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Study on flame detection based on Yolo neural network and machine vision

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Abstract. To improve reliability of the fire pre-warning system, study on flame detection was carried out in combination with YOLO artificial neural network and machine vision detection technology. Firstly, 200 flame pictures were acquired and 1,000 flame imaged were searched online to serve as the training set, and the flame area of each image was labelled artificially, and then YOLOv5s neural network model with small scale and rapid detection was built, and the system was trained by means of supervised learning, and at last, the trained system was used to make real-time detection of the flame. The experiment results showed that, the system could make real-time monitoring of flames, with relatively high recognition accuracy, rapid detection speed and high recognition flexibility.

Keywords. flame detection; neural network, YOLO, machine vision detection technology, YOLOv5s.

1. Introduction

Fire is merciless, and would bring lots of small or big injuries to human beings every year whether being artificial or natural, threatening people's life and property safety all the time, and it is a public energy of human beings. Fire pre-warning system is conducive to reducing injuries brought by fire, and temperature sensor and smoke sensor are mostly used in traditional fire pre-warning system to detect fire, however, both sensors need to make detection at short distance with small detection range, thus having many shortcomings. On the contrary, machine vision is equipped with a very good development prospect due to broad detection range and long-distance detection. With constant development of computer technology, artificial neural network has become increasingly mature, and can realize image classification and object detection functions, etc. via learning, thus having a very good development prospect as well. At present, both artificial neural network and machine vision detection technology have been widely used in development of cutting-edge intelligent detection technology system.

The intelligent fire pre-warning system based on artificial neural network and machine vision detection technology has always been the focus of many scholars in their research field, and flame recognition has been studied by many scholars in combination with artificial neural network model by extracting flame images to establish data sets, with certain achievements. In Literature [1], in order to recognize forest fire, 35,000 images of real forest fires were selected for training and learning of artificial neural network, and for recognition study on forest flame, with test accuracy rate being up to 95.57%; in Literature [2], an improved YOLOv3 neural network was designed by integrating multi-scale features, to carry out real-time detection study on flame in combination with the video images, and in the algorithm, precise recognition of small-flame areas is realized by improving learning ability of network toward shallow image information; in Literature [3], a flame recognition algorithm based on fuzzy neural network was designed by taking shopping-mall flame detection as the study object, having achieved a relatively good effect; in Literature [4], a flame recognition algorithm based on FASTERR-CNN neural network was designed, and in order to reduce interference of lamplight with the flame recognition system, when making the training sets, not only flame images of multiple shapes were selected, but also lamplight images of multiple shapes were selected as the training set to make multi-category recognition, which was good for the system to distinguish the flame and lamplight, thus improving recognition accuracy of the system. It has achieved certain effect in flame recognition by combining artificial neural network model with machine vision detection technology to analyze and compute the image data, but the detection accuracy still needed to be improved, and more scholars were required to be engaged in study in such field. In this paper, YOLO model based on artificial neural network was used in combination with machine vision detection technology to make real-time recognition study on flame.

2. YOLO neural network

2.1. YOLOv5 neural network

YOLO artificial neural network was initially put forward by R. Joseph et al, which computed the object recognition and article classification as a regression problem, predicated the relation between input variable and output variable, thus obtaining a model parameter from centralized learning of the given training data set to predict unknown images. YOLO artificial neural network is characterized by small model, rapid detection speed, good stability and open-source structure, and has significant advantages in object detection and image classification and application, with the network flow as shown in Figure 1 [5-6]. The images to be detected were classified by YOLO network into n×n grids, and each grid was responsible for tracking and recognizing the boundaries and categories of objects whose central position fell on the grid. Such end-to-end detection method was relatively quick, being able to detect dozens of frames of images per second [7].

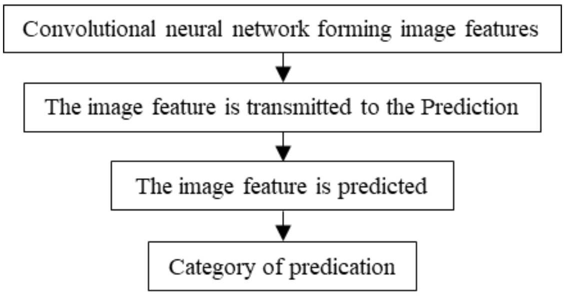


Figure 1. Workflow chart of YOLO network

Later, YOLO neural network has been studied and optimized by many scholars, and multiple different versions have been released successively, the mainstream version of which at present is the open-source YOLOv5 Version. YOLOv5 also consists of four different models i.e. YOLOv5s, YOLOv5m, YOLOv5l and YOLOv5x by network structure, which are largely identical but with minor differences in principle, and of which YOLO_V5S has the rapidest computing speed.

2.2. YOLOv5s network

YOLOv5 consists of 4 network structures, of which YOLOv5s model is only at the size of around 20MB, having the rapidest computing speed, with relatively good real-time detection effect, and is easy to be embedded in other devices for use, therefore, YOLOv5s model was applied in this experiment. Figure 2 is the schematic diagram of network structure of YOLOv5s, which consists of four parts: input, backbone, neck and prediction.

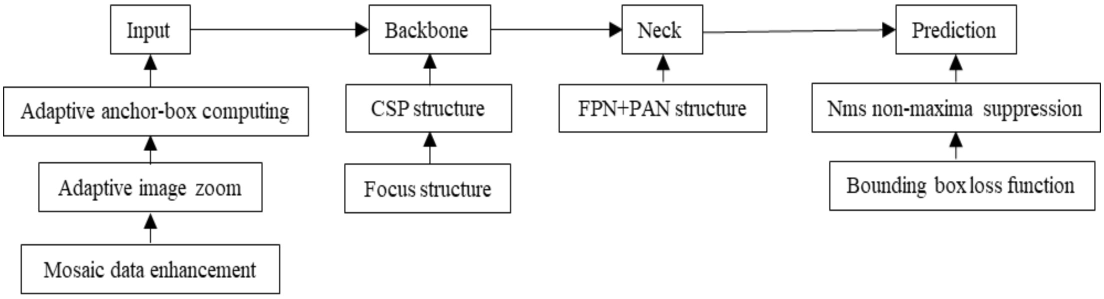


Figure 2. Schematic diagram of YOLOv5s network structure

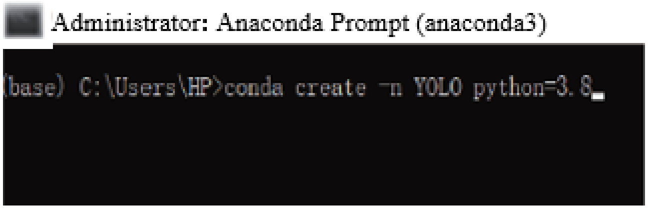
Mosaic data enhancement technology was used in the Input, which made splicing by means of random zooming, cropping and arrangement, and had a good detection effect toward small objects. Initial anchor box was set regarding different data sets, and during the training, predicted anchor box was output by the network based on the initial anchor box, which was then compared with real anchor box for their gap, and then made counter-propaganda and had size modified, so as to achieve adaptive computing of different training sets of the best anchor box value. In YOLOv5s network, different sizes of images were zoomed into images of standard size by the Input first, which were then sent to the subsequent Backbone to make adaptive computing in accordance with original size of the pictures after zooming the original images, to achieve the purpose of minimum black edges, which was conducive to reducing the computing amount and improving computing speed of the network. Backbone mainly consisted of Focus structure and CSP structure, the main task of the former was to use 32 convolution kernels to perform convolution operation on the input data to complete the image slicing task, while the task of the latter was to enhance learning ability of network to train a model of small size but high detection accuracy. Neck adopted FPN+PAN structure, and FPN adopted up-sampling method to integrate features of the upper and lower layers, and later a bottom-up feature pyramid and two PAN structures were added, and features of the high and low layers were integrated by the down-sampling method to output the predicted feature map results [8-11]. Bounding Box loss function included IOU_Loss, GIOU_Loss, DIOU_Loss and other functions [12]. CIOU_Loss function was adopted in this experiment, and the error between predicated anchor box and real box was minimized by multiple computations and adjusting the parameters. Example of the predicated anchor box and real anchor box was as shown in Figure 3, where, the green box was real anchor box, the blue box was predicated anchor box, and the yellow box was the minimum bounding rectangle anchor box between the predicated anchor box and real box.

Figure 3. Example of real anchor box and predicated anchor box

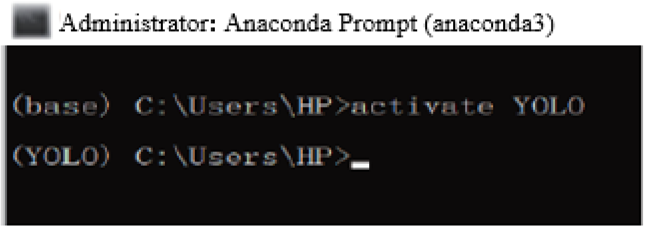
3. Experiment

3.1. Establishment of experiment environment

The command “conda create -n YOLO python=3.8” was input in command box of Anaconda software to establish a YOLO environment based on Python3.8, and the command “activate YOLO” was input to activate the YOLO environment, and the steps were as shown in Figure 4. Pycharm was used to open YOLOv5 model, and the dependent library files in Table 1 were installed in the YOLO environment established previously.



(a) Establish YOLO environment



(b) Activate YOLO environment

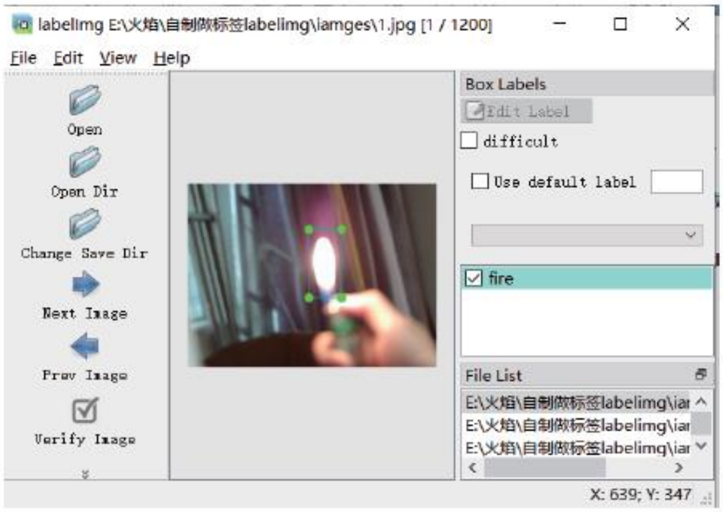
Figure 4. Establish and activate YOLO environment

Table 1. Dependent library file of YOLOv5

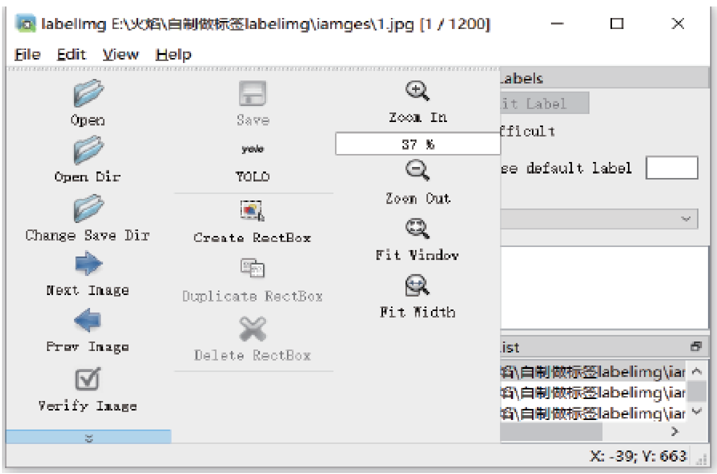
Serial No.	Name of dependent library file	Version
1	Matplotlib	≥3.2.2
2	Numpy	≥1.18.5
3	Opencv-python	≥4.1.2
4	Pillow	——
5	PyVAML	≥5.3.1
6	Scipy	≥1.4.1
7	Torch	≥1.7.0
8	Torchvision	≥0.8.1
9	Tqdm	≥4.41.8

3.2. Establish training set

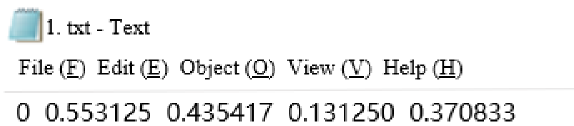
Since supervised learning was adopted in this experiment to train YOLOv5s model, the 200 flame images acquired and 1,000 flame images extracted online shall be labeled artificially. LABELIMG tool was used to label the images, and “.txt” file required for YOLOv5s was generated. Anaconda software was used to open the LABELIMG tool, and LABELIMG tool could be opened by inputting the command “pip install labelimg” in command box of the Anaconda software. LABELIMG was used to open the folder where the data set images were located, and rectangular box was used to select flame area on each image one by one, and the label “fire” was input in the rectangular box, with the Save mode being YOLO, thus the ".txt" file corresponding to the data set image one by one was generated. If there was only one flame area on the image, one label shall be made only, then the ".txt" file consisted of only one group of data; if there are many flame labels on the image, then the ".txt" file consisted of many groups of data. Using LABELIMG tool to label the training set images was as shown in Figure 5.



(a) Select the flame area



(b) Select YOLO mode



(c) Example of ".txt" file data

Figure 5. Example of labelling training set image

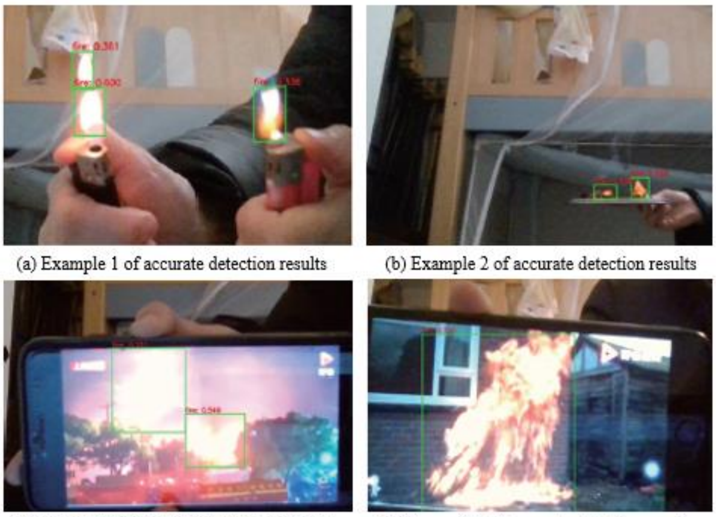
Figure 5(c) was the example of generated ".txt" file, and each line consisted of 5 data, where, the first data was Category label number, and since there was only one category in flame recognition, so "0" referred to the labelled "fire", while the other four data were X/W, Y/H, W_{BOX}/W and H_{BOX}/H, respectively, where, X and Y referred to coordinates of the center of the flame area, W and H referred to the width and height of the image, and W_{BOX} and H_{BOX} referred to width and height of labelling box of the flame area. Since YOLOv5s model has the function of adaptive zoom-in or zoom-out toward input images, therefore, the ".txt" file recorded location information of the flame area in the form of proportional data.

3.3. Training neural network

Upon establishment of data set, Pycharm was used to open YOLOv5 model, to modify the route, class number and label number parameters of the data set. Weighted file was loaded, the attenuation coefficient was set at 0.0004, and the total number of iterations was set at 300, and then train.py file in the model was run to train the data set.

3.4. Experiment results

During the experiment process, 200 test images searched online were detected, with the accuracy rate being up to 97.5%; 20 artificial flames were performed real-time detection, with the accuracy rate being up to 95%, and the system also had a relatively high recognition accuracy rate toward flame videos played on mobile phones, and the accurate detection results were as shown in Figure 6, where, Figures 6(a) and (b) showed the system's recognition of artificial flames, while Figures 6(c) and (d) showed the system's recognition of the flames in fire videos played on mobile phones. The system can detect the tiny flames in the image, with relatively high detection flexibility of the flame, however, the system can still be interfered with by lamplight and was easy to misjudge some lamplight as flame, and the misjudgment result was as shown in Figure 7. Besides, reddish or yellowish flames in pictures of the training set were mostly selected as the training data, and the system's recognition accuracy of the flames in other colors was not so high.



(a) Example 1 of accurate detection results (b) Example 2 of accurate detection results

(c) Example 3 of accurate detection results (d) Example 4 of accurate detection results

Figure 6. Examples of accurate detection results

Figure 7. Example of misjudgment results

4. Conclusions

The flame recognition flame based on YOLOv5s artificial neural network model could realize real-time detection effectively, but could still misjudge some lamplight and other objects as flame, therefore, it still needs to continue to make input in studies, optimize the algorithm and training set, to carry out recognition study on flame in combination with motion, texture and other features.

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