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Fire Detection in Images Using Framework Based on Image Processing, Motion Detection and Convolutional Neural Network

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Abstract: Fire detection in images has been frequently used recently to detect fire at an early stage. These methods play an important role in reducing the loss of life and property. Fire is not only chemically complex, but also physically very complex. The shape and color of the flame varies according to the type of fuel in the fire. This has made fire detection a very challenging problem. Advanced image processing algorithms are also needed to accurately detect fire. To solve this problem, a three-stage fire framework was created in this study. In the first stage, the flame region was extracted from the images containing the fire region with the basic image processing algorithms. At this stage, reduce brightness, HSL, YCbCr, median and herbaceous filters are applied successively to the image. Since the flame image has a polygonal structure by nature, the number of edges of the flame region has been found. In the second stage, the mobility feature of the flame was utilized. For this purpose, the mobility of the flame was determined by comparing the video frames containing the fire image. The CNN method was used to detect the fire in the images. The CNN model was trained with the transfer learning method using the Inception V3, SequeezeNet, VGG16 and VGG19 trained models. As a result of the tests of the models, 98.8%, 97.0%, 97.3% and 96.8% classification success were obtained, respectively. With the proposed fire detection framework, it is thought that the damage caused by the fire can be reduced by early detection of the fire and timely intervention.

Keywords: *Fire detection, Flame detection, Image processing, Motion Detection, Transfer learning*

1. Introduction

Fire is a physical and chemical reaction that occurs suddenly. It can cause great harm to the environment and people in a short time after its emergence. Depending on the social and economic developments and the increasing number of people, the settlements have expanded. In these developments, the number of buildings increased and the complexity of the structures increased. When a fire occurs in these places, the fire can be detected quickly and the fire response time can be shortened and the growth of the fire can be prevented. Sensor-based systems can be used for fire detection in closed areas [1]. However, fire detector smoke, flame and heat sensors are not suitable for fire detection in open areas and complex buildings [2]. In some cases, gas sensors can detect smoke after the gas in the environment increases to a size that will harm people [3]. Smoke sensors can also detect fire smoke as fire smoke by mixing it with water vapor, cigarette smoke and dust [4]. When a fire occurs, different harmful gases are released to the environment according to the type of burning substance [5]. A large number of gas sensors are needed to detect these gases and detect fire [6]. Due to these limitations of sensors, image processing methods and fire and smoke detection have recently gained importance [7]. Studies have been carried out on the detection of fire by making use of the color characteristics of the flame [8]. They also benefited from the movement of the flame to increase the detection accuracy [9]. In addition to these, the fire was determined by temporal and spatial wavelet analysis [10]. In another study, they performed flame detection by comparing the color differences between video frames [11]. There are also studies on flame detection using color, skewness and roughness properties [12]. On the other hand, Khan et al. [13] proposed a video-based method using flame movements using the color properties, perimeter, and area of the flame. They carried out the study using small flames. Seebamrungsat et al. [14] performed flame detection using combinations of HSV and YCbCr. This method has some limitations as flame detection is done using only the color properties of the flame on static images. Kruger et al. [15] proposed a sensor-based fire detection method. The hydrogen sensor used in the study has some limitations depending on the type of fire. In addition, it is not possible to detect fire with this sensor at long distances. Han et al. [16] aimed to detect the fire by using the motion and color characteristics of the fire. Using these two features, they determined the area of the fire. In general, flame detection is made with the color characteristics of the flame (RGB) [17-20], Hue Saturation Value (HSV) [21, 22], YCbCr [23, 24] and HIS [25] filters and their combination filters and their combinations.

Deep learning methods are used to increase the success of detection studies made by using the color, movement and other features of the fire. Convolutional Neural Network (CNN), an end-to-end recognition algorithm that has been used frequently recently, can successfully detect the presence of the desired object in images [26, 27]. In this way, it is possible to detect fire in a large

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area with lower cost and fast detection time [28]. According to Muhammad et al. [29] performed early-stage fire detection on images taken from CCTV cameras with CNN and proposed a network for response. According to Fan et al. [30] succeeded in detecting fire with CNN using long-range infrared images. Wu et al. They benefited from the color and movement characteristics of the flame in order to detect the fire. They realized whether there was a real fire and the marking of the fire area with the CNN algorithm.

Considering the motivations described above, an advanced fire detection method was studied in this study. The work can be summarized as follows:

1. Since the fire may have flames in different shapes and colors depending on the fuel type, flame detection has been made with different image processing algorithms.
2. Since the flame will be active during the burning of the fire, this feature was also used in the detection of the fire.
3. The CNN algorithm is used to find out whether there is a fire in the images used.
4. According to the results obtained from all fire detection methods, the presence of fire was detected with a high success rate.

The rest of the article is organized as follows: In Chapter 2, materials and methods are described. Experimental results are given in Chapter 3 and results in Chapter 4.

2. Material and Methods

Detection of fires at an early or later stage can prevent many material and moral losses [31]. Detection of fire is a challenging problem due to factors such as different lighting conditions, colored objects, moving objects. For this reason, a framework consisting of a set of algorithms has been proposed so that fire detection can be performed with high success considering all scenarios. In this section, information about the proposed framework, the dataset used and the methods used in the framework and performance metrics are given.

2.1. Proposed Framework

Fire can have different colors depending on the type of fuel [31]. The fact that the objects in the environment have the same colors as the flame is one of the most important factors that make it difficult to detect the flame with image processing techniques [32]. However, the fact that the flame is in motion reveals the difference between it and the objects. Apart from these, the presence of fire in the environment can be detected by using deep learning algorithms that can make sense of the entire image [33]. Considering all these factors, a 3-stage fire detection framework has been proposed. In Stage 1, a number of image processing techniques were used to detect the flame. These are, respectively, luminance reduction, HSL (Hue saturation luminance), YCbCr (Y: Luminance, Cb: Chroma (blue minus luma), Cr: Chroma (red minus luma)), median, grassy and edge detection filters. The flame image is extracted from the image passed through these filters. In the 2nd stage, the motion feature of the flame was used. At this stage, after the brightness reduction is made, the movements in the pixels are detected by comparing the previous and next frames. Detected moving pixels are marked. The moving area is detected by passing the marked pixels through the red color filter. In the 3rd stage, the presence of fire is detected in the entire image with the CNN algorithm. The flow chart showing all these stages is shown in Figure 1.

As a result of all stages, a decision is made about the existence of the fire on the image. Necessary actions can be taken as a result of the decision taken.

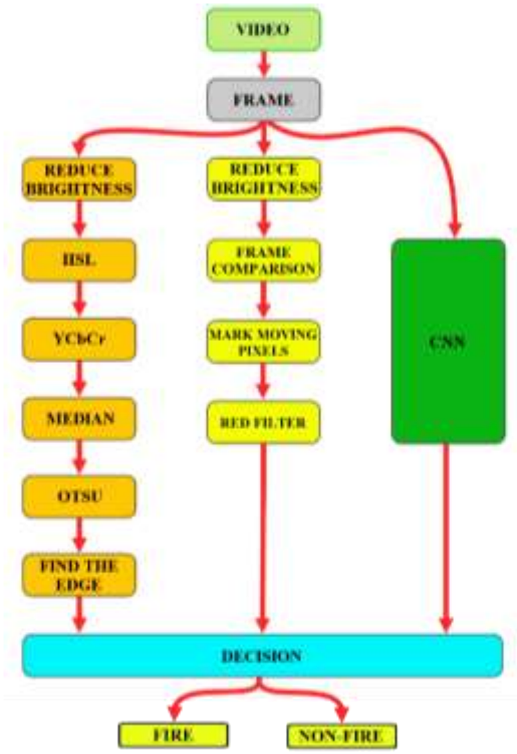

Fig. 1. Suggested framework structure for fire detection on images

2.2. Dataset

The dataset used in the study is an enriched dataset consisting of images obtained from search engines by combining the datasets used in previous studies [29, 34, 35]. The frames obtained from the videos are also included in the created dataset [36]. The dataset contains 3041 images in total. 1900 of these images are natural images without fire zones. 1141 of them consist of images containing various fire zones. Although the number of images in the dataset is small, it has a wide variety of images. The cross-validation method was used for the reliability of the success of the models. The dataset is not divided into train and test parts. Examples of fire images with fire zones in the dataset and non-fire images without fire zones are shown in Figure 2.

Fig. 2. Sample images from the dataset

2.3. Image Processing

In computer vision applications, the human vision mechanism is imitated. In this way, object detection on images or information about the image can be obtained [37]. The human eye performs its optimum vision function by adjusting itself to external environmental conditions. At this stage of the fire detection framework, filters were applied to detect the fire on the images. These filters are dimming, HSL, YCbCr, median, grassy and edge finding filters, respectively. The filter parameters, in which fire detection is performed with the highest success, have been determined after many test processes. The operating modes and parameters of the filters used are as follows, respectively:

Brightness filter: With this filter, the brightness of the image is reduced by 50%. Because the light in the environment increases when a fire occurs, the camera is affected by this light and can obscure other objects [31].

HSL filter: HSL color space is the representation of different colors with their H, S and L values. H (Hue) represents the amount of similarity between red-yellow-green-blue. S (Saturation) represents the intensity of a color. L (Lightness) represents the white and black balance in the image. In this filter, color saturation is adjusted by setting the S value to 0.6.

YCbCr filter: It is used for numerical coding of color information [38]. Y (Limunance) represents Cb (Chroma-blue minus luma), Cr (Chroma-red minus luma). The human eye is sensitive to limunance. It is not very sensitive to Chrominance. Images can be displayed more efficiently with YCbCr. In the study, the Cb value was defined in the range of -0.2 to 0. The Cr value is defined between 0.1 and 0.5.

Median filter: This filter is used to reduce noise in the image. It also ensures that the details on the image are not lost while this process is being applied. It takes the median value of the values of these pixels by looking at the neighboring pixels next to a pixel. In this way, it removes the noise on the image [39].

Otsu filter: It is a filter that can be applied on gray images and ensures that the pixels above a threshold value determined according to the pixel value of the image are white and the pixels below it is black [40].

Finding edge: Since the flame does not have a regular shape, it has many edges and corners. With the Sobel filter, the edges of a shape can be detected and information about its number can be obtained [41].

2.4. Motion Detection

One of the fastest and simplest motion detection methods in video images is the method based on the comparison of two frames. By comparing the previous and next frame pixels in the video, the different pixels are marked. If the difference is large, it means the movement rate is high. It is preferred because of its speed and simplicity in studies requiring only motion detection application. It was used in this study to detect the mobility of the flame. This method alone cannot detect the flame, but the presence of motion can be obtained with this method.

2.5. Convolutional Neural Network

CNN is a deep learning method created by considering the vision mechanism of living things. It is frequently used because successful results are obtained in studies such as motion detection, image classification, and object detection on the image [42, 43]. This is because it can generate a rich feature map using the raw image. Generally, it consists of 3 layers. These layers are convolution, pooling, fully connected layers [44]. The feature is extracted in the Convolution layer. Reducing the size of the extracted feature maps is done with the pooling layer. Image features that pass through many convolution and pooling stages are flattened in the flatten layer and sent to the fully connected layer. This layer has a kind of neural network structure. Classification is made in this layer [45].

The structure of CNN models with high classification success emerges as a result of long trials [46]. The network weights obtained as a result of these trained models can be retrained using our own datasets and successful results can be obtained [47]. This process is called transfer learning. In this study, the weights of the Inception V3, SequeezeNet, VGG16 and VGG19 trained models were used. The reason for choosing these models is that they are frequently used in the literature and have high classification success.

2.6. Performance Metrics

Some metrics are needed to measure the success of classification models [48]. The most frequently used metrics are accuracy, precision, recall and F-1 score [49]. Calculation of these metrics can be done with a table called confusion matrix. Shows the ratios between the predicted and actual class. True positive (TP) value indicating the number of positive samples classified as correctly in the Confusion matrix table, false positive (FP) value indicating the number of positive samples classified as false, true negative (TN) indicating the number of negative samples correctly classified and the number of negative samples classified as false. It has a false negative (FN) value indicating. An example confusion matrix with two classes is shown in Table 1.

Table 1. Two-class confusion matrix

		TRUE CLASS	
		Non-Fire	**Fire**
PREDICTED CLASS	**Non-Fire**	TN	FP
	Fire	FN	TP

Performance metrics are calculated using the values on the confusion matrix. The formulas required to calculate the performance metrics used in the study are given in Table 2.

Table 2. Performance metrics

ABBREVIATION	**FORMULA**
ACC (Accuracy)	$ACC = \frac{TP + TN}{TP + TN + FP + FN}$
FSC (F-1 Score)	$FSC = 2 * \frac{PRE * RCL}{PRE + RCL}$
PRE (Precision)	$PRE = \frac{TP}{TP + FP}$
RCL (Recall)	$RCL = \frac{TP}{TP + FN}$

2.7. Cross Validation

Cross validation is a method used to measure the accuracy of classification models. In this method, the dataset is divided into equal parts according to the specified number value. The specified number value is called k. 1/k part of the dataset is reserved for testing, and k-1 part is reserved for training. This process is continued until each part of the dataset is used as the test segment. So, this process is repeated k times. The overall classification success of the model is obtained by taking the arithmetic average of the classification successes obtained as a result of these processes. In our study, the k value was determined as 10. It is the k value at which the highest classification success is achieved after many trials. Figure 3 shows how the cross-validation method works.

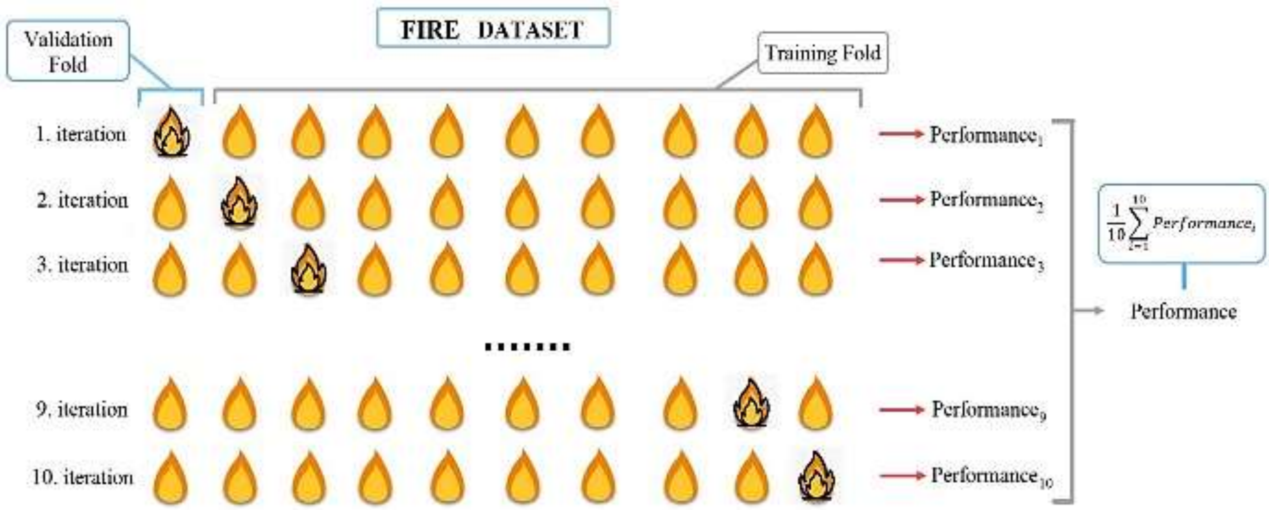

Fig. 3. Cross validation

3. Experimental Results

This section shows the experimental results and comparison of image processing, motion detection and CNN models. Experiments were carried out using the dataset created by combining different datasets. All experiments were performed on a NVidia GeForce GTX 1650Ti with 4GB RAM, Intel Core i5 10200H processor and 16GB RAM computer. Image processing and motion detection Python programming language is used. Tensorflow deep learning framework was used in CNN experiments. In the training and testing of the CNN model, the dataset was not divided into parts, instead the cross-validation method was used. The dataset contains 3041 images in total. 1900 of these images are natural images that do not contain fire areas. 1141 of them consist of images containing fire area. The experiments were carried out in three stages. The first stage is the image processing stage. The second stage is the motion detection stage. The third phase is the training and testing phase of the CNN model.

3.1. Extraction of the flame region from the image with image processing

Various filters were applied sequentially on the image in order to extract the flame region from the image. These filters were applied to 3041 images with and without fire zones. From all images containing the fire zone, the flame zone was extracted with 100% success. However, some parts of the images that do not contain a fire zone are marked as a flame zone. The sample images used in the experiments and the flame zones extracted as a result of the filters applied are shown in Figure 4.

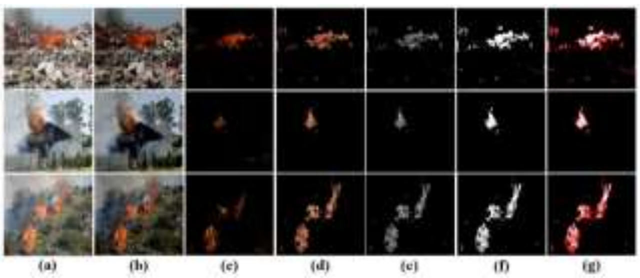

Fig. 4. Examples of removing the flame region from images (a) Input images (b) Reduce brightness images (c) HSL images (d) YCbCr images (e) Median images (f) Otsu images (e) Find the edge images

Figure 4(a) shows the raw images. Figure 4 (b) shows the images with reduced brightness. Figure 4 (c) shows the images passed through the HSL filter. Figure 4 (d) shows the images passed through the YCbCr filter. Figure 4(e) shows the images passed through the median filter. Figure 4 (f) shows the images passed through the herbaceous filter. In Figure 4 (g), the edges of the extracted flame region are determined. After the last stage, it is decided that the flame exists.

3.2. Detection of flame motion with motion detection

Fire flames are in constant motion. For this reason, the mobility feature of the flame can be used in the fire detection stages. The movements of the flame were detected on the live images. Besides the flame, there may be different moving objects in the environment. However, with this method, the presence of a moving object in the environment is detected and sent to the decision system. Together with the 1st and 3rd phases of the fire detection framework, this phase helps in the detection of fire. Via a video, the movements of the flame are detected and the moving areas are marked. Sample images obtained from the experiments are shown in Figure 5.

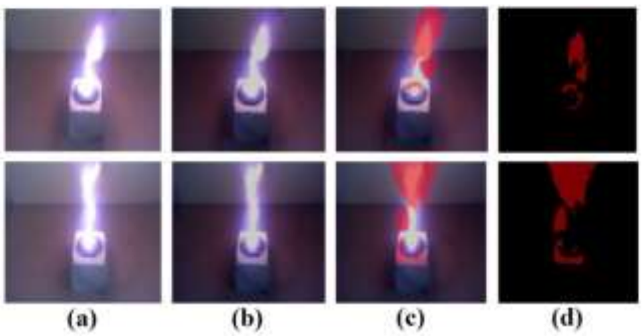

Fig. 5. Detection of flame movements on video (a) Input frame, (b) Reduce brightness, (c) Motion detection and mark pixel with red color (d) Red color filter

Figure 5 (a) shows the frame image taken from the video. In Figure 5 (b), there is an image of the same frame with the brightness reduced by 50%. In the image in Figure 5 (c), the current frame and the previous frame are compared and different pixels are marked with red color. In order to better understand the moving regions, the image was passed through a red color filter. Figure 5 (d) shows the red color filtered image of the frame. By looking at this image, a decision can be made about the presence of the flame.

3.3. Detecting the presence of fire with CNN

Information about the presence of fire on the images can be reached with the CNN algorithm. In the training of the CNN model, 1141 images with a fire zone and 1900 images without a fire zone were used. The CNN model was trained with the transfer learning method using the weights of the previously trained Inception V3, SequeezeNet, VGG16 and VGG19 models. In this way, it is aimed to create a model that can classify more successfully. Tests of the trained models were carried out using the cross-validation method. In this way, classification reliability is increased.

Four different CNN models were compared to find the most successful CNN model. Confusion matrix showing the classification results made with the CNN model trained using Inception V3 is shown in Table 5.

Table 5. Confusion matrix of Inception V3 CNN model

		TRUE CLASS	
		Non-Fire	Fire
PREDICTED CLASS	Non-Fire	1891	9
	Fire	27	1114

Confusion matrix showing the classification results made with the CNN model trained using SequeezeNet is shown in Table 6.

Table 6. Confusion matrix of SequeezeNet CNN model

		TRUE CLASS	
		Non-Fire	Fire
PREDICTED CLASS	Non-Fire	1862	38
	Fire	52	1089

Confusion matrix showing the classification results with the CNN model trained using VGG16 is shown in Table 7.

Table 7. Confusion matrix of VGG16 CNN model

		TRUE CLASS	
		Non-Fire	Fire
PREDICTED CLASS	Non-Fire	1860	40
	Fire	43	1098

Confusion matrix showing the classification results with the CNN model trained using VGG19 is shown in Table 8.

Table 8. Confusion matrix of VGG19 CNN model

		TRUE CLASS	
		Non-Fire	Fire
PREDICTED CLASS	Non-Fire	1855	45
	Fire	51	1090

The performance metrics in Table 9 were obtained as a result of the calculations made using the confusion matrix data of all models.

Table 9. Performance metrics of all models (%)

	Accuracy	Precision	Recall	F-1 score
Inception V3	98.8	98.8	98.8	98.8
SequeezeNet	97.0	97.0	97.0	97.0
VGG16	97.3	97.3	97.3	97.3
VGG19	96.8	96.8	96.8	96.8

When the performance metrics in Table 9 are examined, it is seen that the model with the highest classification success is the Inception V3 CNN model with 98.8% classification success. Parallel to the accuracy of the Inception V3 CNN model, the highest precision, recall and F-1 score values belong to this model. Some examples of images classified correctly and incorrectly by the Inception V3 CNN model with the highest classification success are shown in Figure 6.

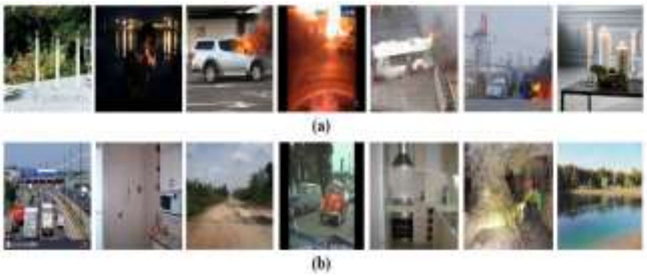

Fig. 6. (a) Examples of images containing a flame zone but classified as no flame, (b) Examples of images classified as having a flame zone although there is no flame zone

Figure 6 shows the images that the VGG16 CNN model misclassified. It is thought that the reason why the flame regions in the images in Figure 6 (a) cannot be detected is that the flame region cannot be detected due to the very small flame region or the color toning. It is thought that the images in Figure 6 (b) are misclassified because they are too complex or their color tones are too similar to flame colors.

4. Conclusions

In this study, it is aimed to detect fire using images containing fire zones. A dataset was created by combining various fire datasets in the literature. The dataset contains 1141 images with fire zones and 1900 images without fire zones. Three methods were used to detect the fire in these images. The first of these methods is made by applying the basic image processing algorithms to the images sequentially. With the image filters applied on the images containing the fire area, it is ensured that the flame area is extracted from the image. These operations are performed by applying reduce brightness, HSL, YCbCr, median, herbaceous filters to the images. The edges of the flame zone obtained after these processes have been determined to make sure that it is really a flame zone. With these filters applied to the image containing 1141 flame regions, the flame region has been removed with 100% success. However, in images that do not contain a flame region, objects that resemble flame color are also removed as flame regions. Therefore, fire detection is not possible with this method alone. Because fire has many color and shape features. Multiple algorithms are needed to detect fire with high success using these features. Therefore, a three-stage fire detection framework has been proposed.

The second method used to detect fire is to detect the mobility of the flame. Flame is an event that is in constant motion. By using this feature of the flame, the movements of the flame were detected through the videos. However, this method alone is insufficient for detecting fire.

The last and most important stage of the fire detection framework is the detection of fire with the CNN model. In order to find the CNN model with the highest classification success, the CNN model was trained with transfer learning method with four different architectures. These architectures are Inception V3, SequeezeNet, VGG16 and VGG19. Four different CNN models were trained using 3041 images. The cross-validation method was used to test the model objectively. The k-fold value is set to 10. As a result of the experiments, 98.8% classification success was obtained from the Inception V3 CNN model, 97.0% from the SequeezeNet CNN model, 97.3% from the VGG16 CNN model, and 96.8% from the VGG19 CNN model. The highest classification success was obtained from the Inception V3 model.

The fire detection framework created with the three methods used in the study has a sufficient success rate to detect the fire. With the results obtained as a result of these 3 methods to be applied to the images, a decision can be made about the existence of the fire. Higher classification successes can be achieved by further developing the fire dataset used. Thanks to this fire framework, it is possible to detect the fire early and take the necessary precautions. Or it can be integrated into an automatically operating fire extinguishing system.

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