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Design and Implementation of Fire Detection System Using New Model Mixing

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Abstract

In this paper, we intend to use a new mixed model of YoloV5 and DeepSort. For fire detection, we want to increase the accuracy by automatically extracting the characteristics of the flame in the image from the training data and using it. In addition, the high false alarm rate, which is a problem of fire detection, is to be solved by using this new mixed model. To confirm the results of this paper, we tested indoors and outdoors, respectively. Looking at the indoor test results, the accuracy of YoloV5 was 75% at 253Frame and 77% at 527Frame, and the YoloV5+DeepSort model showed the same accuracy at 75% at 253 frames and 77% at 527 frames. However, it was confirmed that the smoke and fire detection errors that appeared in YoloV5 disappeared. In addition, as a result of outdoor testing, the YoloV5 model had an accuracy of 75% in detecting fire, but an error in detecting a human face as smoke appeared. However, as a result of applying the YoloV5+DeepSort model, it appeared the same as YoloV5 with an accuracy of 75%, but it was confirmed that the false positive phenomenon disappeared.

Keywords: *CNN, YoloV5, DeepSort, Deep Appearance Deseriptor*

1. INTRODUCTION

Currently, fires have caused environmental problems, human casualties, and many financial losses, so many researchers are trying to minimize the damage. Because there are various and complex correlations between the causes of these fires, many scholars are conducting research to predict the occurrence of fires and minimize damage. According to the Fire Statistical Annual Report of the National Fire Data System of Korea in 2019, out of 426,521 fires from 2010 to 2019, a total of 3,026 people died and 18,792 people were injured. In addition, property damage was 440 million won, resulting in huge casualties and property damage due to fires in Korea [1]. People need a fire detection system that detects fires in the shortest time in buildings, forests, rural areas and other environments to reduce economic losses and casualties.

Existing fire detection methods are mainly divided into fire detection based on a fire sensor and fire detection based on image processing using a camera. Fire sensor-based fire detection has a disadvantage that the performance of the system may be greatly limited depending on various factors in the surrounding environment. In particular, as the location of the sensor installed according to the characteristics of the sensor there is a delay time until the fire element arrives, it is a cost problem to install multiple sensors at regular intervals when detecting a large area. also occurs [2].

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On the other hand, image-based fire detection can solve various problems of sensor-based fire detection, and it can be used at a low cost because existing CCTVs can be used. In addition, it has the advantage of reducing the rate of dispatches due to malfunction of fire detectors because it is possible to check the fire status on the site in advance before dispatch [3]. However, the existing image-based fire detection method is difficult to apply to real situations due to empirical and experimental threshold settings, and since it can generate false alarms for objects similar to flames, many studies using artificial intelligence are being conducted.

In the existing fire detection method, the RGB color-based fire detection method has been proposed [4].

The RGB color-based flame detection algorithm extracts RGB colors from the image and conducts fire inspection using filter conditions. Disadvantages of being recognized as flame are easy to form holes inside the flame, yellow dried grass or smoke from burning flames as distinct characteristics of fire there is this.

The YUV (YCrCb) method is a concept that started with the human visual system and separates it into a luminance (brightness) component sensitive to the human eye and a relatively less sensitive color component. Y means brightness, U is a value obtained by subtracting a brightness value from a blue component, and V is a value obtained by subtracting a brightness value from a red component. RGB color is the most intuitive and common color representation, but YUV color space is used because there is too much data to process everything in RGB.

Based on the Frame Difference [5], the core area is selected according to the YUV color filter model, and a certain limit value is set according to the relationship between the perimeter and the area of the outline, and it is detected through the change of the two frames of the previous frame and the current frame. The method is relatively fast, but the measurement accuracy is low.

In Convolutional Neural Networks Based Fire Detection in Surveillance Videos [6], we applied a Convolutional Neural Networks (CNN) approach to improve the performance of image fire detection technology. In addition, deep learning-based detection methods require significant training data, validation data, and test data. In addition, CNN has an overfitting problem and requires a large data set for training, so it generally takes a large amount of computational cost and time.

Fire detection method using the existing color model can generate false alarms for similar objects, and usually sets the threshold value experimentally, so it is not suitable for application in the real environment. The method of detecting flames through image processing without using a color model detects the occurrence of flames using the characteristics of flames defined by humans, there is a limit to properly detecting the flame.

In this paper, we propose a method to detect fire using the new mixed model of YoloV5 and DeepSort proposed in this paper so that the flame can be detected by automatically extracting the characteristics of the flame in the image from the training data. Therefore, in this paper, we try to improve the detection and tracking method of YoloV5 + DeepSort to solve the problem of high false alarm rate in the fire detection system.

2. RESEARCH METHOD

2.1 YoloV5

Depending on the size of the model, YoloV5 is divided into four versions: YoloV5s, YoloV5m, YoloV5l and YoloV5x. The larger the model, the higher the accuracy and the longer the detection time of a single image. The techniques used for input of YoloV5 include Mosaic Data Enhancement [7], Adaptive Anchor Calculation and Adaptive Image Scaling. Figure 1 shows the network structure of YoloV5s. The backbone has a focus structure and a cross stage paritial network (CSP) [8] structure, the head is YoloV53 [9], and the neck is composed of a Feature Pyramid Network (FPN) [10] and a Path Aggregation Network (PAN) [11].

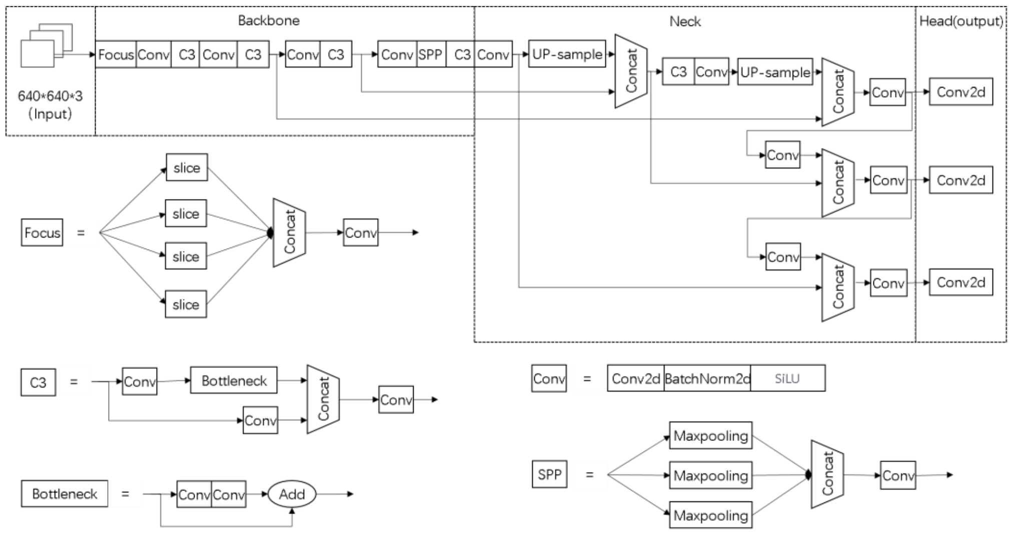

Figure 1. Structure of YoloV5x network

The backbone transforms the input image into a feature map, and the head performs the localization problem of the feature map extracted from the backbone, and performs class probability prediction and bounding box work. The neck is the part that connects the backbone and the head, and the feature map is refined and reconstructed. YoloV4 model has better performance than YoloV5 model however, YoloV5 model is used because it is flexible and fast.

3. IMPLEMENTATION

3.1 Design of YoloV5 + DeepSort Mixed Model

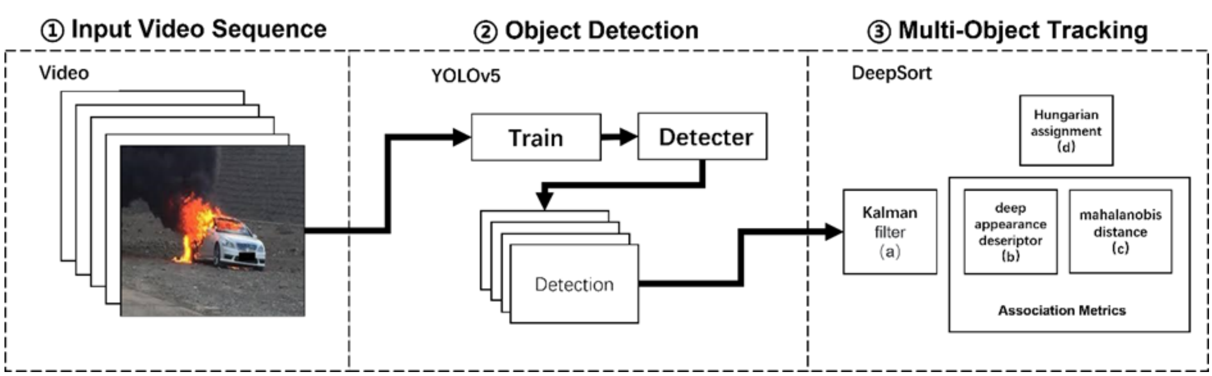

Figure 2. Process YoloV5 and DeepSORT Mixed Model

The explanation of Fig 2 is as follows. First, ① indicates the data of the input value of the image. And in ②, the input value of step ① is detected and displayed with the trained YoloV5 model. In ③, the detection result for each video frame has the input value that has been detected in ① and ②. The Kalman filter (a) outputs the position where the predicted object box is most likely to appear in the next frame based on the result of observing the detection frame of the object in the previous frame.

There are two ways of correlating the results obtained from the prediction and detection models via the Hungarian(d) algorithm and assigning the correct identifiers. First, for small position change, Mahalanobis

Distance(b) is used. Second, for many location changes, deep appearance deseriptor(c) is used. Using a simple CNN in deep appearance deseriptor, we extract the detected object features and represent them as low-dimensional vectors. For each frame of detection and tracking, object features are extracted and stored. Fig. 3 shows the structure of deep appearance deseriptor.

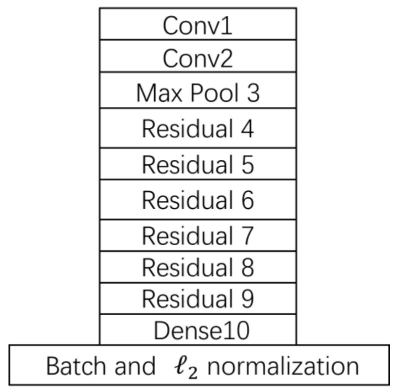

Figure 3. Structure of Deep Appearance Deseriptor

3.2 Process of YoloV5 + DeepSort Mixed Model

Figure 4 shows the YoloV5 + DeepSort Mixed Model proposed in this paper. ①~③ shown in Figure 2 shows the processing process of the data set, and ④~⑥ describes the process of YoloV5 learning and DeepSort, and the result is displayed.

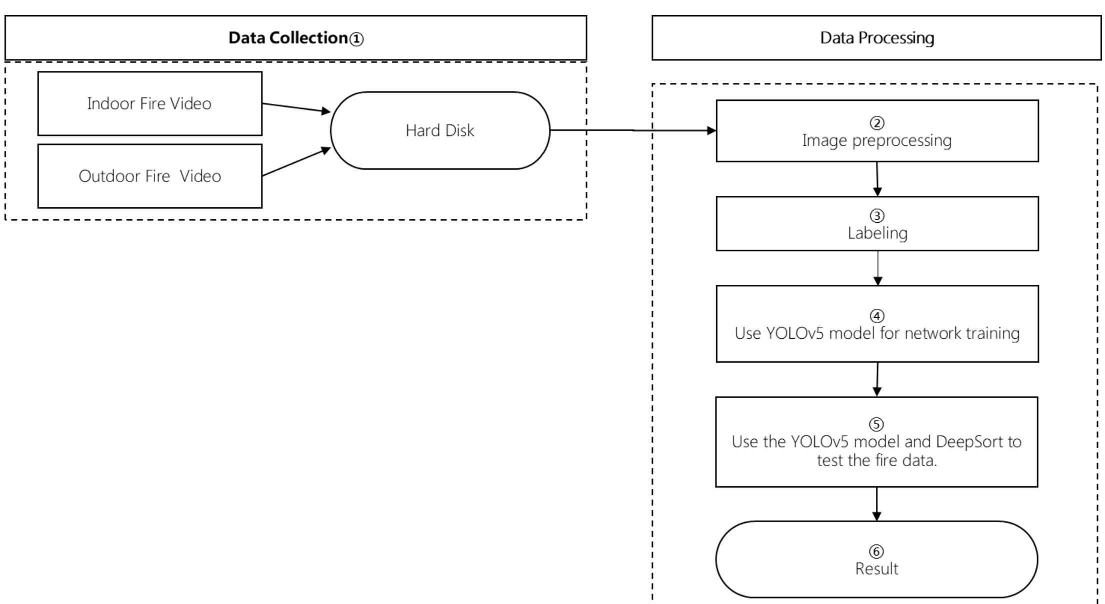

Figure 4. Process YoloV5 and DeepSORT Mixed Model

The process in Figure 2 proceeds as follows. First, data is collected through a network, image data is divided into image frames, and preprocessing is performed. Then, through the labeling of the images obtained in ②, the data processed in ③ are learned using YoloV5. A flame test is conducted using the trained YoloV5 model and DeepSort.

4. RESULTS OF COMPARATIVE TEST BETWEEN YOLOV5 MODEL AND YOLOV5 +DEEPSORT MODEL

For the experimental environment, 2,359 fire images are collected to enrich the data set because there are relatively few data sets currently available on the Internet and the types of scenes are relatively single. The types of data sets are large flames, small flames, building fires, meadow fires, forest fires, vehicles (cars, trucks, motorcycles, electric motorcycles), etc. As shown in table 1, the preprocessing process removes a total of 300 duplicate photos and blurry photos. Because of the relatively small number of samples, the training data set is divided into 70%, the validation data set at 15%, and the test data set at 15%.

Table 1. Proportion of Data set

Dataset	Number of data	ratio
Train Dataset	1,441	70%
Validation Dataset	309	15%
Test Dataset	309	15%
Total	2,059	100%

In this paper, as shown in Fig 5, the labeling tool CVAT can be used to minimize the labeling uncertainty and show good accuracy. The labeling condition proceeds by maintaining the integrity of the flame shape in the bounding box that marks the flame area.

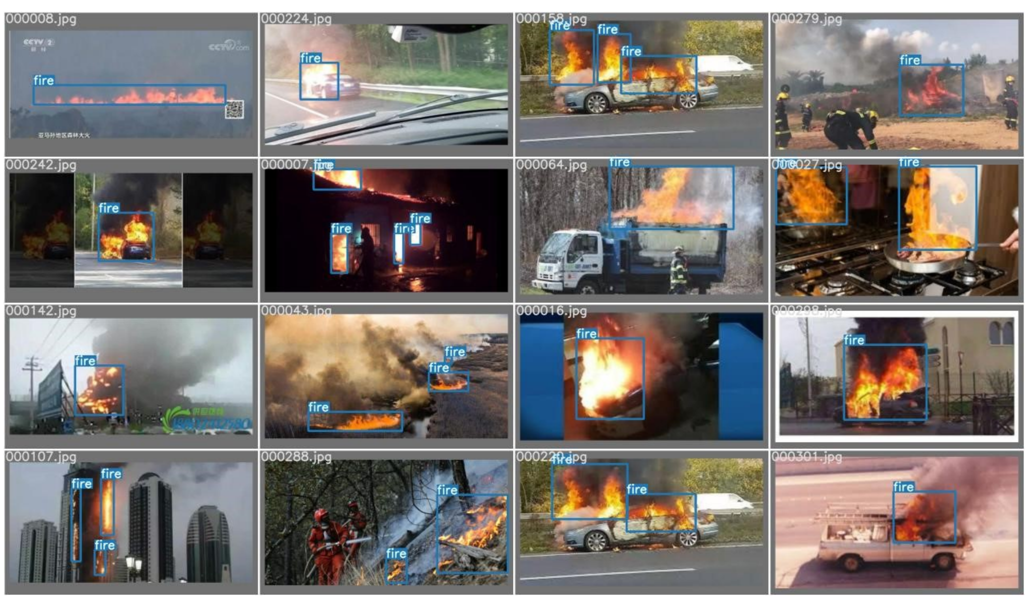

Figure 5. Labeling using CVAT Tool

In the comparative test, the two results of the indoor test and the outdoor test using the YoloV5 model and the YoloV5+DeepSort mixed model through the recorded video were shown through screen captures of the actual results as shown in Fig 6 and 7.

In case of using YoloV5 detection in an indoor environment, it was confirmed that false detection occurred in 253 frames as shown in Fig. 6(a) in the background and flame detection process. When searching at 253frame using the YoloV5+DeepSort model, it was confirmed that false detection did not occur in the background and flame detection process as shown in Fig. 6(b).

In addition, when YoloV5 detection is used in 527frame, it can be confirmed that false detection occurs in the background behind as shown in Fig 6(c) in the background and flame detection process. When the YoloV5+DeepSort model was used in 527frame, it was confirmed that false detection did not occur in the background and flame detection process as shown in Fig. 6(d).

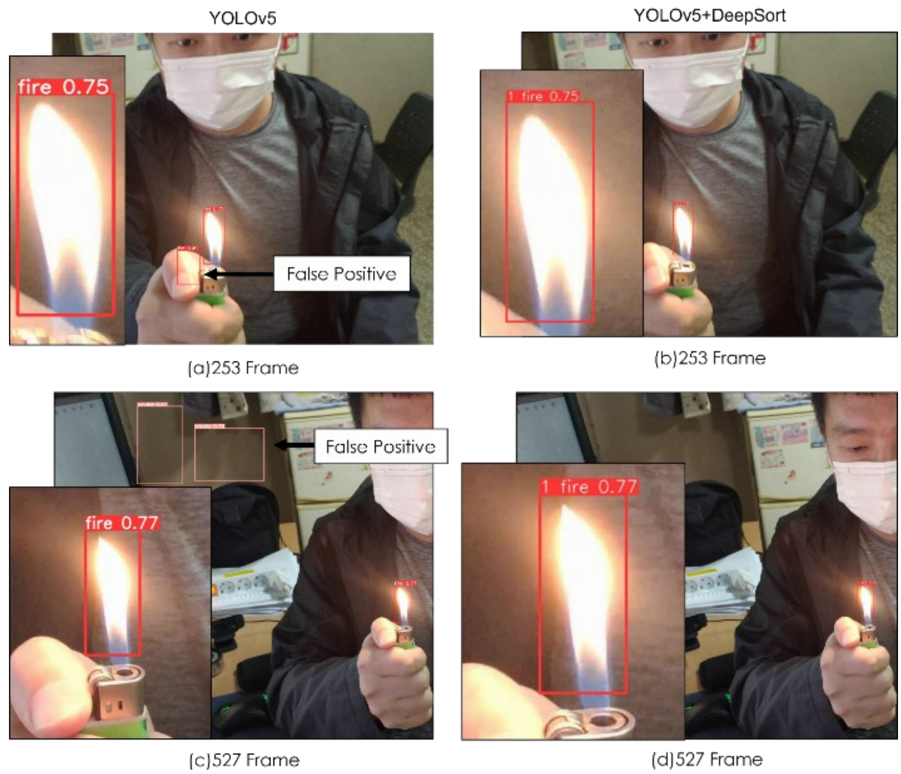

Figure 6. Results of Indoor tests

As a result of the outdoor test of fig 7, the YoloV5 accurately detected fire was 75% accurate, and there was an error in detecting the human face in the upper left as smoke. As a result of applying the YoloV5+DeepSort model, it was the same as YoloV5 with an accuracy of 75%, but it was confirmed that the false detection phenomenon disappeared.

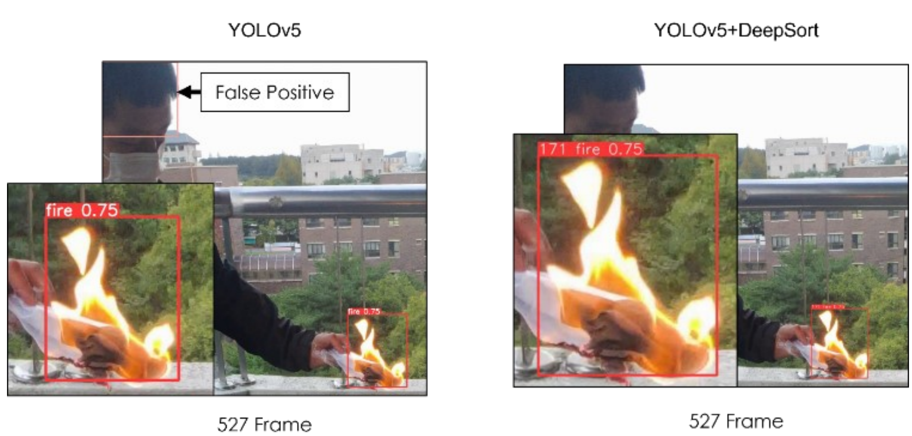

Figure 7. Results of Outdoor tests

As a result of the outdoor test of fig 7, the YoloV5 accurately detected fire was 75% accurate, and there was an error in detecting the human face in the upper left as smoke. As a result of applying the YoloV5+DeepSort model, it was the same as YoloV5 with an accuracy of 75%, but it was confirmed that the false detection phenomenon disappeared.

5. CONCLUSION

As a problem with the existing image-based fire detection method, it is difficult to apply it to real situations due to the empirical and experimental threshold setting, and many studies using artificial intelligence are being conducted to reduce false alarms for objects similar to flames. Therefore, in this paper, the YoloV5 model + DeepSort model was used to improve the rate of false alarm occurrence in the fire detection system.

In order to prove the improved YoloV5 model + DeepSort model, we compared and analyzed the YoloV5 model. As a result, the indoor test results show that YoloV5 has an accuracy of 75% at 253Frames and 77% at 527Frames. In addition, the YoloV5+DeepSort model showed the same accuracy of 75% at 253 frames and 77% at 527 frames, and it was confirmed that the occurrence of smoke and fire detection errors disappeared.

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