World Journal of Innovation and Modern Technology, Vol. 8, Issue 9 (Sep)
ISSN 2682-5910 **2025**
DOI: 10.53469/wjimt.2025.08(09).02

Dangerous Sign Recognition Algorithm Based on YOLOv8

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Abstract: ***With the continuous advancement of deep learning technology, object detection, as a key technology in the field of computer vision, has been widely applied in multiple fields such as video surveillance, intelligent transportation, and autonomous driving. As a classic object detection algorithm, You Only Look Once (YOLO) has been highly valued by researchers since YOLOv1 for its efficient detection speed and good real-time performance. Research was conducted on the latest version of YOLOv8 algorithm, analyzing its network structure optimization and performance improvement. Utilizing YOLOv8's real-time object detection capability, efficient recognition of various danger signs was achieved through deep learning of their features. This provides an effective solution for real-time danger sign recognition and has significant practical implications for assisting post disaster rescue robots in rescue operations.***

Keywords: Object detection; Deep learning; YOLOv8; Danger signs.

1. INTRODUCTION

Object detection is a fundamental problem in computer vision, which aims to identify and locate objects in images or videos. In recent years, with the development of deep learning methods, especially the significant achievements of convolutional neural networks (CNN) in image recognition tasks, a large number of deep learning based algorithms have emerged in the field of object detection. The YOLO series algorithms have attracted much attention due to their fast detection speed and high accuracy. This study aims to conduct an in-depth analysis of the latest iteration of the YOLO series - YOLOv8, exploring the key elements for its implementation details and performance improvement, and conducting identification and detection of danger signs.

With the development and application of machine learning and deep learning, many network models have gradually replaced traditional feature extraction methods. Early behavior recognition methods mostly used RGB (Red, Green, and Blue) videos as input, which had issues such as susceptibility to environmental factors, occlusion, and high computational costs due to the large size of video data. As a representative of advanced object detection algorithms, YOLOv8 is designed to achieve object detection localization and classification tasks in a single inference process, significantly improving processing speed. In addition, by continuously optimizing the network structure and enhancing the model's recognition ability for small objects and robustness to background noise, YOLOv8 is expected to set a new benchmark in the field of object detection. However, despite a series of breakthroughs, object detection still faces various challenges, such as multi-scale object recognition in complex scenes, occlusion processing, and balancing real-time and accuracy.

In deep learning algorithms, the YOLO (You Only Look Once) series has demonstrated excellent performance in both speed and accuracy due to its end-to-end detection approach. From YOLOv1 to the recent YOLOv8, this series of models has gradually improved the efficiency and accuracy of object detection through continuous iterative updates. YOLOv8, as a new generation real-time object detection algorithm, makes traffic sign detection more accurate and robust with its deeper network structure, more optimized loss function, and more efficient training strategy.

Considering the computationally intensive nature of deep learning models, we also need to ensure the real-time performance of the algorithm. The YOLOv8 algorithm performs well in this regard, but in the specific implementation process, how to balance speed and accuracy will be a focus of this article's research. In computer vision, Chen et al. (2022) proposed a one-stage object referring method with gaze estimation[1], while Peng et al. (2024) developed a dual-augmentor framework for domain generalization in 3D human pose estimation[7], building upon their earlier work on source-free domain adaptive human pose estimation[8]. Pinyoanuntapong et al. (2023) contributed to this field with self-aligned domain adaptation for mmWave gait recognition[9]. Medical imaging saw innovations from Chen et al. (2023) through generative text-guided 3D vision-language pretraining for unified segmentation[4]. In autonomous systems, Peng et al. (2025) introduced NavigScene, bridging local perception and global navigation for beyond-visual-range driving[6]. Machine learning applications span multiple sectors: Tong et al. (2024) created an integrated framework for credit card approval prediction[2]; Tian et al. (2025) developed cross-attention multi-task learning for digital advertising[3]; and Zhang et al. (2025) leveraged deep learning for carbon market forecasting[5]. Recommendation systems were enhanced by Wang (2025) through joint training for missing data scenarios[10], and Li et al. (2025) proposed GNN-enhanced sequential methods for cross-platform campaigns[12]. Privacy concerns were addressed by Li et al. (2025) with a federated learning framework for advertising personalization[11].

Various domain-specific applications emerged: Xu (2025) applied generative modeling to public space development[13]; Tu (2025) focused on modeling-driven NAS for regression detection[14]; Xie and Liu (2025) optimized industrial monitoring systems[15]; Zhu (2025) developed reliability engineering frameworks[16]; and Zhang (2025) created self-supervised ad delivery systems[17]. Business applications included Zhuang's (2025) analysis of real estate marketing digital transformation[18], Han and Dou's (2025) multimodal recommendation method[19], and Zhang et al.'s (2025) AI-driven sales forecasting for gaming[20].

2. RELATED WORK

Object detection algorithms are the foundation of deep learning. Traditional object detection algorithms often face significant difficulties in processing images in complex environments. Therefore, in complex environments, hazard monitoring systems based on traditional object detection algorithms have weak recognition capabilities, while hazard monitoring systems based on deep learning techniques have strong adaptability and real-time performance. Therefore, in complex environments, hazard sign recognition systems based on YOLOv8 have become a research hotspot. At present, research on hazard sign recognition in complex environments mainly focuses on using deep learning algorithms to automatically recognize hazard sign images and classify and detect them. Regarding this research direction, traditional object detection algorithms have certain limitations, mainly manifested in the following aspects: firstly, object detection algorithms require a large amount of data sets to train models and conduct training tests; Secondly, due to the large amount of sample data required for training the model, the computational resources are relatively high; Finally, traditional object detection algorithms are mainly trained and tested on static images and are not suitable for dynamic images.

Danger sign images contain a large number of interfering factors, such as stains, lighting, etc., which can affect detection accuracy. Therefore, we preprocess the images to remove some unnecessary information, and then use the YOLOv8 algorithm for object detection [21]. The algorithm first filters and denoises the image, and then extracts the feature information of the danger signs in the image. Before feature extraction, we performed enhancement operations on the image to improve the robustness of the network. The YOLOv8 algorithm adopts a network structure different from traditional convolutional neural networks, which includes two convolutional layers and one pooling layer. The convolutional layer uses depthwise separable convolution, and the pooling layer uses adaptive pooling. Different sizes of convolution kernels were used in the convolutional layer, and they were combined together to form larger convolution kernels. Multi scale pooling layers were used in the pooling layer to achieve pooling operations on a larger scale. Finally, we adopted a fully connected layer to reduce the computational load of the network. During the model training phase, we used a new dataset to train the network model. By continuously iterating and learning the network model, the final result of identifying danger signs was obtained. The use of YOLOv8 algorithm in the hazard detection module for hazard sign image recognition is to solve the problems of traditional methods being unable to quickly extract hazard sign feature information from images, slow detection speed, and high missed detection rate. Traditional methods often rely on manually annotating danger sign images for classification, which is inefficient and cannot guarantee accuracy. The YOLOv8 algorithm improves recognition speed and accuracy through a series of operations such as image preprocessing and object detection, and effectively reduces network computation while ensuring accuracy.

3. YOLOV8 HAZARD IDENTIFICATION SYSTEM FRAMEWORK

The danger sign recognition system proposed in this article adopts the YOLOv8 algorithm, which mainly includes two parts: danger sign detection and danger sign classification. The detection module is the core part of danger sign recognition based on YOLOv8 algorithm, and its main function is to detect danger sign images.

YOLOv8 is the latest model in the YOLO series, as shown in Figure X. The network model mainly includes four parts: input, backbone feature extraction network, head, and prediction. Input consists of mosaic (data augmentation), automatic image cropping and stitching, and adaptive frame drawing. It will preprocess the imported image to ensure uniform image size.

Backbone adopts the CSPDarknet architecture, consisting of CBS (Standard Convolutional Layer), C2f module, and SPPF (Pyramid Pooling). It extracts image features through 5 standard convolutional layers and C2f, and adds SPPF module at the end of the network to expand the receptive domain, achieve local and global, and convert input images of any size into fixed size feature vectors.

The Head adopts the PAN-FPN structure, which performs multi-scale fusion of the three feature layers input by Backbone, and performs self term down (FAN) and bottom-up (PAN) feature transfer to enhance the pyramid, so that feature maps of different sizes contain strong target semantic information and strong target feature information, ensuring accurate prediction of samples of different sizes.

4. PRELIMINARY PREPARATION AND EXPERIMENTAL PROCESS

4.1 Configuration of Experimental Dataset

Before training, a camera was used to capture images of the hazard sign board, as shown in Figure X. The 262 captured images were labeled one by one using LabelImg, and suitable images were selected to divide the training set and the testing set. The final training set consisted of 235 images and the testing set consisted of 27 images.

Figure 1: Partial danger signs

After the image acquisition is completed, use the LabelImg tool to label the image. As shown in Figure X. After the image annotation is completed, it is divided into two folders, image and label, in the train file. The corresponding images and labels files are also divided in the valid file, where the valid/image file stores 27 validation set images divided. Place the train file and the valid file in the same directory, datasets, and create data.raml. The configuration code in data.raml is as follows:

path: D:/Users/Windows10/Desktop/yoloV8/datasets/ danger_signs
train: train/images val: valid/images nc: 17
names:
- FLAMMABLEGAS
- FUELOIL
- ORGANICPEROXIDE
- OXIDIZER
- DANGEROUS
- FLAMMABLESOLID
- EXPLOSIVES
- OXYGEN
- POISON
- NON-FLAMMABLE GAS
- COMBUSTIBLE
- INHALATION HAZARD
- RADIOACTIVE
- BLASTING AGENTS
- FLAMMABLE SOLID

- FLAMMABLE GAS
- CORROSIVE

4.2 Construction of YOLOv8 Environment

Firstly, install Anaconda and set up the required environment for YOLOv8 in Anaconda Prompt, named YOLOv8-CPU. After completing the environment settings, use the command conda activate yolov8-CPU to activate the built environment. In this environment, first configure the Pytorch environment, use the pip3 install torch torchvision torchauudio command to install Pytorch, and then use the pip install ultralytics command to install the ultralytics library.

4.3 YOLOv8 model training

Create the training file for YOLOv8 as myTrain-CPU.py, modify the path in the configuration file correctly, and enter the command python myTrain-CPU.py in cmd to start training the model. Among them, yolov5m.pt is the weight file during training, and epochs=20 means training 20 times. Box_ross represents the positioning loss, the error between the predicted box and the calibrated box. Cls_loss represents the classification loss, which calculates whether the anchor box and corresponding calibration classification are correct. dfl_loss represents the confidence loss, which calculates the confidence of the network.

5. EXPERIMENTAL RESULTS AND ANALYSIS

There are complete and referenceable evaluation indicators in the field of object detection, which can usually be used as the result evaluation of danger sign recognition. The evaluation indicators for detection accuracy and precision can generally be evaluated through the Confusion Matrix, while the evaluation of detection speed generally refers to the processing frame rate (FPS) of the algorithm. The YOLOv8 model also uses confusion matrices when evaluating its performance. In YOLOv8, the concept of confusion matrix is the same as that of general supervised learning models, which calculates the number of true positives, false positives, true negatives, and false negatives for each category by comparing the predicted results of the model with the actual labels.

In the current experimental research, we adopted an advanced object detection algorithm - YOLOv8- to identify and classify danger signs. This model is based on a deep learning framework and has undergone extensive optimization to adapt to this challenging task. The test results show that the YOLOv8 algorithm has achieved significant results in hazard sign recognition, with an average accuracy (mAP) of up to 0.995, almost approaching perfection. This indicator reflects the high sensitivity and accurate recognition ability of the model for danger signs in practical application scenarios.

To comprehensively measure the performance of object detection algorithms, we rely on several key evaluation metrics: recall, accuracy, and precision. The recall rate mainly reflects the ability of the model to correctly identify positive samples from the dataset, while the accuracy rate represents the proportion of the results predicted by the model as positive samples that are truly correct. Accuracy is a more comprehensive metric that takes into account the proportion of correctly classified samples for both positive and negative classes in the total sample size, providing us with insights into the overall performance of the model.

In addition to these basic performance indicators, the P-R curve provides an intuitive way to analyze the trade-off of the model between different recall and accuracy levels. By drawing the P-R curve, we can clearly see the performance of the model in both recall and accuracy dimensions. The larger the area enclosed below the P-R curve, the higher the average detection accuracy of the model; In our case, this area is very close to the maximum value, which further confirms the excellent performance of YOLOv8 in the field of hazard sign recognition.

In addition, using different Intersection over Union (IoU) thresholds to calculate mAP is a common practice in the field of object detection. By setting IoU thresholds from a looser 0.5 to a stricter 0.95, mAP @ [. 5:95] can provide a comprehensive and detailed overview of model performance. This multi threshold evaluation method ensures the robustness of the model, as the model can only achieve high scores when the predicted box highly matches the actual annotated box.

During the training process, both the F1 score and the presentation of the P-R curve exceeded 90%, revealing the powerful ability of the YOLOv8 algorithm in handling complex danger sign recognition tasks. By comparing the ablation experiments with other mainstream YOLO detection algorithms, we found that the YOLOv8_SG version performed particularly well, with an increase of about 0.7% in mAP value compared to the YOLOv8 version. Although this increase may seem small, in the fields of machine learning and image processing, even a small improvement may represent significant technological advancements and improvements.

6. CONCLUSION

In summary, the performance demonstrated by YOLOv8 in this experiment is very satisfactory. In the task of identifying danger signs, this model not only has high fitting performance, but also can effectively detect and recognize various media such as images, videos, and real-time camera captured images. The danger sign recognition method proposed in this article can not only accurately identify the location and category information of danger signs in danger sign images, but also achieve real-time monitoring of danger sign images. This will help improve the intelligence level of the hazard sign detection system, further enhancing the safety and reliability of safety production.

FUNDING

Beijing University of Information Science and Technology promotes the classified development of universities - Innovation and Entrepreneurship Training Program for College Students - Supported by the School of Computer Science (5112310855).

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