers calculate responses based on Haar-like features, and if a region passes through all stages of the cascade, it is considered a positive detection of fire. A complete structural and functional overview of the proposed Haar cascade classifier is illustrated in Fig. 2.

B. Fire Detection and Training Phase

We used an open-source dataset [10] that included 2826 fire images and 9325 non-fire images for training our model. Additionally, we added our own sample fire and non-fire images (100 samples each) that were captured with the ESP32 camera module under various environmental situations to evaluate our developed prototype. The dataset's size was adequate for testing the prototype we developed. More diverse positive and negative samples can be added to the dataset in the case of practical deployment to strengthen the classifier even more. Fig. 3 shows sample fire and non-fire images from our generated dataset. To maintain uniformity throughout the training phase, the resolution of each image in the dataset was reduced to 32x32 pixels. Data augmentation technique was also used to improve the classifier's performance and resiliency in detecting fire in a variety of settings.

The classifier proceeds to identify the precise location of the fire by enclosing it within a bounding box. This bounding box provides essential information, including the x and y coordinates, and the width, and height of the detected fire. After training the classifier, the testing phase was performed on unseen live images. In both the training and testing phases, the classifier achieved over 99% accuracy. Fig. 4 shows the performance of the trained classifier while testing against unseen live images. The figures indicate that the developed classifier is quite robust in detecting fire from live images.

C. Calculation of Optimal Stopping Distance

After identifying a fire in the live feed, the system calculates the distance to the fire from the camera. This estimation is based on the camera's focal length and the known distance to the target. Utilizing data such as the fire's x and y coordinates, width, and height, the system determines the focal length by comparing the known distance and object height. The calculated distance is then used in conjunction with the fire's direction to guide the vehicle's movement. The NRF module transmits a string of numbers to the vehicle's controller, which interprets them as instructions for various maneuvers, including forward motion, reverse, left and right turns, and halting.

To determine the distance of fire from the SmartFire vehicle, Fig. 5 displays a reference image with a reference object and a moving object with a known height, 'h' in the real plane. In this case, the reference object is placed at a distance, 'd' from the lens, and the moving object is kept at a distance, 'm' from the reference image. These images' projections appear at the lens's focal length, 'f' in the camera sensor plane. In this case, the height of the projection of the reference object and

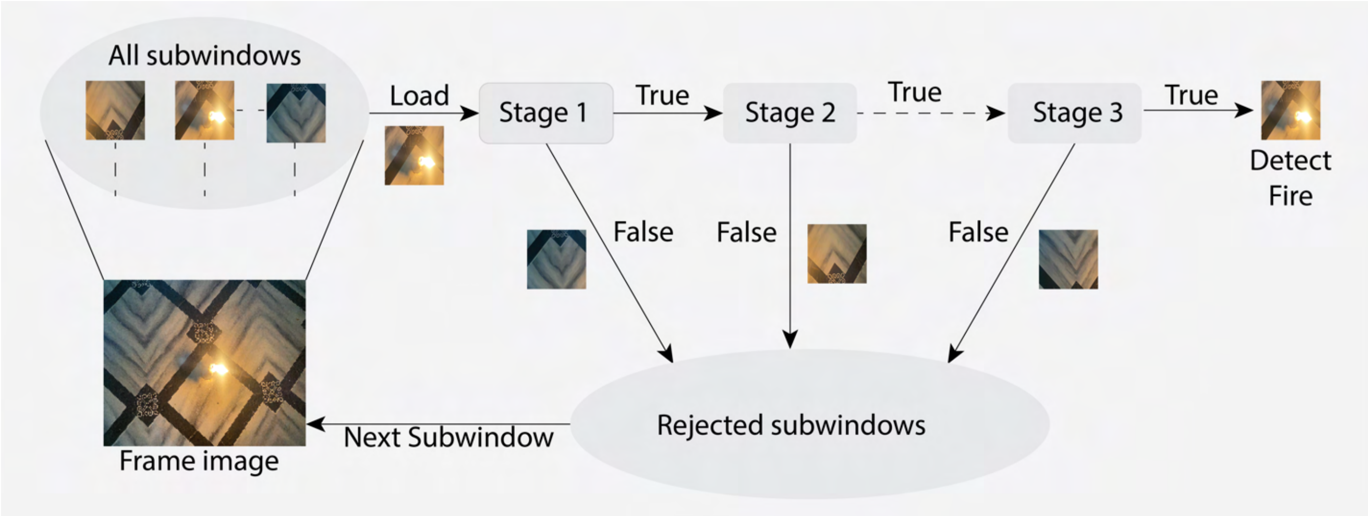

Fig. 2: Haar Cascade classifier for fire detection utilizes a cascade structure of multiple stages to efficiently evaluate regions in an input image or frame. By training on a diverse dataset of fire (True) and non-fire (False) examples, the classifier learns to distinguish between the two classes using Haar-like rectangular features. During detection, a sliding window approach is employed, with regions passing through the cascade stages considered positive fire detections.

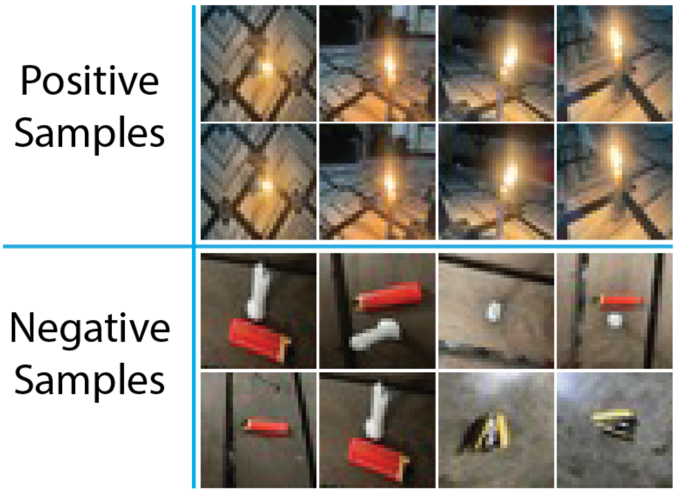

Fig. 3: The image showcases a collection of positive and negative samples. The positive images depict instances of fire, while the negative images represent non-fire scenarios.

the moving object is considered to be 'a' and 'b' respectively. The focal length, 'f' of the camera lens is first calculated by using the following formula,

$$focal\,length, f = \frac{a}{\tan(\theta_1)} = \frac{a * d}{h} \tag{1}$$

After obtaining the focal length of the lens, the distance of a moving image from the lens, 'd+m' is calculated by the following equation,

$$distance, d + m = \frac{h}{\tan(\theta_2)} = \frac{h * f}{b} \tag{2}$$

D. Movement Control of the SmartFire car

The movement of the SmartFire Car is governed by a logical framework that considers both the distance and direction of the fire. This framework adheres to a predetermined set of rules to guide the car's actions. For instance, if the distance between the camera and the fire is more than a predefined safe distance (set to 30 inches while testing the prototype), the SmartFire Car moves forward toward the fire. If the fire is situated on the left or right side of the bounding box, the SmartFire Car executes corresponding turning maneuvers just after a backward movement. Upon reaching the fire (within 20 inches to 30 inches), the car comes to a halt and activates its built-in fire extinguisher for fire suppression. This logical framework, while straightforward, ensures controlled and efficient extinguishment of the fire.

III. Results and Discussions

A. Hardware implementation

The hardware implementation of our prototype car involved the utilization of two Arduino microcontrollers, two NRF24L01+ modules, an L293D motor shield, an ESP32-CAM module, and a micro submersible water pump. One Arduino, along with the motor shield and NRF module, was integrated into the car itself to facilitate control and communication. The other Arduino and NRF module was connected to a laptop for image processing purposes, receiving live video feed from the ESP32-CAM module mounted on the car. When the car reached its designated position near the fire, a micro submersible water pump was employed to spray water from a reservoir, aiding in fire suppression.

The developed prototype of the SmartFire car is illustrated in Fig. 6 and the performance of the developed prototype at different distances is shown in Fig. 4. It is observed that the developed prototype controls the direction of its movement according to the measured distance between the vehicle and the fire source. Furthermore, the prototype has been designed in a way to minimize the cost of such a vehicle. The overall cost of the developed prototype can be found in Table 1. Obviously, the final model will cost significantly higher than the developed prototype, however, the proposed idea of

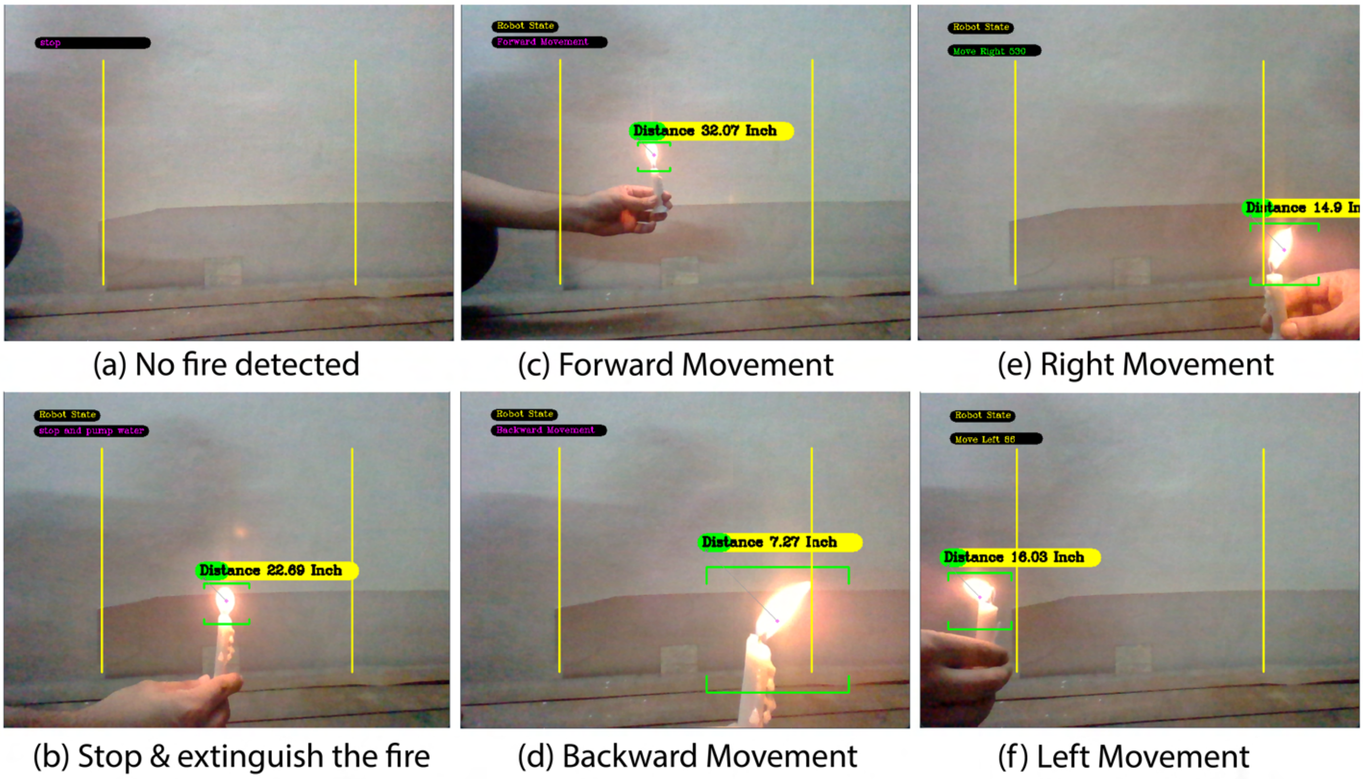

Fig. 4: Demonstration of fire detection under various instances. (a) No fire is detected, indicating the stop signal. (b) Fire detected within the optimal range (20-30 inches) of the stopping distance, triggering the stop signal and activating the water pump. (c) The fire is located a considerable distance (greater than the stopping distance) from the vehicle, prompting the vehicle to move toward the fire location. (d) The fire is close (less than the stopping distance) to the vehicle, resulting in a backward movement of the vehicle as a safety precaution. (e) The fire is situated on the right side of the vehicle, necessitating a right turn to approach the fire at an appropriate angle. (f) The fire is positioned on the left side of the vehicle, requiring a left turn to maneuver toward the fire at an appropriate angle.

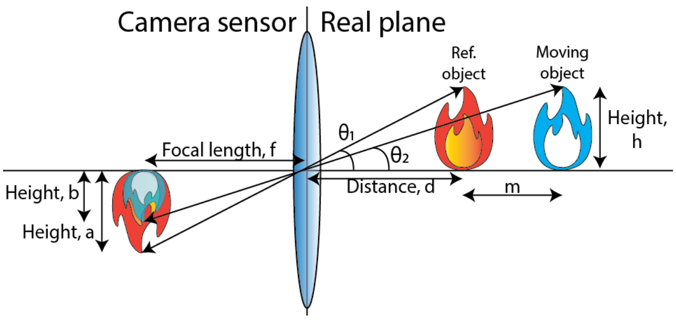

Fig. 5: To measure the distance of fire from the SmartFire Car, a reference image with a known height and distance from the camera is required. This example illustrates how the distance between the fire source and the SmartFire car is measured.

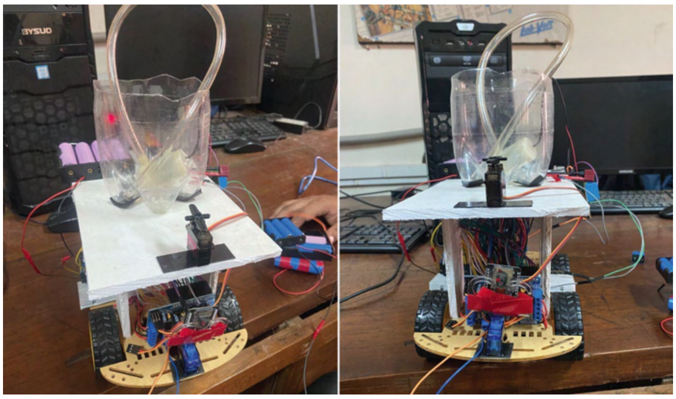

Fig. 6: Developed prototype of the Image processing and artificial intelligence-based SmartFire car.

implementation of such SmartFire cars will surely be more cost-effective than the existing methods.

B. Analysis of Distance Measurement Error

The accurate measurement of distance is crucial for controlling the SmartFire car and ensuring precise positioning for fire extinguishing. To observe the distance measurement performance, 25 individual measurements were taken at different distances between the vehicle and the fire source using the developed prototype. The graph displayed in Fig. 7(a) represents the relationship between the actual distance and the measured distance between the vehicle and the fire source. Here, it can be observed that the measured distance is comparatively greater than the actual ones. Fig. 7(b) illustrates the relationship between the actual distance in inches and the corresponding error percentage in distance measurement. It is observed that there is an increase in the error percentage at smaller distances between the vehicle and the fire source, which is attributed to the fluctuation in fire height.

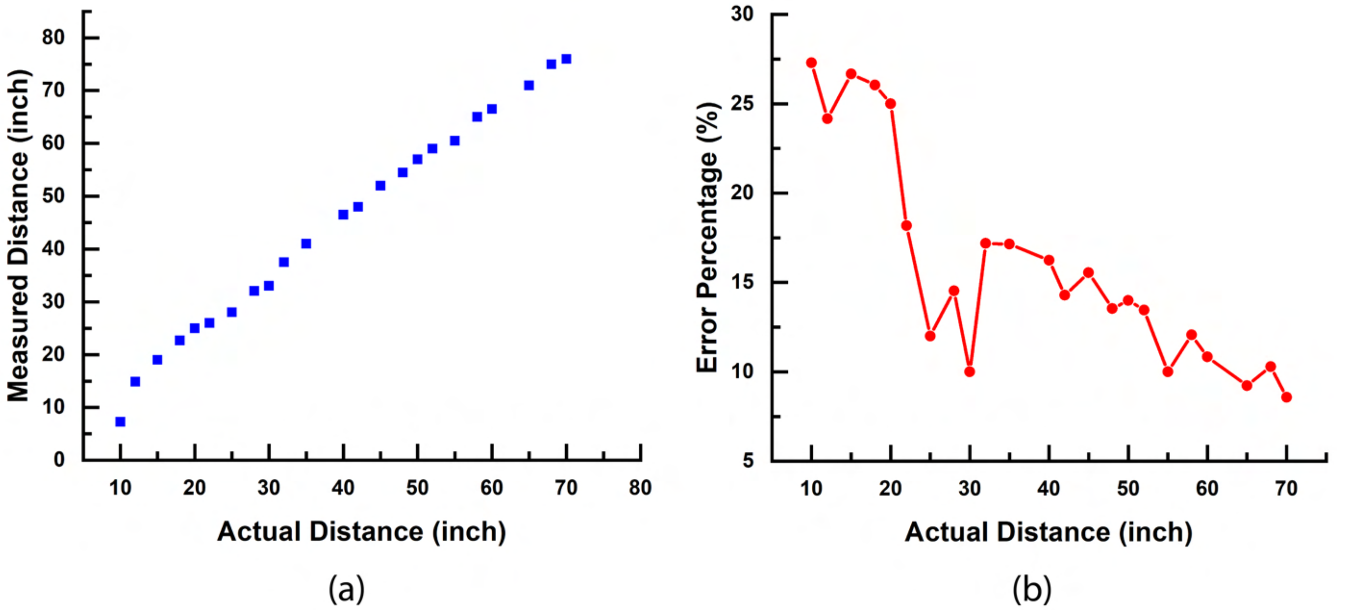

Fig. 7: Distance measurement performance analysis of the developed prototype. (a) the relationship between the actual and the measured distance between the fire source and the SmartFire car is shown. (b) The error percentage is plotted as a function of the actual distance between the fire source and the SmartFire car.

Components	Price (in USD)
Arduino Uno (x2)	$ 20.00
L293D motor shield	$ 1.00
NRF24L01+ wireless transceiver module (x2)	$ 2.00
ESP32 CAM module	$ 5.25
Micro submersible water pump	$ 1.25
Chassis, motors, and wheels	$ 5.00
Battery, connectors, and others	$ 9.50
Total	**$ 44.00 (Approx.)**

TABLE I: Approximate cost breakdown of the developed prototype. Costs may vary depending on location and quantity.

However, it is worth noting that for the prototype under consideration, this error does not have a significant impact as the vehicle stops at the optimal distance and successfully extinguishes the fire. It should be noted that the size of the flame is subject to fluctuations caused by factors such as wind, leading to variations in the height of the flame over time. Consequently, the distance calculation is influenced by these fluctuations. However, when the SmartFire Car is positioned at a greater distance from the fire, the impact of these fluctuations on distance measurement decreases. Additionally, the effect of flame height fluctuation is more pronounced for fires with smaller heights compared to fires with larger heights. The results influenced the optimal stopping distance for the vehicle from which it will start working to extinguish the fire. For the experimental setup, the optimal stopping distance was chosen between 20 to 30 inches, as the measurement error is relatively small in this range. Although there is a presence of negligible error in the distance measurement stage, the developed prototype was capable of extinguishing the fire in all 25 different trial runs.

C. Minimum Fire Size for Detection

We also investigate the minimum fire size required for successful detection by the proposed model. The model has been designed to respond to fires that occupy an area larger than 0.3% of the total frame. This threshold indicates that for the model to detect a fire, it must be of sufficient size. Hence, the minimum fire size is another important parameter to be considered while setting the optimal stopping distance for the vehicle. It is to be noted that larger fire sources are more easily detected, even at greater distances.

D. Handling Multiple Fire Sources: Detection and Prioritization

The proposed algorithm demonstrates the ability to detect and prioritize multiple fire sources simultaneously within a single frame. Upon identifying the closest fire source from the vehicle, the system initiates the extinguishing process and subsequently proceeds to the next fire source. In situations where multiple fires have equal distances, the algorithm randomly selects a fire source to address first. This approach ensures a systematic and efficient response to multiple fire incidents. Notably, the system provides information regarding the distance to the nearest fire source, allowing for accurate assessment and effective resource allocation. This functionality enhances the system's effectiveness in handling multiple fire sources, providing a robust solution for real-world fire scenarios. A visual demonstration of the presence of multiple fire sources is shown in Fig. 8.

IV. HUMANITARIAN IMPACT

According to the National Fire Protection Association journal [17], there were 64 fatalities recorded among on-duty firefighters in the United States in 2018, resulting from injuries sustained during specific incidents. These numbers highlight the inherent risks faced by firefighters in their line of duty. Additionally, global statistics from the World Health Organization (WHO) indicate that burns contribute to approximately 180,000 deaths annually [18]. To address these challenges,

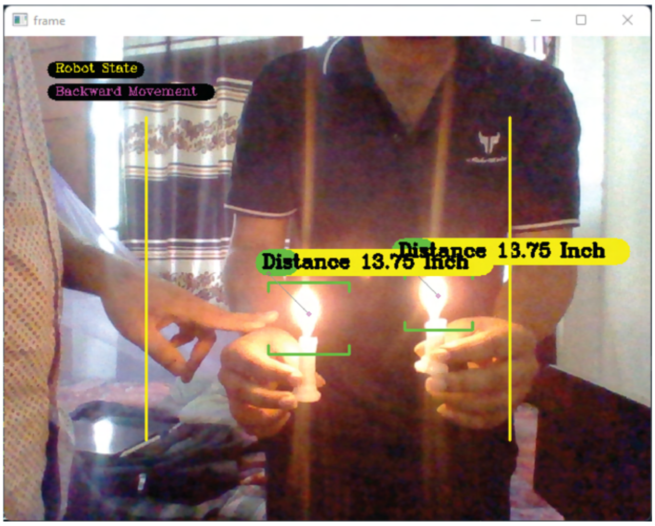

Fig. 8: Presence of multiple fire sources in a single video frame. The system is capable of identifying both sources separately and it proceeds to suppress them simultaneously.

it is imperative to implement comprehensive fire management strategies and incorporate effective land-use planning. Its mobility and fire extinguishing capabilities make it an invaluable tool for addressing fires in inaccessible or hazardous areas. Furthermore, the SmartFire Car's ability to detect and extinguish fires in their early stages can effectively hinder their progression and minimize extensive environmental damage.

V. Conclusion

A unique image processing and artificial intelligence-based fire detection and extinguishing system has been introduced in this work. The system is created in a way that makes it feasible for developing nations to generate large quantities of it at a low cost and digitize their conventional fire-fighting system. The Haar cascade classifier has been proposed as an excellent tool for detecting fire in real-time video feeds. The system then determines the ideal stopping distance from which to start its fire-extinguishing procedures after successful fire detection. Real-world scenarios have been used to assess how well the SmartFire automobile extinguishes fires. And to that end, a prototype that maintains the system's cost-effectiveness has been constructed and tested. The produced SmartFire car prototype performs admirably when it comes to distance measurement analysis, and it is capable of functioning effectively even when there are several fire sources present.

In order to lessen the devasting effects of fire-related threats, it is crucial to build an effective firefighting system capable of quick fire detection and suppression. In densely populated residential areas, traditional fire detection techniques have shown limits in terms of dependability and application. The SmartFire Car provides a wider range of fire detection capabilities while boosting safety and efficiency by doing away with the requirement for traditional flame and smoke sensors. Future developments in fire detection and suppression technology have an exciting prospect with more research and development in this area. The SmartFire car will gradually gather more data as it begins to operate in real-world hazards, which can be used to train the car even more effectively with the use of autoencoders and generative adversarial networks.

Data Availability

To facilitate future research endeavors in this field, interested individuals can obtain access to the source code and dataset by submitting a request via email.

References

[1] S. Dina, M. Mahalekshmi, V. Kokila, R. JeyaPreetha, and S. Sankarakumar, "Fire fighting robotic vehicle using arduino," in *2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC)*. IEEE, 2022, pp. 346–350.

[2] J. Suresh, "Fire-fighting robot," in *2017 International Conference on Computational Intelligence in Data Science (ICCIDS)*. IEEE, 2017, pp. 1–4.

[3] R. C. Luo and K. L. Su, "Autonomous fire-detection system using adaptive sensory fusion for intelligent security robot," *Ieee/Asme Transactions on Mechatronics*, vol. 12, no. 3, pp. 274–281, 2007.

[4] J. Zhu, W. Li, D. Lin, H. Cheng, and G. Zhao, "Intelligent fire monitor for fire robot based on infrared image feedback control," *Fire Technology*, vol. 56, pp. 2089–2109, 2020.

[5] S. Gao, Z. Zhang, Z. Zhao, and M. M. Jamali, "Vision and infra-red sensor based fire fighting robot," in *2018 IEEE 61st International Midwest Symposium on Circuits and Systems (MWSCAS)*. IEEE, 2018, pp. 873–876.

[6] N. Rashid, M. A. F. Hossain, M. Ali, M. I. Sukanya, T. Mahmud, and S. A. Fattah, "Autocovnet: Unsupervised feature learning using autoencoder and feature merging for detection of covid-19 from chest x-ray images," *biocybernetics and biomedical engineering*, vol. 41, no. 4, pp. 1685–1701, 2021.

[7] N. Rashid, M. A. F. Hossain, M. Ali, M. Islam, T. Mahmud, and S. A. Fattah, "Transfer learning based method for covid-19 detection from chest x-ray images," in *2020 IEEE REGION 10 CONFERENCE (TENCON)*. IEEE, 2020, pp. 585–590.

[8] M. Ali, A. N. Haque, N. Sadik, T. Ahmed, and M. Z. Baten, "Predicting strongly localized resonant modes of light in disordered arrays of dielectric scatterers: a machine learning approach," *Optics Express*, vol. 31, no. 2, pp. 826–842, 2023.

[9] M. Ali, M. A. F. Hossain, M. I. Sukanya, and R. Chakraborty, "Real-time density-based dynamic traffic light controller using fpga," in *2021 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)*. IEEE, 2021, pp. 25–28.

[10] D. Wu, C. Zhang, L. Ji, R. Ran, H. Wu, and Y. Xu, "Forest fire recognition based on feature extraction from multi-view images." *Traitement du Signal*, vol. 38, no. 3, 2021.

[11] G. Marbach, M. Loepfe, and T. Brupbacher, "An image processing technique for fire detection in video images," *Fire safety journal*, vol. 41, no. 4, pp. 285–289, 2006.

[12] W. Phillips Iii, M. Shah, and N. da Vitoria Lobo, "Flame recognition in video," *Pattern recognition letters*, vol. 23, no. 1-3, pp. 319–327, 2002.

[13] B. C. Ko, K.-H. Cheong, and J.-Y. Nam, "Fire detection based on vision sensor and support vector machines," *Fire Safety Journal*, vol. 44, no. 3, pp. 322–329, 2009.

[14] D. Van Hamme, P. Veelaert, W. Philips, and K. Teelen, "Fire detection in color images using markov random fields," in *Advanced Concepts for Intelligent Vision Systems: 12th International Conference, ACIVS 2010, Sydney, Australia, December 13-16, 2010, Proceedings, Part II 12*. Springer, 2010, pp. 88–97.

[15] A. U. Khan, N. Saleem, F. H. Tauqeer, A. Nawaz, K. Zaman, S. Ahmed, and A. Ali, "A proposed fire detection survelliance through machine learning based on haar cascade classifier," *JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES*, 2022.

[16] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001*, vol. 1. Ieee, 2001, pp. I–I.

[17] N. F. P. A. J. 2019, "Firefighter fatalities in the united states in 2018," https://www.nfpa.org/News-and-Research/Publications-and-media/NFPA-Journal/2019/July-August-2019/Features/Firefighter-Fatalities#:~:text=Fires%20and%20explosions%20claimed%20the%20lives%20of%2025,fire%2C%20and%20one%20at%20a%20gas%20line%20explosion.

[18] W. H. O. (WHO), "Burns by world health organization (who)," https://www.who.int/news-room/fact-sheets/detail/burns#:~:text=Burns%20are%20a%20global%20public%20health%20problem%2C%20accounting,in%20the%20WHO%20African%20and%20South-East%20Asia%20regions.