ISSN: 1813-4890

Research on Fire Target Detection Algorithm Based on YOLOv8

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Abstract

Fire is a highly hazardous public safety event, which not only causes casualties and property damage, but also has a huge impact on the ecological environment. Therefore, studying how to improve the accuracy and detection speed of fire detection models has great social significance. At present, fire detection technology mainly detects fires through sensor components. Although these devices have high sensitivity in practical use, their detection efficiency is low and they are easily affected by complex external environments. With the improvement of computer hardware performance and the increasing maturity of object detection technology based on computer vision algorithms, some object detection models with strong generalization and high detection accuracy have emerged. This deep learning based object detection model can automatically extract fire characteristics from input images, achieving end-to-end detection methods. At the same time, the detection speed and accuracy of fires have been greatly improved. Therefore, this paper studies fire detection algorithms based on a one-stage object detection model. This article is based on YOLOv8's fire target detection algorithm, using cosine learning rate, mixed accuracy, and different parameter methods to study the effectiveness of YOLOv8 in fire detection. On this basis, compare and analyze with other detection algorithms such as YOLOv7 and YOLOv5. The experimental results show that compared with other mainstream algorithms, this algorithm has better detection performance and is more suitable for fire detection in natural environments.

Keywords

Deep Learning; Object Detection; Yolov8; Fire Detection; Fire Prevention.

1. Introduction

T Fire detection is an important task that can protect human life and property safety. Fires can occur at any time, and once they occur, they are highly likely to be destructive and dangerous. Therefore, it is necessary to detect and take measures in a timely manner to prevent the spread of the fire. [1] In recent years, computer vision technology has developed rapidly, making image-based fire detection algorithms increasingly feasible. Among them, object detection algorithms based on deep learning are the most promising type. These algorithms have the advantages of high accuracy and speed, and can be used for fire detection in real-time environments. By using object detection algorithms, we can detect fires faster and take measures to maximize the protection of human life and property.

YOLO (you only look once) is a popular real-time object detection algorithm widely used in various fields such as vehicle unmanned driving, robotics, and monitoring. This algorithm was initially proposed by Joseph Redmon and Ali Farhadi in 2016, and has since undergone multiple updates and improvements. The original YOLO algorithm used a single convolutional neural network (CNN) to measure objects in images. It divides the image into grids and assigns each grid unit to the task of detecting objects within it. This allows YOLO to process images in one iteration, which is much faster than other object detection algorithms that require multiple iterations. In subsequent versions of YOLO, the algorithm improves the detection accuracy of objects with different shapes by modifying the architecture of CNN and adopting anchor boxes.

In addition, these versions of YOLO use feature pyramid networks (FPN) [3] to handle objects of different scales, making them more adaptable to different object sizes.

The latest version of YOLOv8 [4] introduces many new features and improvements compared to previous versions, and this article aims to study the impact of the latest YOLO series in fire detection and prevention.

This article mainly achieves the following results:

(1) Apply the collected fire dataset images to the latest YOLO series (YOLOv8) object detection;

(2) Adopting the cosine learning rate [5] learning method in YOLOv8 to update and adapt the learning rate of the fire automatic detection algorithm;

(3) Using the method of mixed precision [6], improve the inference speed and reduce computational resources of the object detection algorithm in YOLOv8 for fire datasets.

(4) Applying the fire dataset to the previous YOLO series, the detection algorithm introduced in this article achieved relatively good detection results.

2. Yolov8 Network Structure

This experiment uses a lightweight yolov8n.pt model. The model structure design of YOLOv8 [3] is shown in Figure 1. The main structure of its model is divided into Backbone, Neck, and Head.

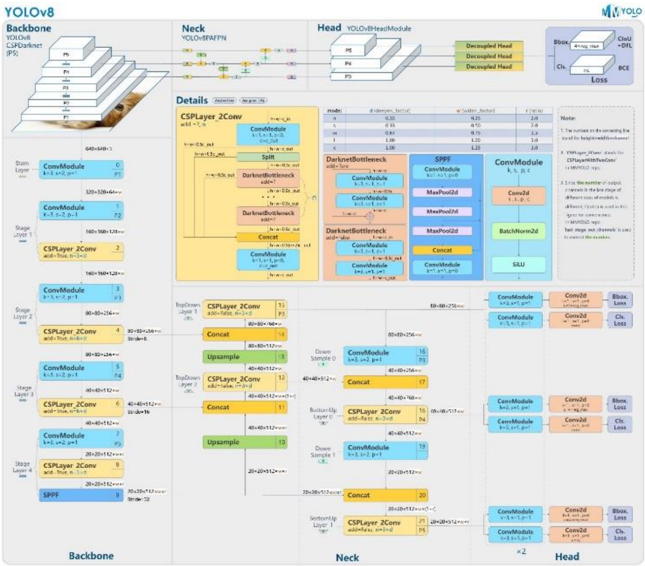

Figure. 1 Model structure diagram of YOLOv8

2.1. Backbone And Neck Structures

The specific changes in the backbone network and Neck compared to the previous series are as follows: the kernel of the first convolutional layer has changed from 6x6 to 3x3, and all C3 modules have been replaced with C2f. The structure is shown in Figure 2, and it can be observed that more hop layer connections and additional Split operations have been added, removing the two convolutional connection layers in the Neck module. The number of blocks in C2f in Backbone has been changed from 3-6-9-3 to 3-6-3.

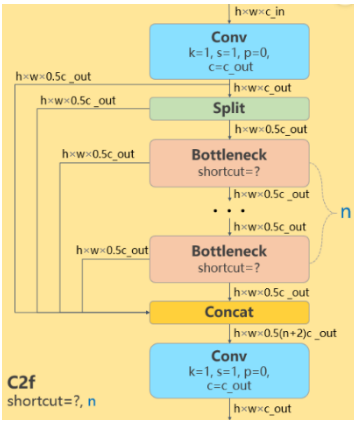

Figure.2 Backbone and Neck network structure of YOLOv8

2.2. Head Structure

The Head section in YOLOV8 has the greatest change, changing from the original coupling head to the understanding coupling head, and from Anchor Based in YOLOv5 to Anchor Free. Its structure is shown in Figure 3. There are no longer the previous objectiness branches, only decoupled classification and regression branches, and their regression branches use the integral representation method proposed in Distribution Focal Loss.

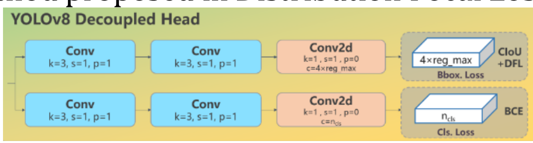

Figure.3 YOLOv8 Head Structure

3. Loss Function

The loss calculation process includes two parts: positive and negative sample allocation strategy and loss calculation. Most modern object detectors focus on positive and negative sample allocation strategies, such as YOLOX's simOTA, TOOD'sTask Aligned Assigner, and RTMDet'sDynamic SoftLabelAssigner. These types of assigners aremostly dynamic allocation strategies, while YOLOv5 still uses static allocation strategies. Considering the superiority of the dynamic allocation strategy, the YOLOv8 algorithm directly references TOOD's Task Aligned Assigner. The matching strategy of TaskAlignedAssigner can be summarized as follows: selecting positive samples based on the weighted scores of classification and regression.

$$t = s^{\alpha}+u^{\beta} \tag{1}$$

As shown in formula (1) above.S is the predicted score corresponding to the annotation category, and u is the iou of the prediction box and the gt box. Multiplying the two can measure the degree of alignment.

4. Dataset

4.1. Dataset Introduction

The dataset used in this article is an open-source fire dataset collected on the Roboflow official website [7]. The target categories to be identified in the dataset include one category (fire source), with a total of 800 images, as shown in Figure 4.

ISSN: 1813-4890

Figure. 4 Fire Dataset

The coordinate position and width height size of the label are shown in Figure 5.

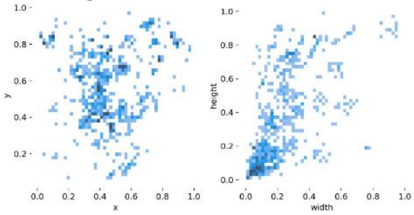

Figure.5 Label coordinate position

4.2. Dataset Preprocessing

The collected fire dataset is shown in Figure 6, divided by the number of training set, validation set, and test set 620:90:90.

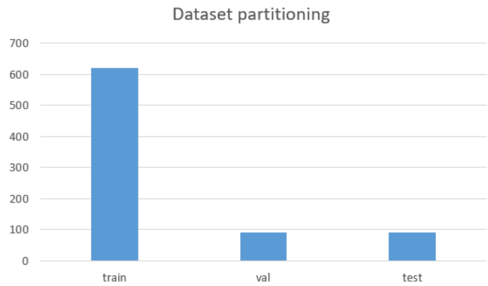

Figure.6 Dataset partitioning

5. Experimental Results And Analysis

5.1. Experimental Environment

The hardware experimental environment studied in this article is to conduct algorithm experiments on RTX2080Ti * 3 GPU and Linux operating system. The development environment is Python 3.9.16, CUDA version is 12.0, and the deep learning framework is PyTorch.

5.2. Evaluation Indicators

Using precision P (precision) and mAP as evaluation indicators. Precision P, recall R, and average precision AP are three commonly used indicators to evaluate the performance of object detection algorithms.

Accuracy is a measure of the accuracy of positive predictions, which is the proportion of true predictions among all positive predictions in a model. In other words, it is the proportion of correct predictions among all predictions in the model.

Recall rate is a measure of the actual number of positive predictions correctly identified by the model. It is the proportion of true predictions among all actual positive predictions. In other words, it is the proportion of correct predictions among all actual predictions.

The average precision is the average value of the precision recall curve. It is a measure of the overall performance of object detection algorithms. AP is a commonly used indicator in object detection research and competitions (such as PASCAL VOC and COCO Challenge). AP is a good indicator for measuring the overall performance of object detection algorithms, as it considers accuracy and recall, and can handle multiple types of targets and targets of different sizes. However, it is worth noting that a high AP does not necessarily mean that the algorithm has a good balance between accuracy and recall, so it is necessary to look at the accuracy recall curve to understand the algorithm's performance in terms of accuracy and recall.

In addition, there is often a trade-off between accuracy and recall, where an improvement in one metric may lead to a decrease in another metric. For example, models that perform a large number of detections may have high recall but low accuracy, while models that perform fewer detections may have high precision but low recall. Therefore, when evaluating the performance of object detection algorithms, it is necessary to consider both accuracy and recall, as well as the trade-off between them.

Experimental Results

The rationality of the selected training model was not verified, and a comparative experiment was designed to compare the YOLOv8 algorithm under different network architectures. In each YOLO series algorithm, multiple pre trained models are officially provided. Based on the preprocessed data in this article, four different versions of YOLOv8n, YOLOv8s, YOLOv8m, and YOLOv8l are selected for comparative experiments. The model size, detection speed, and accuracy of each version are different. The comparative experimental results are shown in Table 1.

Table 1 Comparison of detection performance of YOLOv8 algorithm under different network architectures

Algorithm	Network Structure	Model Volume(MB)	P(%)	R(%)	mAP(50) (%)
YOLOv8	YOLOv8n	8.7	90.3	78.0	86.5
	YOLOv8s	28.6	89.2	79.8	83.3.
	YOLOv8m	78.9	89.7	77.0	79.1
	YOLOv8l	165.2	93.5	82.3	86.0

5.3. Comparative Analysis of Results

Compared with other structures, the YOLOv8n network model has a smaller volume and the highest detection accuracy; Compared to YOLOv8l, although the recall rate of YOLOv8n network is slightly lower, the model size is very small, suitable for training on a small number of datasets, and the model is relatively lightweight. In summary, due to its excellent detection performance, fast speed, and easy deployment, it is reasonable to choose Yolov8n as the training model in this article.

5.4. Algorithm Detection Effect Experiment

To more intuitively demonstrate the smoke and fire detection effect of YOLOv8 in natural fire scenes, this article randomly selects multiple images from the test set for detection. The detection image is shown in Figure 7, and it can be seen from Figure 7 that the model can also achieve good detection results. (The label fire is replaced by the number 0).

Figure.7 Example of detection effect

6. Conclusion

This experiment can accurately identify smoke and fire targets in natural living environment fire detection, providing technical reference for remote real-time monitoring and extinguishing. This study aims to enhance the dataset by using different model parameter methods for

ISSN: 1813-4890

refinement. The detection model based on YOLOv8 can monitor image or video streams in real-time and quickly detect the occurrence of fires. This helps to take emergency measures in the early stages of a fire and minimize losses. By learning a large amount of data, more complex fire characteristics and patterns can be learned, which improves detection accuracy compared to traditional methods. This helps to reduce false positive and false negative rates, ensuring a more reliable system.

The machine vision fire detection system can monitor a wide range of areas, covering areas that are difficult for human vision to cover or cannot be detected in a timely manner. This is particularly important for fire monitoring in large buildings, warehouses, forests, and other areas. Overall, implementing machine vision fire detection through deep learning can improve the efficiency, accuracy, and timeliness of fire monitoring, which has important social and economic significance for preventing fires, protecting life and property safety.

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