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Development of early fire detection model for buildings using computer vision-based CCTV

Yusun Ahn [a], Haneul Choi [b], Byungseon Sean Kim [a,*]

[a] Department of Architecture & Architectural Engineering, Yonsei University, Seoul, 03722, South Korea
[b] Energy ICT Convergence Research Department, Korea Institute of Energy Research, Daejeon, 34129, South Korea

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ABSTRACT

A fire in a building directly affects the lives of its occupants. Therefore, a safer environmental system that can minimize the damage caused by a fire occurring indoors needs to be developed. Recent studies on computer vision-based rapid fire detection methods aim to overcome the limitations of general fire detectors and prevent false alarms using advanced deep learning technology. However, studies considering the development of a video fire detection model for indoor usage and its implementation in an actual test room are lacking. We developed a computer vision-based early fire detection model (EFDM) using an indoor closed-circuit television (CCTV) surveillance. The proposed EFDM derives the fire detection time through actual fire tests. The possibility and necessity of using fire detectors indoors is confirmed by comparing the results with the fire detection times of a general fire detector. The developed model achieves a recall, precision, and $mAP_{0.5}$ performance of 0.97, 0.91, and 0.96, respectively. The fire recorded in the indoor fire video test dataset was detected within 8 s. The possibility of fire detection from three combustibles according to Underwriters Laboratories (UL) 268 B is confirmed via experimentation. A difference of up to 307 s is observed when the fire detection times of the EFDM and general fire detectors are compared. The useable range is confirmed by detecting a fire within 1 s of the maximum visible range of the CCTV. The proposed method can help contribute to the reduction of unfortunate property damages or casualties caused by a fire.

1. Introduction

According to a report by the National Fire Agency [1], 38,659 fires occurred in Korea in 2020. Of the total number of fire incidents, fires in buildings and structures accounted for 64.5%, wherein 82.2, 82.6, and 88.7% resulted in deaths, injuries, and property damage, respectively. Essentially, the largest number of casualties and property damage occurred in the architecture and structure. In addition to Korea, of the total number of fire incidents, the United State of America (USA) reported 74% of deaths and 76% of injuries (as of 2020) [2], London reported 78% of deaths (in 1996–2000) [3], and China reported 39% of deaths (in 2007–2010) [4]. Therefore, conducting an analysis and implementing measures to reduce the number of fire accidents that occur in buildings is needed. In addition, researchers have found that large-scale fires affect the emotions and risk perception of individuals who have experienced fires, which emphasizes the importance of developing technologies to minimize fire accidents [5].

One approach for minimizing the damage caused by a fire accident is to promptly report the fire while it is in an early stage. The

Abbreviations: VFD, Video Fire Detection; ESFDM, Early Fire Detector Model; CCTV, Closed-Circuit Television; CNN, Convolutional Neural Network.

* Corresponding author.
E-mail addresses: ahnew@yonsei.ac.kr (Y. Ahn), chn7960@kier.re.kr (H. Choi), sean@yonsei.ac.kr (B.S. Kim).

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Seoul Institute [6] analyzed the extent of damage based on the time when the fire started and the arrival time of firefighters for fire accidents that occurred in Seoul from 2010 to 2014. The analysis results indicate that property damage increases by 3.6 times, and casualties by a factor of 1.5, if the fire prime time of 5 min is exceeded. These results suggest that prompt fire detection and reporting are key factors for minimizing property damages and casualties.

The building code mandates the installation of fire detectors in buildings to ensure rapid fire detection [7–9]. Heat, smoke, and flame detectors are typically used to detect fire; however, despite the use of these fire detectors, there are often cases when the early detection of a fire is delayed, which further delays the reporting of a fire. There are three main reasons for the delay in reporting a fire that can be attributed to fire detectors [8,9]. First, typical heat detectors detect a fire when the environment around the detector reaches a certain temperature; however, it is difficult for a heat detector to detect an early fire because the temperature of the surrounding environment rises when the fire spreads to a certain extent. According to a reproduction experiment by Sakong et al. [10], the response characteristic of a heat detector was 8 min slower than that of a smoke detector. Second, the smoke detector detects a fire only when smoke is present. Smoke detectors are widely used because they detect fires faster than heat detectors; however, the recent increase in the installation of ventilation systems or air conditioners in buildings has led to an increase in the number of factors that generate airflow in buildings. When the airflow velocity increases, the spread of smoke due to the fire can delay smoke detection [11]. Aralt et al. [12] reported that the fire detection time increased from 58 to 67 s based on the ventilation velocity. Third, the flame detector detects flames as either ultraviolet or infrared; however, false alarms may be triggered by causes other than fire, such as floating objects [13,14]. A flame detector does not delay fire reporting. However, the reliability of this fire detector is reduced if false alarms repeatedly occur, which can lead to a delay in reporting fires by occupants [8]. Therefore, early fire detection and false-alarm prevention methods need to be further developed to overcome the limitations of fire detectors installed in buildings [8,15].

A recent study reported that there has been an increase in the study of fire detection that uses computer vision-based closed-circuit television (CCTV) surveillance to solve the limitations of general fire detectors or methods to prevent false alarms [16]. Recently, several researchers [17–21] developed a new video fire detection (VFD) model by training various fire-related datasets. Researchers [22–28] have focused on large fires that occur in specific environments, such as forest fires [29,30], to improve the accuracy because most of the studies trained the datasets by mixing outdoor and indoor fire image datasets. In studies focusing on large-scale fires, most developed models focusing on outdoor areas where large-scale fires frequently occur. In contrast, only a few researchers have conducted studies on indoor areas. Pincott et al. [31] developed a flame and smoke detection model for indoor usage using a convolutional neural network (CNN).

The models developed in the aforementioned studies focus on expressing the performance of the model through various indicators, such as the detection rate, precision, true-positive rate, and false-positive rate. However, it is difficult to determine the early fire detection speed, which is a significant advantage of CCTV-based fire detectors, by verifying only the model performance. Few researchers have derived the performance verification of the VFD model and the fire detection speed (frames per second (FPS)) to quantitatively identify the possibility of fire detection. Wu et al. [22] measured the detection speed of identifying a factory fire. The VFD model was trained based on fire images collected for an outdoor fire image dataset. Thus, a fire detection rate of 98.4% and detection speed of 36 FPS were derived. Li et al. [20] studied the flame and smoke image datasets using various models considering both outdoor and indoor environments. They achieved an accuracy of 83.7% and detection speed of 28 FPS. Jiao et al. [26] developed a new model that was trained using flame and smoke images for forest fire detection; they achieved a detection rate of 83% and detection speed of 3.2 FPS. However, studies that present the actual fire detection performance (e.g., fire detection time according to distance and comparison of detection time with fire detection) rather than the training performance of the model are lacking. Table 1 summarizes the current research regarding fire detection using computer vision-based CCTV.

The knowledge gap derived by reviewing the related studies is summarized as follows.

Table 1
Literature review.

Researcher	Trained location	Image dataset	Result
Bu et al. [17]	Outdoor/indoor	Flame/smoke	Detection rate, precision
Muhammad et al. [18]	Outdoor/indoor	Flame	Accuracy
Wang et al. [19]	Outdoor/indoor	Flame	AUC, Precision-Recall
Hashemzadeh et al. [21]	Outdoor/indoor	Flame	Detection rate
Chen et al. [32]	Outdoor/indoor	Flame	Detection time
Zhang et al. [22]	Outdoor	Smoke	Detection rate
Saker et al. [23]	Outdoor	Smoke	Detection rate
Wu et al. [24]	Outdoor	Flame	Detection rate, Detection speed
Sharma et al. [25]	Outdoor	Flame	Detection rate
Jiao et al. [26]	Outdoor	Flame/smoke	Accuracy
Zhang et al. [27]	Outdoor	Flame	Accuracy, detection rate, false alarm rate
Frizzi et al. [33]	–	Flame/smoke	Low detection rate, high false-alarm rate
Li et al. [20]	Outdoor/indoor	Flame/smoke	Precision, Detection speed
Jiao et al. [28]	Outdoor	Flame/smoke	Detection rate, detection speed
Pincott et al. [31]	Indoor	Flame/smoke	Accuracy, precision, recall
This study	**Indoor**	**Flame/smoke**	**Precision, recall, $\mathbf{mAP_{0.5}}$, detection time**

- Most studies used the fire image dataset only for outdoor usage or without distinction between indoors and outdoors. Studies regarding fire detection for indoor usage in buildings are still lacking. A significant amount of damage is caused by indoor fires; therefore, research on indoor fire detection is required.
- Research regarding the learning or verifying of datasets focusing on early fires, which is an advantage of CCTV fire detection, remains insufficient. It is critical to conduct research that can quickly detect a fire at an early stage because it has a prime time.
- There is insufficient research to quantitatively compare the detection time of the developed model with the fire detector used in buildings. This comparison is important to confirm the need for a computer vision model using CCTV in indoor environments.

In this study, the following was attempted to fill the previous knowledge gap: (1) A fire image dataset focusing on indoor fires was collected. (2) A new early fire detection model (EFDM) was developed based on the early fire of the collected image dataset. (3) The developed model was implemented in a test room to quantitatively evaluate the fire detection time for the possibility and necessity of an EFDM, which was subsequently compared with a general fire detector and the performances were analyzed. The framework of this study is presented in Fig. 1.

This study proposes a novel method to minimize the fire detection time using the latest ICT (Information & Communications Technology) for a safely built environment system. The results of this study are expected to contribute to the reduction of unfortunate property damage or casualties caused by fire. Furthermore, this study contributes to the improvement of fire detector reliability for occupants by combining the functions of a generally used fire detector and those of a CCTV fire detector. This study is expected to

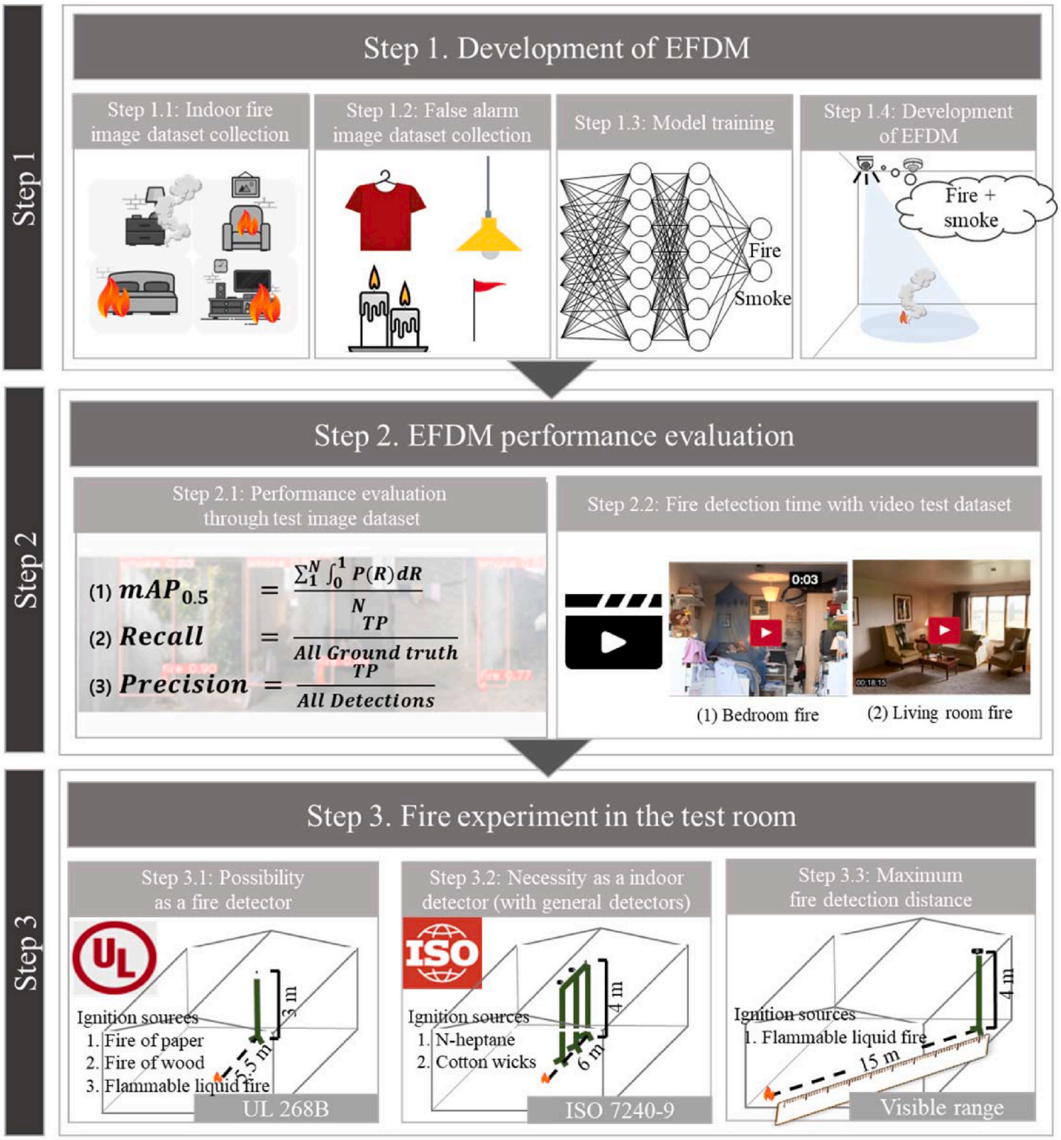


Fig. 1. Framework.

develop from a building level and evolve to the community and city level, and eventually become part of the safety net construction technology.

2. Research methodology

2.1. Research outline

This study aims to develop a computer vision-based EFDM using CCTVs installed indoors. The following three research topics will be addressed:

- The ability of computer vision-based EFDM to detect an early fire indoors
- Speed of the developed EFDM compared to the general fire detector
- The detection range in meters for the EFDM

This study only investigates early fires that occur indoors. The applicability and necessity of early fire detectors used indoors are confirmed by comparing the model developed with a general fire detector by implementing them in an actual test room.

2.2. Model development and test

2.2.1. Fire and smoke dataset

This section describes the types and characteristics of the image datasets collected for training as well as similar image datasets used for preventing false alarms. In recent fire detection-related model development studies, the models were trained using flame images [18,19,21,24,27]. However, one study reported that two-thirds of the deaths due to fires occurred in buildings where smoke detectors were not working [14]. Therefore, in this study, a model considering the flames and smoke was developed to detect them both.

The fire (flame, smoke) images collected in this study were obtained from data provided by AI HUB [34]. A total of 10,163 pieces of data satisfying the criteria of early fires and indoor fires were selected and used. The two categories of flame and smoke were used for training, an example of which is shown in Fig. 2.

We collected an image dataset comprising of images that can be mistakenly recognized as an indoor fire. Factory Mutual (FM) 3232 [35], an American insurance company, established the following false alarm test response items for video fire detectors: direct sunlight and solar-related sources, electric welding, black body sources (electric heater), and artificial lighting (incandescent lamp, fluorescent lamp, halogen lamp). In this study, candles, rainbow, laundry, flags, red shirts, yellow wires, light reflections, and cigarette smoke, which are frequently used indoors, and the false alarm test items suggested by FM 3232 were added to the training images. Therefore, the image dataset proposed by FM 3232 and the additional image dataset generated indoors were combined and 514 image datasets were used for training to prevent false alarms. The image dataset used in this study was collected through an AI HUB and Google searches. The collected image dataset was labeled using RoboFlow [36].

2.2.2. You only look once (YOLO)

Object detection involves setting an area through a bounding box for a specific object such as a person [37], car [38], building [39], or cloth [40]. This computer vision technology performs automatic identifications. YOLO [41] is an object detection model where deep learning is applied; herein, the image is divided into a certain area and weights are assigned to the “probability of an object” for appearing in each area. Furthermore, it has the advantages of real-time video recognition because it is a unified detection method that can find the location of an object and classify it. This advantage can increase the speed of object recognition. Therefore, YOLO, which presents an excellent real-time performance, is selected because the goal of this study is to rapidly and accurately detect a fire. In this study, the YOLO model was trained using a custom flame and smoke image dataset for fire detection. Thus, YOLOv5s [42] was selected as the pre-trained model to start training, which is the smallest and fastest model available.

2.2.3. Model training

YOLOv5 was designed using Python 3.7 and implemented on PyTorch. In this study, the default hyperparameters of YOLOv5s included an epoch of 300 and batch size of 32. Herein, 70, 20, and 10% of the entire image dataset was used for training, validation, and testing, respectively.

The hardware used was a Windows 10 computer with an AMD Ryzen Threadripper PRO 3995WX 64-Core CPU having a base

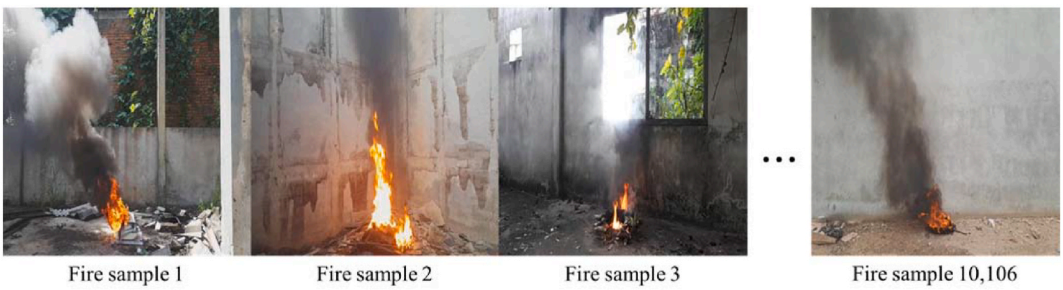


Fig. 2. Indoor early fire sample.

frequency of 2.7 GHz, 128.0 GB RAM, and NVIDIA GeForce RTX 3060 GPU. A total of 30 h of computer training was required for the developed EFDM.

2.2.4. Performance evaluation indicators

The computer vision-based model performance was verified using the following indicators.

$$\textbf{Precision} = \frac{TP}{TP + FP} = \frac{TP}{All\ Detections} \tag{1}$$

$$\textbf{Recall} = \frac{TP}{TP + FN} = \frac{TP}{All\ Ground\ truth} \tag{2}$$

$$\textbf{mAP} = \frac{\sum_{1}^{N} AP_k}{N} \tag{3}$$

$$AP_k = \sum_{k=0}^{k=n-1} [Recalls(k) - Recalls(k+1)] \times Precisions(k) \tag{4}$$

where TP and FP represent true and false positives, which indicate correct and false detections, respectively. Equation (1) presents precision, which is a ratio of the correctly detected results. Equation (2) presents recall, which is the ratio of the correctly predicted results to the correctly detected results. Precision and recall tend to be inversely proportional to one another, and it is not advisable to evaluate the performance using only one value; therefore, a precision–recall curve is used. The precision–recall curve evaluates the performance of the threshold value change with respect to the confidence level, which is a value that indicates the confidence of the detection. A higher value indicates a greater confidence in the detection result. The precision–recall graph can help understand the overall performance of a model; however, it is inconvenient to quantitatively compare the performance of two different models. Therefore, the average precision (AP) is used to evaluate the performance of the precision–recall graph as a single number. The algorithm performance is considered to be excellent if the AP is high. In the field of computer vision, the performance of image classification models is evaluated using AP. The AP is obtained for each class when there are several classes of objects; subsequently, the performance is measured using the average, which is called the mean average precision (mAP). In Equation (3), N represents the number of categories. The performance of the EFDM developed in this study is evaluated in terms of precision, recall, and mAP.

2.2.5. Video sets for testing the model

The developed model was applied to video test sets to evaluate the performance. Indoor fires were verified using two video test sets. The difference between the times when the fire occurred and when it was detected was derived. In addition, the presence or absence of false alarms was verified using indoor images shown in the video test sets.

The video test sets are presented in Table 2. The first set includes a video of a fire in a bedroom caused by placing a hair dryer on the bed and covering it with a blanket. When the blanket began to vaguely emit smoke, the timecode started at 0 s. The video contains a light, doll, and red object as everyday objects used in the bedroom that can be recognized as a flame; additionally, it includes a mosquito net that can be recognized as smoke. The second set includes a video of a fire in a living room, wherein the fire originates

Table 2
Video test sets.

Test video title	Description	Example
Bedroom fire test [43]	Video of fire caused by a dryer covered with a blanket on the bed	 [43]
Living room fires with and without a fire sprinkler (Timecode) [44]	Video of a fire from a curtain half hidden on a sofa in a living room	 [44]

from the curtains in the living room. The fire starts but is partially hidden behind the sofa. The video shows the fire as soon as it starts, and the start time node was set to 16 s. The video also includes lighting that can be recognized as flames, curtains that can be recognized as smoke, and skylights, among other similar objects.

2.3. Fire detection experiments

2.3.1. Case description

In this study, a case study was conducted to verify the indoor EFDM. The case study was divided into three categories based on the purpose of measurement. The three cases are listed in Table 3.

In Case 1, fire detection is confirmed by the EFDM. In Case 2, the necessity of an indoor fire detector is confirmed. In Case 3, the useable range of the EFDM is verified.

The performance of the EFDM was verified based on "the video image fire detector" proposed by UL 268 B to verify the fire detectability in Case 1. As a video image fire detector, the presence or absence of fire detection was derived within 4 min.

In Case 2, the "fire detection and alarm system" standard suggested by ISO 7240 was used as the test standard for general fire detectors. The detection time of the developed EFDM was compared to that of general fire detectors.

Finally, in Case 3, the fire detection time was derived based on the visible range of the webcam used in this study to check the useable range of the EFDM. Essentially, the possibility of a fire detection at a distance that matches the webcam performance was confirmed.

2.3.2. Experimental setup

In this study, an indoor environment was used for the fire experiment. There are differences between outdoor and indoor environments in terms of various factors. For example, there is a difference in air speed, which is considered in this study. The indoor air speed is lower than the outdoor air speed and is within 0.15 m/s [45]. Therefore, in this study, the experiment was conducted while limiting the airspeed to 0.15 m/s or less. Furthermore, all the experiments were performed twice, and the results were derived from the average of the two experimental values. The time was measured when the combustible was on fire. Because this study compares the EFDM and general fire detectors, the conditions for both the video image fire detectors and general fire detectors must be satisfied. The test room used in this study is presented in Fig. 3 (a), and the size of the room is presented in Fig. 3 (b), which satisfies all the conditions required for this experiment. The length, width, and height of the room was 15, 8, and 4 m, respectively.

The real-time hardware utilized in this experiment was a Windows 10 computer with an Intel (R) Core(TM) i7-7700HQ CPU having a base frequency of 2.81 GHz, 16.0 GB RAM, and NVIDIA GeForce GTX 1060 GPU. The webcam (PRODEAN SH003) used for real-time shooting had full HD 1080P resolution with 2 million pixels, frame rate of 30, a 3.6 mm fixed lens, and 90° angle of view. In this study, a webcam was used to implement CCTV surveillance.

2.3.2.1. Experimental setup for Case 1. First, Underwriter Laboratories (UL) 268 B [46] suggests test standards for video image fire detectors to proceed with Case 1, which are summarized in Table 3. The following three major types of combustibles required for the experiment are proposed: paper fire, wood fire, and flammable liquid fire. A fire is proposed to be generated according to the combustibles listed in Table 4 under the relevant conditions; the performance is recognized only when the video image fire detector detects it within 4 min. In this study, paper, wood, and flammable liquid fires were tested as combustibles according to the three standards suggested by UL 268 B.

UL 268B defines the test room as having a length, width, and height of 11, 6.7, and 3.0 m, respectively. Furthermore, UL 268 does not specify the distance or height between the combustible and webcam. Therefore, an experiment with a length and height that can be adjusted in the test room was considered. The height of the webcam was adjusted to 3 m from the floor, and the webcam was installed at a distance of 5.5 m (11 m/2) or more from the combustible. The environment of the test room was the same as that of Case 1 shown in Fig. 3.

2.3.2.2. Experimental setup for Case 2. Case 2 is the criterion applied to a general fire detector. Before listing the criteria, the types of fire detectors are presented herein. The National Fire Safety Code (NFSC) 203 [48] states the following installation standards for fire detectors in buildings: smoke detectors should be installed in living rooms used for similar purposes, such as sleeping, lodging, and hospitalization.

A photoelectric detector uses the principle of smoke blocking or reflecting light; when smoke enters a room, the light is scattered and is recognized as a fire. The photoelectric detectors used operate at 10%/m. However, false alarms by smoke detectors may occur in locations that manage significant fires, such as kitchens and boilers; a heat detector should be installed in such areas. In this study, a fixed temperature detector, which has the widest application range among the heat detectors, was used for comparison. The fixed-

Table 3
Case study.

	Title	Standard
Case 1	Deriving EFDM fire detectability and detection time	Test criterion: UL 268B Goal standard: detection within 4 min
Case 2	Deriving fire detection time by distance (2, 4, and 6 m each) for indoor fire detector needs (with general fire detectors)	Test criterion: ISO 7240 Goal standard: fire detection time of heat detector and smoke detector
Case 3	EFDM useable range	Test criterion: webcam maximum visible range

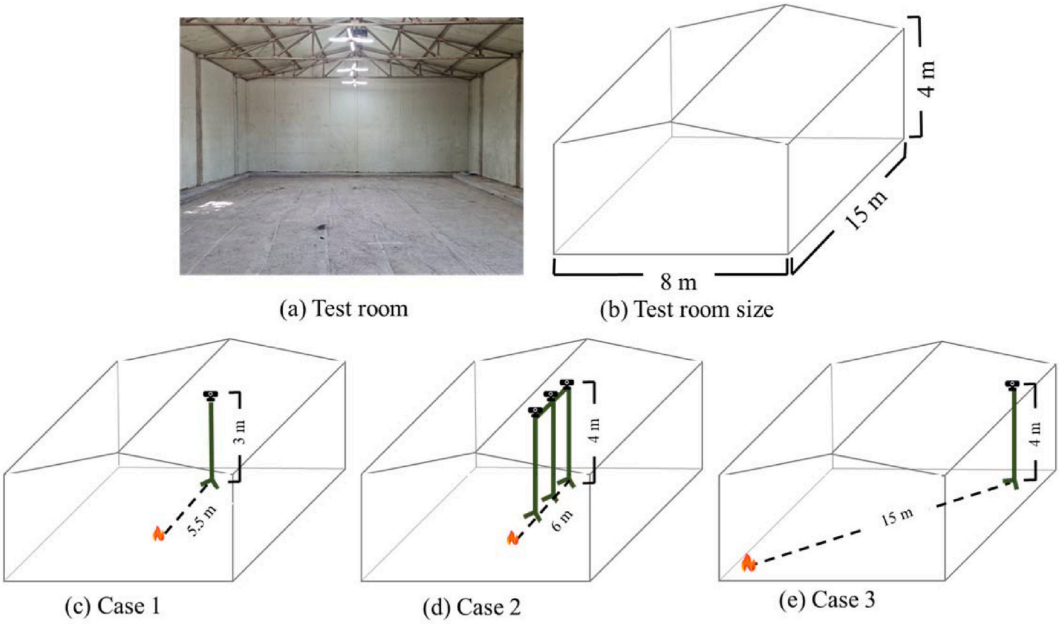


Fig. 3. Test room.

temperature detector operates when the ambient temperature is above a certain temperature and the nominal operating temperature range is 65 °C [49].

The performances of the photoelectric detector used as a smoke detector and the fixed-temperature detector used as a heat detector were compared with those of the developed EFDM. The experimental values reported by Choi et al. [49] were used for the fire detection time of the general heat and smoke detectors. This experiment measured the effect of air speed on fire detection time by installing an air conditioner system and a general fire detector in the test room. the fire detection times were checked by installing 16 fire detectors using distance, as shown in Fig. 4. Choi et al. [49] conducted measurements in the test room suggested by ISO 7240-9 (length, width, height of 10, 7, 4 m, respectively). The performances of the heat and smoke detectors were measured with N-heptane and cotton wicks, respectively. In this study, the experiment was conducted at an air speed of 0 m/s. As shown in Fig. 4, detectors (A) and (D) were at a distance of 2 m and 6 m from the combustible, respectively. However, a distance of 4 m from the combustible, between (A) and (D), was unable to be observed. Therefore, the data for detectors (B) and (C) were used, which indicate the results for the left and right fire detectors located at the same distance of 4 m from the combustible. Thus, the fire detector dataset obtained at a distance of 4 m used the average value of two data points at the same distance.

ISO 7240-9 specifies the combustibles for testing general fire detectors. In this study, the experiments were conducted using n-heptane and cotton wicks according to the two standards suggested by ISO 7240-9; the results of the general fire detectors and EFDM were then compared. The combustibles are listed in Table 4.

ISO 7240 defines the test room as having a length, width, and height of 10 ± 1, 7 ± 1, and 4 ± 0.2 m, respectively. The environment in the test room was the same as that in Case 2, as shown in Fig. 3. A total of three webcams were installed up to a distance of 6 m at intervals of 2 m with respect to the combustible. Currently, a detection radius of up to 150 m^2 per fire detector is stipulated in Korea; therefore, it must be detected within a maximum of 6.9 m. Thus, in Case 2, the experiment was performed at intervals of 2 m considering a distance of up to 6 m. The webcam was installed 4 m above the floor.

2.3.2.3. Experimental setup for Case 3. In Case 3, the useable range was checked by performing a fire test in the maximum visible range of the EFDM. Flammable liquid was used as the combustible and the fire conditions were set according to those for combustibles suggested by UL 268B, as summarized in Table 4. This combustible was used because it covers fires of different sizes and caused the smallest fires among those that occurred during the experiment.

The webcam used in this experiment suggests a visible range of 10–15 m. Therefore, the combustible was placed and measured at a distance of 15 m, as shown in Fig. 3 (e) Case 3. In addition, the webcam was installed at a height of 4 m to cover the experimental conditions of both Cases 1 and 2.

3. Results

3.1. Results of model performance

Table 5 demonstrates that the performances of the developed model that were derived for validation resulted in recall, precision, and $mAP_{0.5}$ values of 0.93, 0.94, and 0.96, respectively. The test image dataset had recall, precision, and $mAP_{0.5}$ values of 0.97, 0.91, and 0.96, respectively. A few samples of the test image dataset are shown in Fig. 5.

Table 4
Combustibles of fire detectors.

Standard	Combustible	Contents of the test
Case 1- Video image fire detector (UL 268B) [46]	Fire of paper 	Combustible: chopped newspaper consisting of black ink Combustible specification: side of 6–10 mm Longitudinal length, mass: 25.4–102 mm, 42.6 g Preprocessing conditions: 50% humidity, 23 °C, 48 h
	Fire of wood 	Combustible: Kiln-dried fir strip Size of the cut surface: 19.1 mm^2 × 152 mm (length) Overall dimension: 152 × 152 × 64 mm^3 Ignition: 4 ml of mixed combustible materials
	Flammable liquid fire 	Combustible: mixed flammable liquids (25% toluene and 75% N-heptane) Preprocessing: 158 mm diameter and 32 mm height Material: stainless steel
Case 2- General fire detector (ISO 7240) [47]	N-heptane 	Combustible: N-heptane, mass of 650 g (100% purity) Preprocessing: 36 cm diameter (= 33 cm × 33 cm) and 5 cm height 5
	Cotton wicks 	Combustible: cotton wicks Combustible specification: 80 cm (length) × 90 cm and a mass of 3 g

Table 6 summarizes the results of applying an indoor fire video to the EFDM. When the video was applied to the EFDM, an early fire was detected at 8 s based on the timecode. In the video, smoke was vaguely generated for approximately 5 s after the ignition started but could not be identified. However, the flame was visually confirmed after 6 s and detected with a confidence of 0.62 at 8 s after 2 s. In the second video, a flame with a confidence of 0.64 was detected at 22 s per the timecode; the start-time of the video began from 16 s. Therefore, the early fire was detected 6 s after the video began. Both video test sets detected a fire within 8 s.

In the video, objects other than flames in the bedroom and living room were not recognized as flames or smoke. In the bedroom video, various bedroom props were shown before the fire test, but none were captured as flames or smoke. Essentially, false alarms did not occur. The video test sets helped confirm that the EFDM proposed in this study worked as an early fire detector within 8 s.

The EFDM was trained using an early fire; therefore, early fires were quickly recognized. However, it did not recognize a fire when it turned into a large fire, that is, when the fire spread across the entire house. This is because the training in this study focused only on early fires. Thus, additional training will be required to detect large fires.

3.2. Results of the fire detection experiments

3.2.1. Results of the video image fire detector detectability (Case 1)

As shown in Fig. 6, an experiment suggested by UL 268 B was conducted to confirm the early fire detection time and indoor use of the EFDM. As previously stated, UL 268 B indicates that a video-image fire detector must detect a fire within 4 min. Table 7 presents the fire detection time results for each combustible in Case 1.

The fire was detected more slowly for the flammable liquid than for the paper or wood fires because flammable liquid fires are

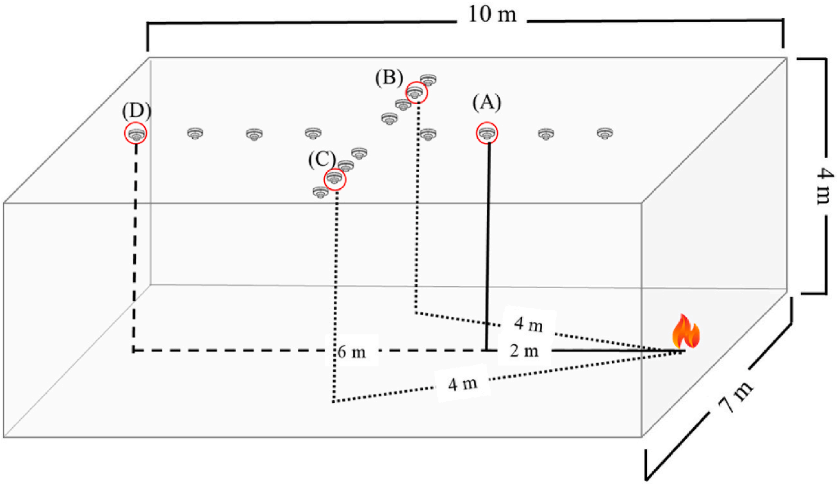


Fig. 4. General fire detection test room (ISO 7240-9) [49].

Table 5
Performance of EFDM.

	Recall	Precision	$mAP_{0.5}$
Validation	0.93	0.94	0.96
Test image dataset	0.97	0.91	0.96

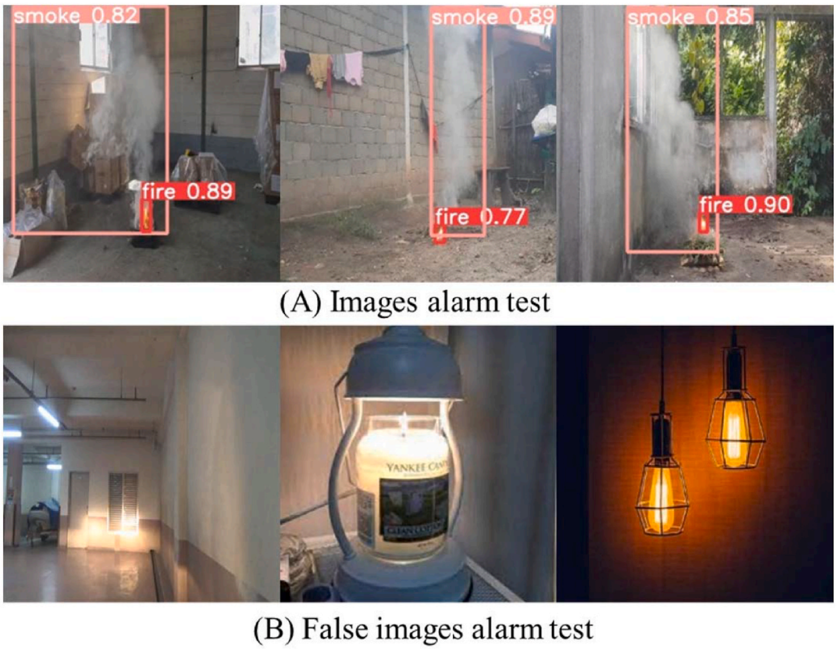
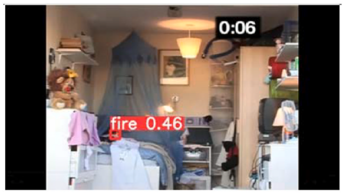


Fig. 5. Test image dataset.

smaller than those of other combustibles. The disadvantage of YOLO is that it is difficult to recognize shapes that are too small. Therefore, the slow detection time of the flammable liquid fire was owing to the size of the fire being small, which makes it difficult to clearly distinguish the shape.

Smoke was not detected in any of the three combustibles; considering the flammable liquid fire, this is because smoke is unable to be visually detected. Considering the paper and wood fires, vague smoke can be visually confirmed in the field; however, the webcam quality is limited despite showing the vague smoke occurring in the early fire. Therefore, the smoke from combustibles that was unable

Table 6
Results of video test sets.

Test video title	Example	Time (s)
Bedroom fire test [43]		8 s (start-time: 0 s)
Living room fires with and without fire sprinkler (Timecode) [44]		6 s (start time: 16 s)

(A) Fire of paper (B) Fire of wood (C) Flammable liquid fire

Fig. 6. Fire test.

Table 7
Results of Case 1 (Max: 4 min).

	EFDM (Video image fire detector)	
	fire	Smoke
(1) Paper fire	1.34 s	–
(2) Wood fire	1.63 s	–
(3) Flammable liquid fire	15.25 s	–

to be viewed by the CCTV screen was not captured. In addition, a vague smoke image dataset was trained for detection; however, there was an increase in false alarms, such as detecting gray floors or vinyl floors as smoke. This result indicates that the image quality of the webcam used in this study is limited when detecting vague smoke.

Based on test Case 1, fires were detected in all three combustibles proposed in UL 238B within 16 s by using the EFDM. Thus, the EFDM developed in this study has the detectability of a fire because it satisfies the "test standards for the video image detector" within 4 min.

Table 8
Result of Case 2 (s).

	Distance from combustible	EFDM		Heat detector (min:s) Choi et al. [49]	Smoke detector (min:s) Choi et al. [49]
		Flame	Smoke		
N-heptane	2 m	2.32	–	101 (1:41)	
	4 m	1.31	–	196 (3:16)	
	6 m	1.25	–	266 (4:26)	
Cotton wicks	2 m	12.79	139.3		147 (2:27)
	4 m	6.97	139.5		185 (3:05)
	6 m	7.36	141.1		448 (7:28)

3.2.2. Results of the EFDM distance detection and comparison with general fire detectors (Case 2)

The distance at which a fire can be detected was measured and the results were compared with those of a general fire detector. The real-time fire detection time results are listed in Table 8; Fig. 7 presents the fire videos.

Table 8 indicates that most flame detections using EFDM were delayed because they were closer, which can be attributed to the webcam angle. As shown in Fig. 2, most image datasets trained in the EFDM were captured at an angle of 45° or less between the combustible and webcam. Therefore, slightly more time was required to recognize a fire at a distance of 2 m, where the angle was larger than that of the trained image dataset.

The flame and smoke were detected at different times because cotton wicks generate a large amount of white smoke after the flame is extinguished, in addition to the vague smoke. Therefore, the two results appeared with a time difference for cotton wick fires.

Fig. 8 presents the difference in the fire detection times between the EFDM and general fire detectors based on distance. The EFDM results are shown with decimal places rounded up for readability. Differences of 99, 194, and 264 s at 2, 4, and 6 m were observed when the heat detector and EFDM were compared, respectively. Considering the EFDM, a fire can be detected faster than that using a heat detector by a minimum of 99 s to a maximum of 264 s, depending on the distance. A difference of 7, 45, and 306 s at 2, 4, and 6 m occurred when comparing the smoke detector and EFDM with the smoke, respectively. Essentially, the EFDM was confirmed to detect fires faster than the smoke detector by at least 8 s–307 s, depending on the distance.

Fig. 9 presents the difference based on the distance for each type of fire detector. The y-axis represents the type of fire detector, and the x-axis represents the detected time (s); the number at the right end of the bar graph represents the detection time difference ranging from 6 to 2 m.

First, the heat detectors that were 2 and 6 m distant from the combustible exhibited a difference of 165 s from one another at a 4 m distance. A detection difference of up to 301 s occurred at a 2 m and 6 m distance from the combustible (4 m) even if the smoke detector was the same. Fire detection using smoke detectors was slower than that using heat detectors because the distance from the combustible increased. This is because a general fire detector requires heat or smoke to directly reach the fire detector and the speed of heat is faster than that of smoke. For the EFDM, a difference of 1.07 s (n-heptane) and 1.80 s (cotton wicks) occurred at a distance of 4 m. Unlike the general fire detector, which differs up to 263 s or more depending on the distance of 2 m, the difference was not larger than 6 s for the EFDM.

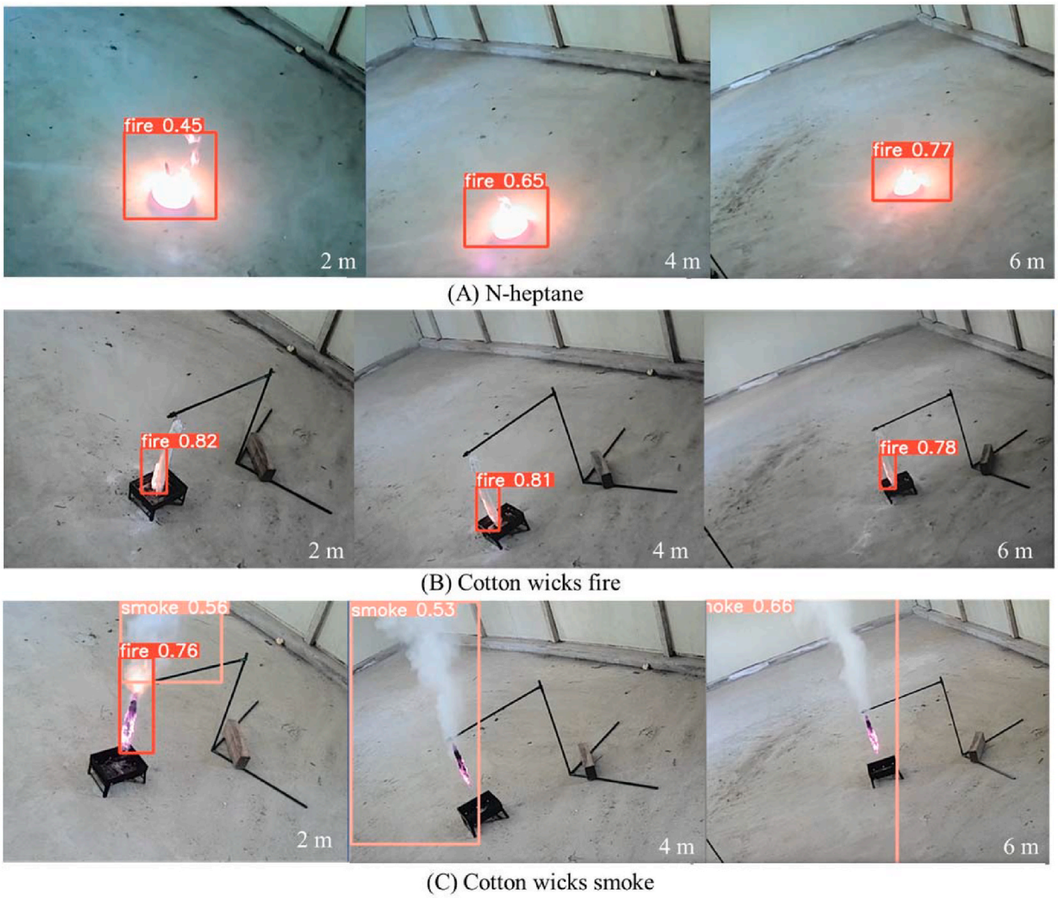


Fig. 7. Fire detector comparison experiment (standard of general fire detector).

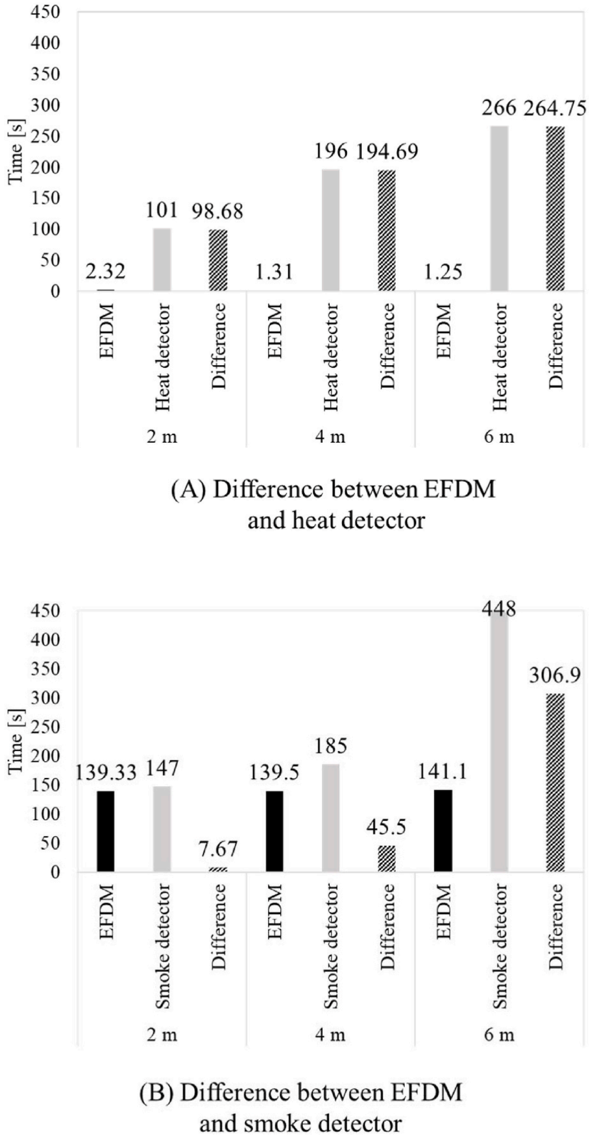


Fig. 8. Difference in fire detection times based on distance (EFDM vs. general fire detector).

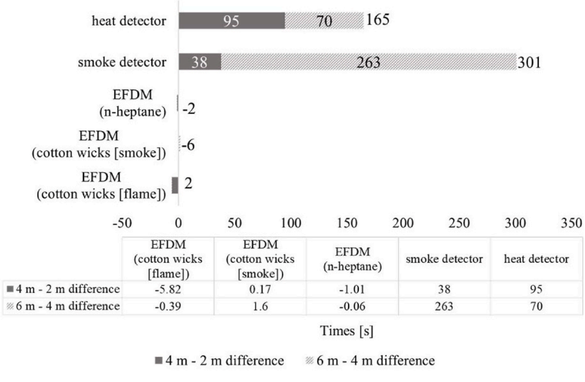


Fig. 9. Difference by distance based on the type of fire detector.

These experimental results suggest that EFDM has a significant advantage considering that it can detect a fire without it being physically near the CCTV, unlike general fire detectors that require a certain amount of heat or smoke to be near the fire detector.

As shown in Fig. 7 (A), a fire was rapidly detected in all N-heptane experiments within 3 s; however, it was a fleeting moment. After an average of 2 s, it was no longer detected despite a fire occurring. A fire was only detected just before the fire was extinguished because it appeared as light caused by the increase in the size of the fire owing to the quality limitation of the webcam used in this experiment. Therefore, additional experiments were conducted. The additional camera (iPhone XS) had 12 megapixels, a frame rate of 30, and HD 1080P performance.

The initial fire detection results were obtained at 1.75, 1.14, and 1.48 s at 2, 4, and 6 m when the n-heptane fire test was conducted under the same conditions except for the camera performance, respectively. Essentially, all fires were detected within 2 s. In addition, even after the fire was detected, it was continuously detected as a fire and not as light. Essentially, the indoor CCTV quality needs to be adjusted based on the size of the fire that can occur indoors. To use EFDM, the size of a fire that can occur indoors and the quality of CCTV are important factors that need to be considered. A captured video sample of the experiment with an additional camera is shown in Fig. 10.

The experiments presented in this section helped to confirm that EFDM can detect flames within 13 s and smoke within 142 s. In addition, it was possible to confirm the necessity of a computer vision model using a CCTV indoors by comparing it with a general fire detector. Furthermore, limits based on the size of the fire and quality of the webcam were derived, confirming that the CCTV quality conditions need to be considered based on the fire conditions that may occur indoors.

3.2.3. Results of fire useable range (Case 3)

In this section, the useable range of EFDM in Case 3 was investigated. Fig. 11 presents the fire detection results in the useable range.

The EFDM detected a fire with an average of 0.89 s. In addition, it was rapidly detected without a delay compared to that in other experiments because the angles of the combustibles and webcams were similar to those of the trained fire image dataset. Thus, it was confirmed that a fire can be detected up to 15 m distant from the camera, which is the proper visible range of the webcam used in the experiment. Furthermore, fire detection was not significantly affected when the size and distance of the fire were within the visible range. These results suggest that an early fire can be detected when it occurs in a space where a CCTV is installed to fit the visible range.

4. Discussion

This study confirmed the novel possibility of using fire detectors along with a computer vision-based CCTV indoors. This fire detector can achieve early fire detection, which suggests that casualties or property damage can be minimized. In addition, if a building uses CCTV, it can be used without installing additional devices, which can help minimize additional costs. In addition, it can be utilized without the time required for an individual to directly check the situation of a fire. When a fire occurs, the damage is significant in buildings that require a long time to evacuate (e.g., hotels), buildings without someone continuously watching a CCTV for 24 h (e.g., residential buildings), and large buildings with a high floor to ceiling fire. Therefore, the proposed system can be used in buildings where it is difficult to detect fires (e.g., department stores, auditoriums). The EFDM developed in this study can be actively used in the automatic alarm systems of buildings, as shown in Fig. 12. This study contributes in the development of the fire protection field to reduce individual and building property damage. Additional research will be conducted regarding the safety of building environments, which remains lacking.

Despite these meaningful results, certain issues remain unaddressed. In this experiment, neither heat nor vague smoke that could be detected by the webcam were derived. The model was retrained to lower the confidence or detect vague smoke; however, the number of false smoke alarms detected increased. Frizzi et al. [33] suggested that smoke may be difficult to detect and locate owing to the various shapes and textures, and Yu et al. [50] reported a significant deterioration in the smoke detection accuracy at a low resolution depending on weather conditions. Kim et al. [51] suggested that certain blobs can be detected when the camera is zoomed, which can result in a lower accuracy.

Therefore, studies regarding fire detection using infrared (IR) rather than visible fire detection are increasing [52–54]; however, it is relatively expensive [16]. Owing to these limitations, it is difficult to use the developed EFDM alone. Therefore, it can be considered a reliable fire detection system with a high accuracy and speed in various situations only when combined with a general fire detector. Furthermore, additional training will be required for considering the size of a fire that can occur indoors because the developed EFDM was trained with an emphasis on early fires. According to Chen et al. [32], an atypical flame color may not be recognized. Therefore, an additional review is necessary for use in large fires that can cause explosive fires.

5. Conclusions

This study developed an EFDM using CCTV for rapid fire detection in the case of an indoor fire by adding 10,000 flame and smoke image datasets and 500 false-alarm image datasets. The developed indoor EFDM is based on the YOLO model. The indoor fire performance of the developed model was verified. First, recall, precision, and $mAP_{0.5}$ values were derived from the test image dataset of the developed model, and the detection time was derived from the indoor fire video test sets. Second, we conducted an experiment that met the UL 268 B condition to confirm detectability as a video image fire detector in Case 1. Third, a fire test that meets the ISO 7240-9 conditions was conducted to confirm the necessity of an indoor fire detector for the EFDM in Case 2. The early fire detection times were measured and compared with those of typical fire detectors. Fourth, the fire detection time was measured in the maximum visible range of the webcam to determine the maximum fire detection distance of the webcam used as the CCTV in Case 3. The following results were obtained:

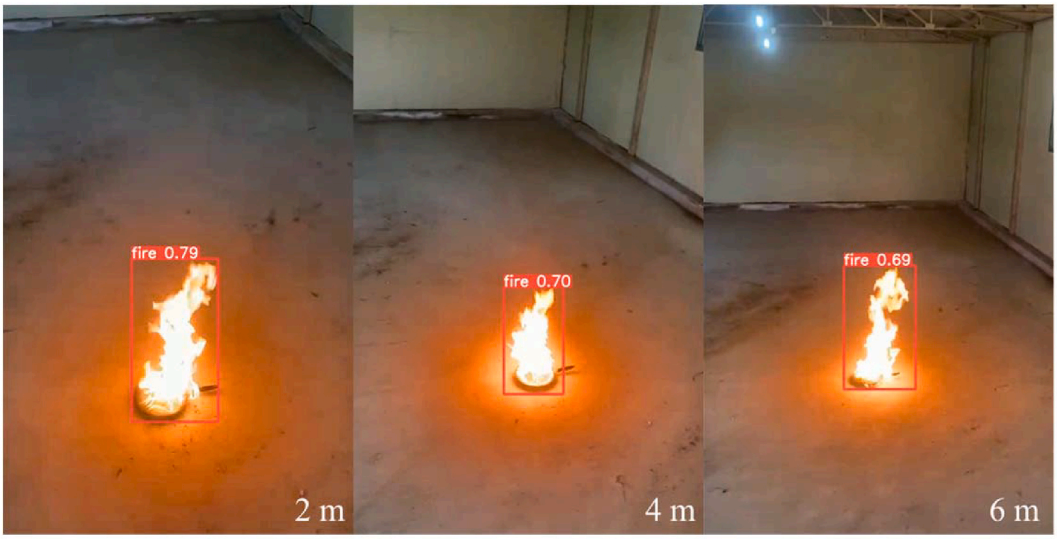


Fig. 10. N-heptane addition experiment (iPhone XS).

Fig. 11. Fire detection experiment while using the maximum distance sample of the image dataset.

1. The performance of the developed EFDM was derived with a recall, precision, and $mAP_{0.5}$ of 0.97, 0.91, and 0.96, respectively. The fire detection time was within 8 s for the two video test sets of indoor fires; the other objects were not recognized as fire (flame or smoke).
2. EFDM detected a fire within 16 s for all three proposed combustibles. Fire detectability was confirmed using a video image detector because it met the criteria of detection within 4 min.
3. Compared with the heat detector, the detection time of EFDM was 99, 195, and 265 s at 2, 4, and 6 m, respectively. Compared with the smoke detector, the detection time of EFDM differed from 2, 4, and 6 m to 8, 46, and 307 s, respectively. In addition, a difference of up to 165 s (heat detector) and 301 s (smoke detector) occurred in the general fire detectors when the fire detector was 4 m from the combustible; however, EFDM detected them all within 2 s. Therefore, EFDM can detect fires despite heat and smoke not being physically near, unlike general fire detectors, and the effect of the CCTV installation distance from the combustible is small. Thus, there is a need to develop an indoor EFDM fire detector.
4. The last experiment was measured by installing a combustible in the maximum visible range of the CCTV webcam used in this experiment. The indoor early fire was detected within 1 s on average. Thus, the CCTV was confirmed to detect fires within the maximum visible range.

Author statement

Yusun Ahn: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing – Original, Draft Visualization, Visualization, Haneul Choi: Methodology, Software, Data Curation, Resources, Writing - Review & Editing, Byungseon

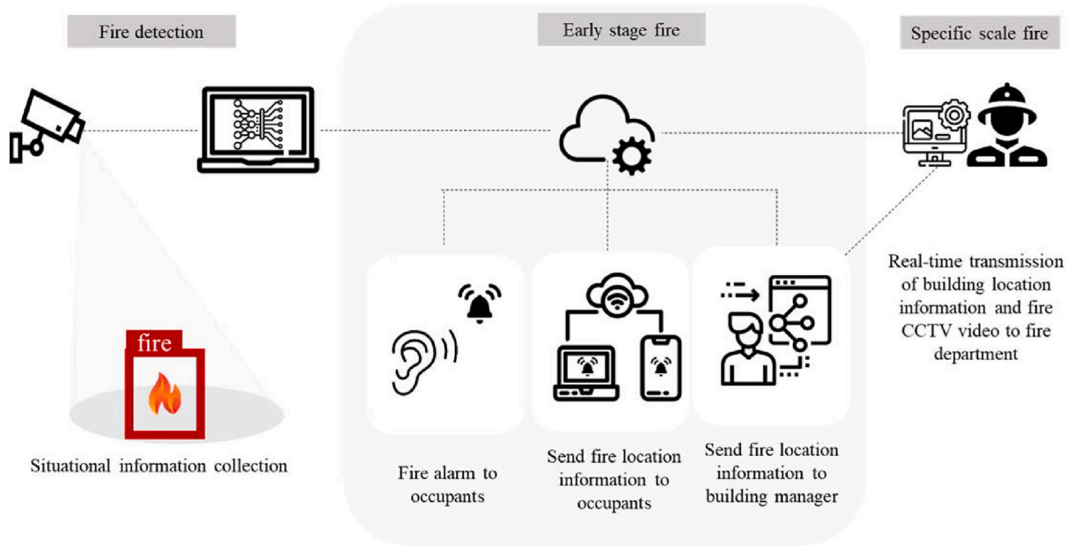


Fig. 12. Automatic alarm application process.

Sean Kim: Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Object recognition

Computer vision is a task in which a computer recognizes objects and extracts meaningful information through mathematical algorithms [55]. In other words, computer vision refers to the ability of a computer to see objects and perform functions similar to those of humans. Object recognition is a technology that uses computer vision to identify objects in an image or video. There are three representative methods of object recognition, as shown in Figure 13: classification, object detection, and segmentation. Among them, object detection refers to specifying the location of several objects as a bounding box and simultaneously classifying the meaning of several objects [56]. The representative models used include YOLO, the region-based convolutional neural network (R–CNN), and single-shot detector (SSD). In this study, we used a method that classifies flame and smoke by object detection and applies a bounding box that can simultaneously determine the location.

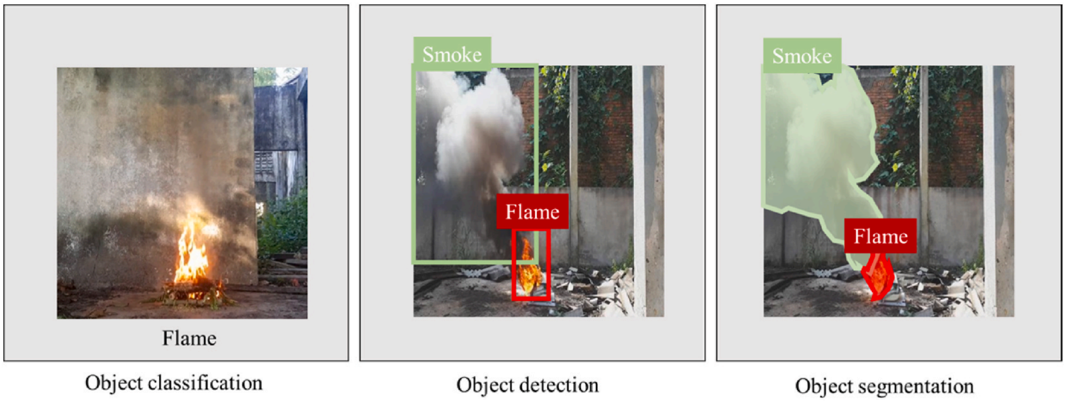

Fig. 13. Object recognition

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