DESIGN OF AN INTEGRATED INTERACTIVE EXPERIMENTAL SYSTEM FOR TEACHING DEEP LEARNING-ORIENTED OBJECT DETECTION

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Artificial intelligence has become an important part of university education worldwide. Deep learning courses are offered in many universities as core courses in the field of artificial intelligence. To enable students to comprehensively understand and master the knowledge system and content of deep learning, this paper has developed an integrated interactive experiment system based on years of teaching experience in deep learning courses. It enables students to understand the core content of deep learning from the entire process of basic concepts, dataset construction, processing procedures, model design, parameter evaluation, and result analysis through a better human-computer interaction mode. Furthermore, through an improved fire target detection comprehensive experiment based on YOLOV5, students can further learn and understand related knowledge. This integrated interactive experiment system can well complement the teaching content of deep learning and effectively enhance students' practical operation ability.

Keywords: Deep learning, integrated interactive experimental system, comprehensive experiment, target detection

1. Introduction

At present, artificial intelligence is developing rapidly, and its theories and technologies have become an important field for innovative applications, attracting

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great attention from numerous scholars both at home and abroad [1-4]. Chinese higher education is keeping pace with the times, which is conducive to the development of artificial intelligence education. Many domestic universities have established related majors, such as artificial intelligence, intelligent science and technology, and internet of things engineering [5,6]. The deep learning course, as the core course of these majors, has also received much attention from many scholars [7]. However, there are two challenges in this field: 1) Existing research mostly focuses on the theoretical aspect and has not seen the development of targeted experimental teaching platforms or experimental contents, resulting in insufficient practicality and scalability; 2) The interactivity and completeness of the experiments related to deep learning provided by various universities are insufficient, and the experiments are disconnected from actual scenarios, unable to form a closed loop between experiments and practice.

To address these challenges, this paper develops an integrated interactive experiment system based on the characteristics of deep learning teaching and years of course teaching experience. It comprehensively considers the interactive understanding of related concepts and the characteristics of the entire experimental process, through a better human-computer interaction mode, combined with the teaching content of deep learning, can effectively enhance students' practical operation ability.

2. Related works

Owing to the strong practicality of deep learning and the close integration of its theory and practice, relevant research has been conducted by scholars on the combination of theoretical knowledge and experimental design. Wei et al. [8] carried out the reform of curriculum and textbook construction for the integration of deep learning theory and practice, laying a solid foundation for the integration of theory and practice from the perspective of teaching carriers. Zhao [9] explored the construction and practice path of deep learning curriculum oriented to domain applications, making the curriculum design more in line with the practical application needs of the industry. Qi et al. [10] conducted teaching reform practice on the core course Deep Learning and Its Applications, promoting the on-the-ground implementation of the integration of theory and practice in basic courses. Jiang et al. [11] designed the deep learning curriculum teaching based on a project-driven mode, and Lv integrated the topic-driven approach into the teaching reform of postgraduate deep learning courses. Both approaches strengthen students' practical application abilities through different task-oriented models. Bai et al. [12] carried out teaching exploration and practice on the postgraduate course Deep Learning Algorithms and Implementation, improving the theoretical and practical teaching system for algorithm-related professional courses. Yang et al. [14]

integrated the artificial neural network course with the deep learning course and constructed a blended teaching reform model, realizing the cross-curriculum integration of knowledge and practice. Wang [15] focused on the specialized course of target recognition in the era of artificial intelligence and conducted research on laboratory teaching.

However, most of the above studies only remain at the theoretical level and have not been truly popularized and applied in actual teaching. Moreover, they fail to provide students with real scenarios for conducting interactive experiments. For this reason, this paper develops a comprehensive interactive experimental system.

3. Framework of an integrated interactive experimental system

The integrated interactive experimental system for deep learning teaching is designed based on the concept of full-process integration. It comprehensively considers the basic concepts, common functions, typical methods and other contents in deep learning teaching. Through interactive understanding and full-process experiments, it aims to achieve the goal of students' rapid understanding and practical operation. This system consists of two stages: knowledge understanding and experimental operation. The knowledge understanding stage includes three modules: concept understanding, process understanding and experimental understanding, which are further divided into ten sub-modules. The experimental operation stage includes four modules: model preparation, model loading, data loading, and model inference. It is further divided into 12 sub-modules. Fig. 1 shows the framework of the integrated interactive experimental system, and Fig. 2 shows the main interface of the system.

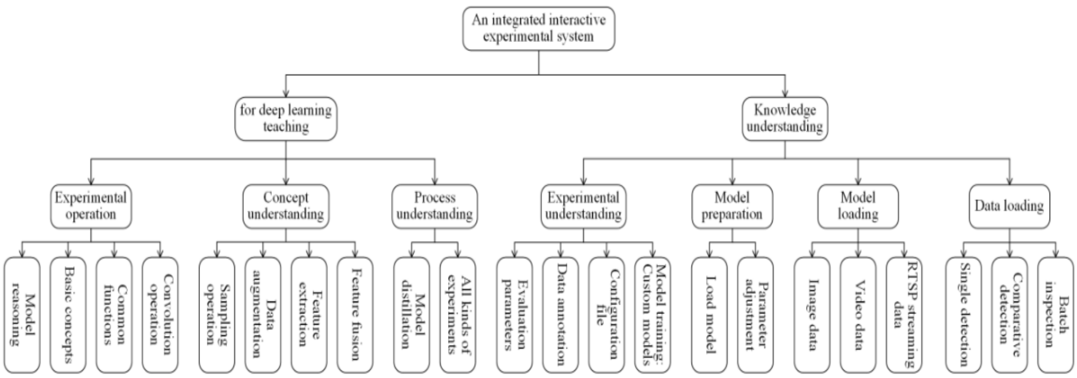


Fig. 1. Architecture of the integrated interactive experimental system

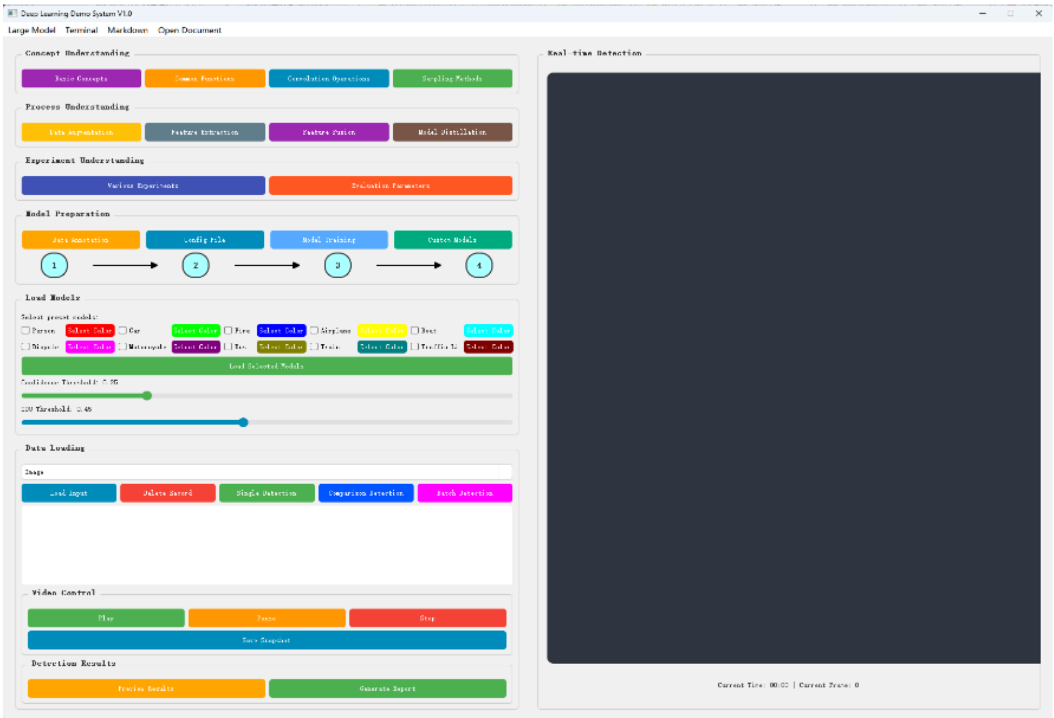


Fig. 2. shows the main interface of the integrated interactive experiment system

4. Core functions of the integrated interactive experimental system

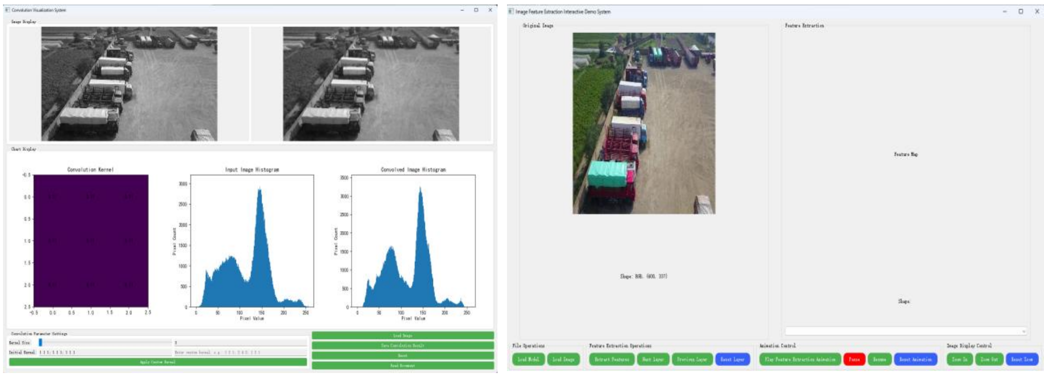
This system acts as an efficient practical carrier for deep learning teaching, and its core strengths lie in addressing the problems of the disconnection between theory and practice, insufficient interactivity and integrity of experiments in traditional teaching, while also filling the gap caused by the lack of specialized experimental platforms. Structured into two stages—knowledge comprehension and experimental operation—the system enables interactive and visual understanding of deep learning concepts and methods through multiple modules, and fully covers the entire experimental process from data annotation to model inference. It not only helps students consolidate their theoretical foundation, but also rapidly enhances their practical operation capabilities and the ability to comprehensively apply knowledge, ensuring that the experimental progress is better aligned with the course schedule.

Its potential teaching method is phased closed-loop teaching: students first complete the learning of basic deep learning theories and methods via interactive modules, then conduct full-process practical training based on the experimental operation modules and intuitively demonstrate the effect of model improvement by means of comparative experiments, thus forming a teaching closed-loop of "theoretical comprehension - practical training - effect verification".

The integrated interactive experimental system is divided into two stage functions: knowledge understanding and experimental operation. It guides students to complete all the knowledge from basic concept understanding, common function recognition, typical method observation to the overall process understanding of deep learning, and then to the entire process of experimental operation, which is conducive to students' in-depth understanding of relevant knowledge and mastery of practical operation content.

4.1 Knowledge understanding

Knowledge comprehension is the first stage of the system, consisting of three modules: concept comprehension, process comprehension, and experimental comprehension. Among them, concept comprehension includes four sub-modules: basic concept comprehension, common function comprehension, convolution operation comprehension, and sampling method comprehension. The convolution operation comprehension module is shown in Fig. 3(a). Process comprehension includes four sub-modules: data augmentation comprehension, feature extraction comprehension, feature integration comprehension, and model distillation comprehension. The feature extraction comprehension module is shown in Fig. 3(b). Experimental comprehension includes two sub-modules: various experimental comprehension and evaluation parameter comprehension.



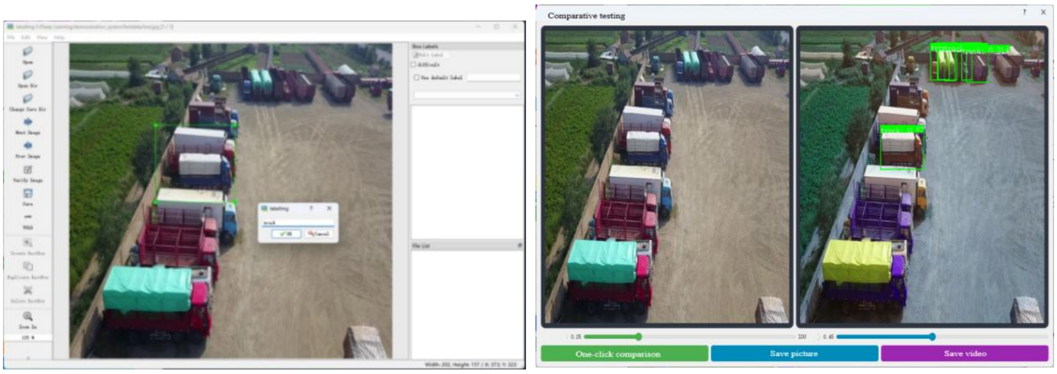
(a) Convolution operation (b) Feature extraction

Fig. 3. Functions of the knowledge understanding stage

4.2 Experimental operation

Knowledge operation is the second stage of the system, consisting of four modules: model preparation, model loading, data loading, and model inference. Among them, model preparation includes four sub-modules: data annotation, configuration file, model training, and custom model. The data annotation module is shown in Fig. 4(a). Model loading includes two sub-modules: loading the model and adjusting parameters. Data loading includes three sub-modules: image data, video data, and RTSP stream data. Model inference includes three sub-modules:

single detection, comparative detection, and batch detection. The comparative detection module is shown in Fig. 4(b).



(a) Data annotation (b) Comparative detection
Fig. 4. Functions of the experimental operation stage

5. Object detection experiment

Object detection is a classic research and teaching direction in the field of deep learning and is often widely used as an introductory experiment. This paper takes object detection as an example and designs and implements detailed experimental content by using an integrated interactive experimental system. Among them, Yolov5 is adopted as the basic algorithm, and the algorithm improvement experimental design and verification are carried out.

5.1 YOLOv 5

YOLOv5 is an advanced object detection algorithm, featuring four scales: small, medium, large and xlarge. Its characteristics are presented in Table 1.

Table 1

Model Size and Characteristics of YOLOv5

Model Size	Number of parameters	Reasoning speed	mAP
YOLOv5-small	7M	Fastest（~140fps）	Lowest
YOLOv5-medium	21M	Medium（~90fps）	Medium
YOLOv5-large	47M	Slower（~50fps）	Higher
YOLOv5-xlarge	89M	Slowest（~30fps）	Highest

This model achieves rapid target localization and classification by dividing the image into grids and predicting bounding boxes and category probabilities in each grid. YOLOv5 has been optimized in terms of network architecture, adopting a more lightweight design. This enables it to significantly enhance inference speed while maintaining high precision, making it suitable for operation in resourceconstrained environments. YOLOv5 also introduces technologies such as data augmentation, automatic learning anchor boxes, and multi-scale prediction, further enhancing detection performance.

The YOLOv5 backbone network is composed of the CBS module, C3 module and SPPF module, and has a strong feature extraction capability. The Neck part adopts the structure of Path Aggregation Network (PAN) and Feature Pyramid Networks (FPN), which can perform detection on feature maps of different scales. It is mainly used for fusing the features extracted from the backbone network. The Head section consists of three output layers of different scales, which are respectively used to detect images of large, medium and small scales. This method can effectively enhance the performance of the detection model while maintaining a relatively small number of parameters and computational load. The structure of YOLOv5 is shown in Fig. 5.

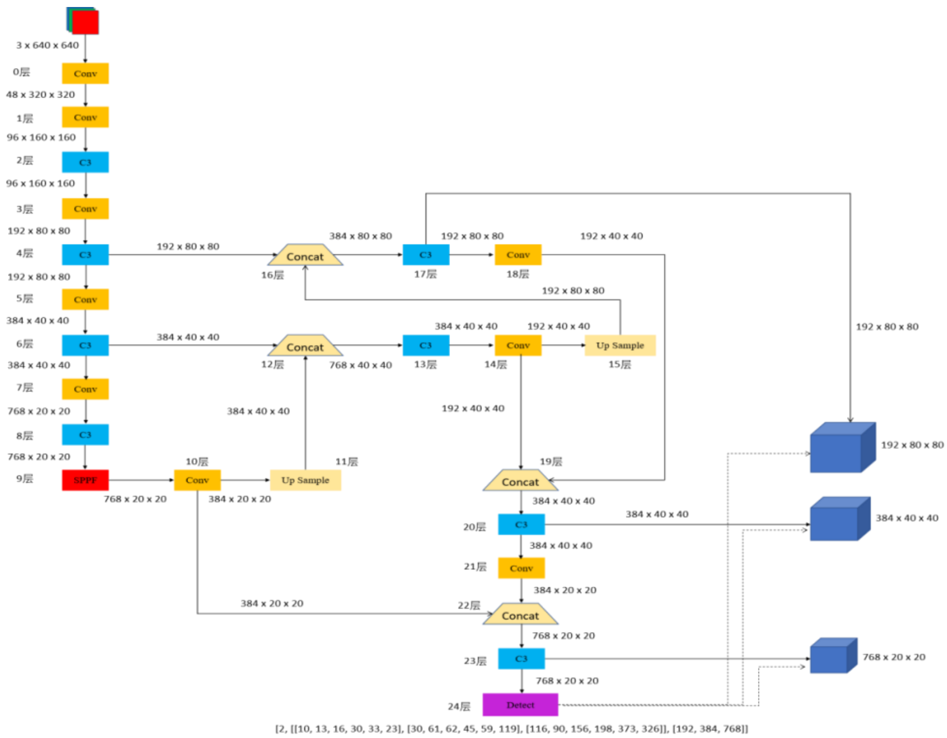


Fig. 5. Structure of YOLOv5m

5.2 YOLOv5m-CBAM

To experiment on how to improve deep learning models and help students fully understand the relevant operations, the CBAM attention mechanism was added based on the YOLOv5m model. CBAM consists of two attention mechanisms: the channel attention mechanism and the spatial attention mechanism.

Starting from the two scopes of channel and space, a sequential attention structure from channel to space is implemented. Spatial attention enables neural networks to focus more on the pixel regions in the image that play a decisive role in classification and ignore the unimportant regions. Channel attention is used to handle the allocation relationship of feature map channels. Meanwhile, the attention allocation of the two dimensions enhances the improvement effect of the attention mechanism on the model performance. The addition of CBAM can effectively enhance the feature extraction ability, model robustness and detection accuracy of the original YOLOv5m model, while reducing the computational load and the number of parameters and accelerating model convergence. The improved model is YOLOv5m-CBAM, and its structure is shown in Fig. 6.

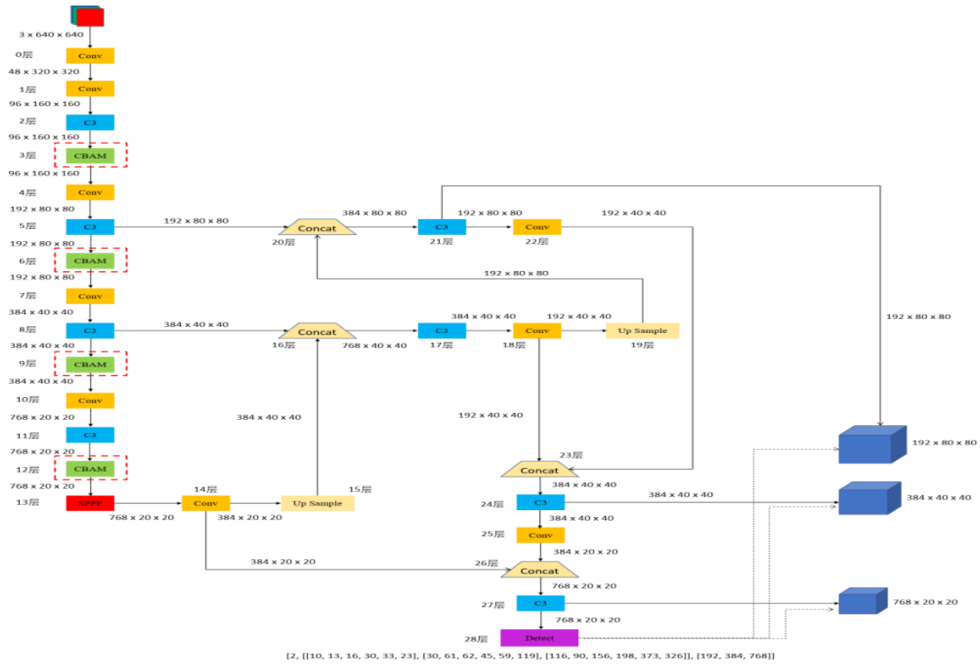


Fig. 6. Structure of YOLOv5-CBAM

5.3 Data Training and Experimental Comparison

In light of the experimental situation, it should be noted that we are not using the most advanced algorithm. This is mainly a demonstration of the algorithm improvement experiment. Therefore, only the original YOLOv5m and YOLOv5m-CBAM are compared to show that the detection effect of YOLOV5M-CBAM is superior to that of the original YOLOv5m, but the effect may be lower than that of the current most advanced fire detection algorithm.

(1) Dataset

A total of 21,527 images from the fire dataset on the Kaggle data platform were adopted, including smoke and flame types. The data was randomly divided into a training set, a validation set, and a test set at a ratio of approximately 7:1:2. The training set contains 14,122 photos, the validation set contains 3,099 photos, and the test set contains 4,306 photos. The division of data is shown in Table 2.

Table 2

Data Division

	training sets	validation sets	test sets	Total
Quantity	14122	3099	4306	21527
Proportion	0.66	0.14	0.2	1

(2) Training parameters

The training parameter Settings are shown in Table 3. During the training process, batch-size is set to 16, worker to 8, epoch to 500, and IoU to 0.7. In addition, with the early cessation of training mechanism, the patience was 50. When the epoch exceeds 50 but there is no significant improvement in the training effect, the model stops training. This can prevent overfitting of the model during the training process, and also save computing resources and reduce training time.

Table 3

Training Parameters

Parameter	Numerical value
epoch	300
batch-size	16
worke	8
IoU	0.7
patience	50

(3) Evaluation indicators and experimental results

To evaluate network performance, accuracy rate P, recall rate R, average precision P_a and mean average precision P_{mA} are used as the indicators for assessing network performance. The calculation formulas are shown in Equations (1) to (4).

$$P = \frac{P_T}{P_T + P_F} \tag{1}$$

$$R = \frac{P_T}{P_T + N_F} \tag{2}$$

$$P_a = \int_0^1 P(R)dR \tag{3}$$

$$P_{\mathrm{m}A} = \sum_{i=1}^{N} \frac{P_a(i)}{N} \tag{4}$$

In the formula, P_T represents the number of correctly identified flames and smoke. P_F is the number of times the background is identified as flames and smoke. N_F is the quantity that turns the flame and the smoke into the background respectively. P(R) represents the relationship curve between precision and recall.

The detection performance of YOLOv5m-CBAM on the test set is shown in Table 4. The average accuracy of model recognition has reached 81%, indicating that the model has relatively high detection accuracy for smoke and flames. The average recall rate reached 72.9%, which means that the model can successfully capture most smoke and flames. The mean average accuracy mAP@0.5 reached 78.3%, that is, when the threshold was 0.5, the average accuracy of the model for detecting smoke and flame was 78.3%. The mean average accuracy mAP@0.5:0.95 reached 45.9%, that is, when the threshold is between 0.5 and 0.95, the average accuracy of the model in detecting smoke and fire is 45.9%. From Table 4, we can also see that the detection performance of YOLOv5m-CBAM for smoke is superior to that for flames. This is because flames have more samples than smoke.

Table 4

Performance of YOLOv5m-CBAM on the test set

Category	Precision(%)	Recall(%)	**mAP@0.5**	**mAP@0.5:0.95**
Flame	**75.7**	**67.5**	**72.9**	**39.2**
Smoke	**86.3**	**78.4**	**83.7**	**52.5**
Average value	**81**	**72.9**	**78.3**	**45.9**

Fig. 7 shows the detection results of YOLOv5m-CBAM. It can be seen that it can detect flames and smoke in the image relatively high.

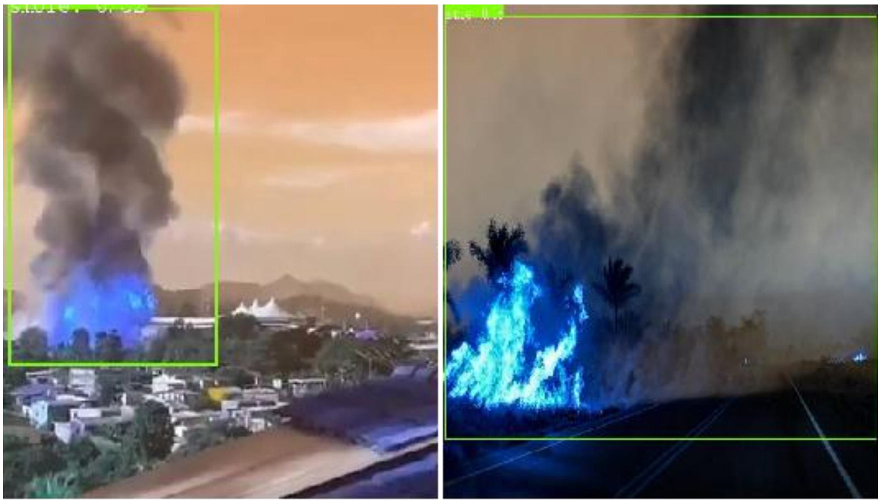


Fig. 7. Detection results of YOLOv5m-CBAM

The improved YOLOv5M-CBAM was compared with the original YOLOv5m, and the experimental results are shown in Table 5.

Table 5

Comparison of Experimental

Algorithm	mAP @ 0.5(%)	Precision(%)	P(M : million)	Number of model layers(L)
YOLOv5m	72.2	75.8	21.17	290
YOLOv5m-CBAM	78.3	81	20.86	260

In comparison, YOLOv5m-CBAM has better detection performance than the original YOLOv5n. Especially in the most important detection mean average accuracy mAP@0.5, it has been improved by 8.4% compared with the original YOLOv5m, and both the number of model parameters and the number of model layers are superior to the original YOLOv5m.

6. Conclusions

Deep learning is a core content in the professional curriculum systems of majors such as artificial intelligence, intelligent science and technology, and Internet of Things engineering. Based on the concept of full-process integration, this paper designs and develops an integrated interactive experimental system for deep learning. The system includes interactive understanding of basic concepts such as fundamental concepts, common functions, and convolution operations, as well as full-process understanding of experiments like data augmentation, feature extraction, feature fusion, and experimental evaluation, and integrated practice of data annotation, model improvement, model training, and experimental verification. Based on the developed integrated interactive experimental system, a comprehensive experiment on fire target detection based on the improved YOLOV5 was designed, enabling students to have a deeper understanding of the main basic concepts and experimental procedures of deep learning. In this way, through an interactive approach, students' comprehension ability, practical ability and the ability to comprehensively apply the knowledge they have learned can be cultivated, stimulating their interest in further learning and mastering deep learning, which can effectively enhance the teaching effect.

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