The Management System of IoT Informatization Training Room Based on Improved YOLOV4 Detection and Recognition Algorithm

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Abstract*—In response to the problems of low recognition rate and long system operation time in equipment detection management in the existing IoT information training room management system. A research has proposed an IoT information training room equipment detection management system on the ground of an improved YOLOV4 detection and recognition algorithm to solve the above problems. Firstly, it used the YOLOV algorithm to detect and identify equipment in the IoT information training room. Then, it used clustering methods to improve the YOLOV algorithm, thereby enhancing the detection accuracy and robustness of the algorithm, and thereby enhancing the performance of the equipment management system in the equipment management process of the training room. Finally, performance validation of the training room management system was conducted using datasets and simulation experiments. The results showed that the loss value of the training room equipment management system constructed using the improved YOLOv4 algorithm during the training process was 0.16. The accuracy and recall rates of device recognition were 95.71% and 92.83%, respectively. And the detection false alarm rate during the device detection and recognition process was only 2.15%, with a mAP value of 91.66%, and the detection and recognition indicators are higher than those of the comparison method. This indicates that the training room equipment management system constructed in the study has good adaptability in equipment detection and recognition in IoT information training rooms. The research aims to provide effective technical support for the management system of IoT training room equipment.

Keywords*—*YOLOV4 algorithm; Internet of Things informatization; training room; management system; detection and recognition

I. Introduction

As the boost of Internet of Things (IoT) technology, IoT information training rooms, as a new type of teaching and practical environment, are widely used in various universities. Çobanoğlu et al. investigated the laboratory operation needs of K-12 teachers and students using a survey method [1]. Automated detection and identification of equipment can improve the efficiency and accuracy of equipment management, Kan et al. conducted a study on the management of training in basic operating rooms using new evaluation criteria [2]. However, due to the diverse types, shapes, and sizes of equipment in the training room, traditional detection and identification management systems are difficult to meet practical needs, Sturt et al. conducted a study on effective review of managers of practical training rooms using a supervisory framework [3]. Therefore, a device detection management system for IoT information training rooms on the ground of an improved YOLOV algorithm has been proposed in the study. The YOLOV algorithm is an extensively utilized algorithm in the object detection (OD) and recognition. It transforms the OD and recognition problem into a regression problem and directly forecasts the category and position of the target through a neural network. Majeed et al. conducted an in-depth study on Facial Recognition and Attendance system for monitoring system in practical training room through YOLOv5 model [4]. However, the YOLO algorithm suffers from inaccurate positioning and missed detections in some complex scenarios, thus requiring improvement Hasanvand et al. explored vehicle recognition technology using specific image processing techniques [5]. Meanwhile and other scholars conducted an optimization study on the process of detecting small targets by target detector using improved YOLOv4 network [6]. The study first uses the YOLOV algorithm to detect equipment in the IoT information training room, and then improves the YOLOV algorithm using clustering methods to enhance its detection accuracy and robustness. The IoT information training room equipment management system (TREMS) not only accurately monitors and identifies the status of the training room equipment, but also manages the reasonable utilization of equipment. This can enhance the overall effectiveness of the management system. The research aims to construct a device detection management system model that can provide effective technical support for device management in IoT training rooms. Meanwhile, it also provides new research ideas for OD and classification in other similar scenarios.

In summary, Section I and Section II of the study analyzes the training room equipment management now while summarizing the research of YOLOV algorithm in equipment detection and identification; Section III firstly improves the YOLOV algorithm by using the method of clustering, and constructs the equipment management system system model of the IoT informatized training room on the basis of the improved algorithm; the third part is to verify the performance of constructing the equipment management system model of the IoT informatized It is to verify the performance of constructing the model of equipment management system system of IOT informationization training room, and the verification of the performance is carried out with simulation experiments and practical applications; Section IV is to analyze and summarize the obtained experimental results, and to get the advantages and shortcomings of the model constructed by the research. Finally Section VI concluded the paper.

II. Related Works

The management system of training room equipment is one of the key factors in maintaining the stable and reliable development of IoT information technology training rooms. It can enhance the effective management ability of equipment in the training room. But currently, the management system of the training room still has problems such as low efficiency and longtime consumption in equipment identification. To promote the scientific development of IoT information technology training rooms, many experts and scholars have conducted in-depth research on the detection and recognition of equipment in the training rooms. To improve the detection performance of training models on device images, scholars such as Obaid I proposed a device detection and recognition method on the ground of Tiny YoloV3. This method can detect and recognize devices on the ground of the performance and execution time of the training model. The outcomes showcased that the recognition probability of large objects increased from 75% to 90%, and the detection and recognition of small objects increased by 20% [7]. Zhao J et al. proposed a data adaptive amplitude method on the ground of spatial and channel attention to enhance the utilization of priority devices in two-level neural networks. This study utilizes feature approximation to generate adaptive amplitudes and minimizes the difference between real values and 1-bit convolutions. The results showed that a 64.0% efficiency was achieved on the Pascal VOC dataset, with storage and computation savings of 18.62 times and 15.77 times, respectively. On ImageNet, storage space savings of 11.04 times and 10.80 times were achieved compared to fully accurate counterparts [8]. Chinta R et al. proposed a visual framework to improve the performance of object recognition technology. This framework can utilize novel and fast algorithms to construct frameworks for objects, and then perform deep recognition on these frameworks. The outcomes showcased that the proposed framework can be executed on a humanoid robot and also extends its self-sufficiency in learning and communicating with humans [9]. Jiaxu L and other scholars proposed a bidirectional feature fusion method for enhancing the detection performance of small targets. This method can improve the performance of small OD and recognition from different aspects such as feature fusion, context learning, and attention mechanism. The results indicate that research on feature fusion, context utilization, and attention mechanisms is of great value in improving small OD in complex scenes. The detection accuracy of small target objects was enhanced by 10.3% [10].

F Li et al. proposed a deep convolutional recognition algorithm for small targets on the ground of an improved YOLOv4 network for addressing the issue of inaccurate detection of small targets in mainstream OD. This study requires obtaining more target feature information and introducing spatial pyramid pools with different pool kernel sizes. The outcomes showcased that compared to the original YOLOv4, the improved network has increased the average detection speed and accuracy by about 30% and 7%, respectively [11]. Scholars such as S Lu proposed a real-time video OD algorithm on the ground of YOLO network to apply deep learning technology to OD and recognition. This study eliminates the influence of image background through image preprocessing, and then trains a fast YOLO model for OD for getting target information. The results indicate that the YOLO network has been improved by replacing the original convolution operation with a small one, reducing the quantity of parameters and greatly shortening the time for OD [12]. Wang K proposed a high-precision remote sensing detection method on the ground of the advanced YOLOv4 framework for enhancing the detection performance of large-scale targets. A clustering algorithm that combines object scale knowledge is studied for generating a prior anchor box with high matching degree. The feature extension module is designed for expanding the receptive domain of the backbone network and getting essential contextual information. The results indicate that the feature extension module is designed for extending the receptive domain of the backbone network and getting essential contextual information [13]. To improve the detection performance of small objects and objects with varying scales, Y Ma et al. introduced a densely connected feature pyramid strategy and constructed a scale aware attention module. The study utilizes dense network blocks and median frequency balancing mechanism to process data, and then utilizes OD algorithms for detection. The results showed that AP increased by 6.22% and 5.09%, respectively. AP is 1.82% higher than YOLOv4 [14].

In summary, the design and research of the IoT TREMS model on the ground of the improved YOLOV4 algorithm is of great significance. It uses clustering algorithm to improve YOLOV4 algorithm, analyzes the detection and recognition of equipment in the training room, and obtains the specific situation of the equipment, providing more effective information for the equipment management system. The research aims to provide effective technical support for device detection and classification in IoT training rooms.

III. Design of IoT TREMS on the Ground of Improved YOLOV4 Algorithm

The design of an IoT TREMS on the ground of the improved YOLOV4 algorithm is a comprehensive solution that combines deep learning, IoT technology, and information management technology. Its main goal is to improve the detection and recognition accuracy and efficiency of IoT training room equipment by improving the YOLOV4 algorithm, thereby providing reliable support for the management system.

A. Research on IoT Training Room Equipment Detection and Recognition on the Ground of YOLOV4 Algorithm

In the equipment management system of the IoT training room, equipment detection and identification are important links. In the process of device detection, the collected video and image information, as well as their clarity and resolution, will affect the judgment of device detection and recognition results. Therefore, it is necessary to increase the accuracy of data collection for IoT training room equipment. The YOLOv4 algorithm is a deep learning based image recognition technology mainly used for OD. It can recognize targets in the images of IoT training room equipment and detect whether the equipment in the training room is working properly or missing, Lou completed a study on the counting of non-contact surveillance area based on YOLOv4-tiny algorithm [15]. By detecting and identifying the equipment in the IoT training room, it is possible for ensuring the safe operation of the equipment and prevent it from being left vacant or damaged or stolen. Dewi et al. conducted an in-depth analytical study on the performance of video vehicle recognition using Yolo V4 algorithm [16]. Through research on the detection and recognition of IoT training room equipment, it has been found that if intelligent detection of equipment is carried out using images, it is necessary to collect, analyze, and calculate the detected dataset and images. To better collect equipment related data, a YOLOv4 algorithm was used to construct an IoT training room equipment detection and recognition model. The network structure diagram of YOLOv4 is showcased in Fig. 1.

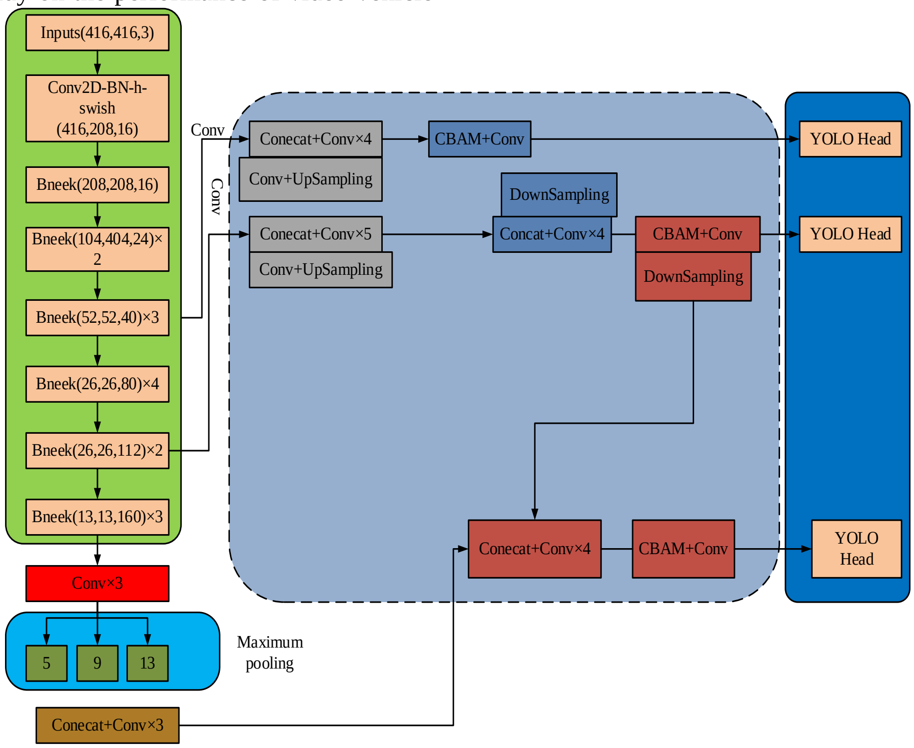


Fig. 1. Network structure diagram of YOLOv4.

When using the YOLOv4 algorithm for OD, for ensuring the accuracy of the data, it is necessary to pay attention to the convergence speed. The convergence speed refers to the speed at which a model gradually approaches the optimal solution during the training process. This speed is affected by the loss function. To improve convergence speed, research needs to consider the boundary values and confidence coefficients of the data. The boundary value of data refers to the minimum and maximum size of the target object in the dataset, which can help the model learn the size range of the target object. The confidence coefficient is used to measure the model's level of confidence in each target object. By setting reasonable boundary values and confidence coefficients, the convergence speed of the model can be accelerated, thereby improving the accuracy of the data. When traditional algorithms perform regression on bounding boxes, the coordinates of the center point and the width and height data are used as independent variables for calculation, Li and other scholars combined YOLOv4 with attention mechanism for the study of traffic sign detection in clothing context [17]. To reduce this part of the error, the study abandoned the least squares method and used the Jaccard index to solve the variable relationship between the parameters and the center coordinate. And on the ground of the problems with the Jaccard index, corresponding optimizations were made to the target detection loss function, the distance loss function between the predicted box and the true box in the target detection model, the target detection loss function, and the confidence loss function. The Jaccard index can be expressed using Formula (1).

$$L_{Jaccard} = 1 - Jaccard(A, B) \quad (1)$$

In Formula (1), A, B respectively represent the difference in IOU in the predicted box and the true box. The improved OD loss function incorporates a penalty term, which can prevent gradient problems during data detection and can be represented by Formula (2).

$$L_{GIOU} = 1 - IOU + \frac{\left|C - B \cap B^{gt}\right|}{\left|C\right|} \quad (2)$$

In Formula (2), B represents the true box value. C is the minimum bounding box generated by the intersection of A, B. B^{gt} represents the center point of the true box value. Due to the insufficient calculation of area in the process of OD loss function, it is necessary to use the loss function of the distance in the predicted box and the actual box in the OD model for representing the relationship in the predicted value and the actual value. This can also increase the convergence process of the loss function. Formula (3) can be used to represent the loss function of the distance in the predicted box and the true box in the OD model.

$$L_{DIOU}=1-IOU+\frac{\rho^2(b,b^{gt})}{c^2} \tag{3}$$

In Formula (3), c represents the diagonal length that covers the minimum range in the true value and the predicted value. ρ is a constant. b^{gt} represents the coordinates of the center point. The improvement of the target detection loss function mainly involves optimizing the overlap area, spacing at the center position, and the ratio of length and width in the coverage area. It can be represented by Formula (4).

$$\begin{cases} LCIOU=1-IOU+\frac{\rho^2(b,b^{gt})}{c^2}+\alpha v \\ \alpha=\frac{v}{(1-IOU)+v} \\ v=\frac{4}{\pi}(\arctan\frac{\omega^{gt}}{h^{gt}}-\arctan\frac{\omega}{h})^2 \end{cases} \tag{4}$$

In Formula (4), ω^{gt} serves as the width of the true value. h^{gt} serves as the height of the true value. b^{gt} serves as the coordinates of the center point. ω represents the width of the predicted value. α represents the trade-off parameter. v represents the consistency between the candidate value and the aspect ratio of the target object. ρ is a constant, representing the Euclidean distance. The confidence loss function can be calculated using Formula (5).

$$\begin{cases} L_{cla}(O,C)=-\sum_{i\in Pos}\sum_{i\in cla}(O_{ij}\ln(\hat{C}_{ij})+(1-O_{ij})\ln(1-\hat{C}_{ij})) \\ \hat{C}_{ij}=Sigmoid(C_{ij}) \end{cases} \tag{5}$$

In Formula (5), O_{ij} represents a constant, with a value of 1 or 0. $\hat{C}_{ij}$ represents the probability that the predicted value i contains the j target. The entire process of detecting equipment in the YOLOv4 IoT training room mainly consists of three parts: creating a dataset, training the dataset, inputting it into the model to calculate the confidence of the results. The entire process is shown in Fig. 2.

B. Construction of Equipment Management System Model on the Ground of Improved YOLOV4 Algorithm

Through the study of YOLOv4 algorithm in device detection and recognition, it was found that the backbone network CSPDarknet in YOLOv4 has greatly improved in performance. However, it is still a heavyweight network that cannot meet the requirements of low consumption and high efficiency in the detection and recognition process. Zhang utilized YOLOv4 for the recognition study of the posture of welding studs [18]. Although YOLOv4 has significant advantages in the model of device detection and recognition in IoT training rooms, there is still a problem of excessive training parameters in the actual operation process, Liu and other scholars utilized YOLOv5 algorithm for fast detection study of infrared device images [19]. To solve this problem, the K-means clustering algorithm was applied to the prior boxes of the YOLOv4 algorithm dataset to cluster the data. K-means clustering can first select the center point of the initial cluster in the prior box, and then perform clustering. Meanwhile, due to the uneven scale distribution in the detection image, K-means clustering can forcibly cluster objects of similar sizes, thereby improving the accuracy of detection. The perspective scale for identifying cameras in the IoT training room equipment detection management system is fixed. This study utilizes K-means clustering to cluster different specific sizes, but it still needs to meet the requirements of sample clustering. The requirements for clustering can be expressed using Formula (6).

$$D\sim u(0,r) \tag{6}$$

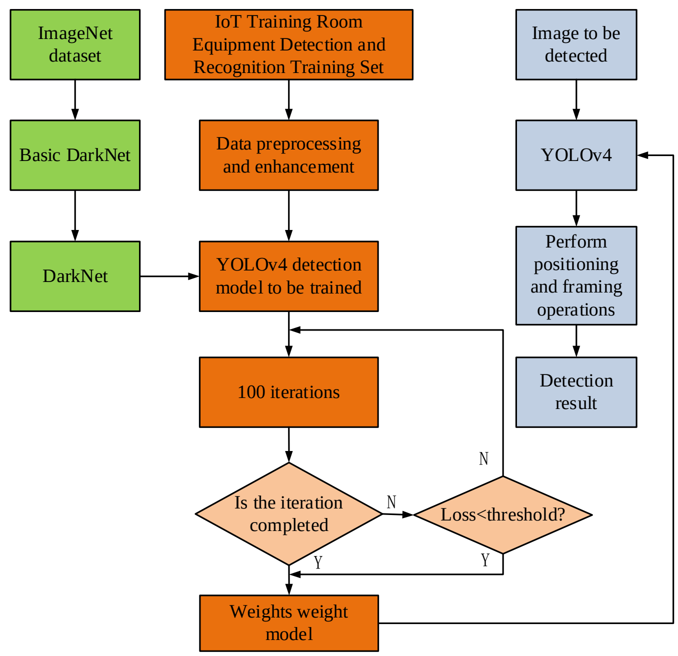


Fig. 2. Detection flowchart on the ground of YOLOv4 algorithm.

In Formula (6), $D=(d_1,d_2,\cdots,d_n)$ represents the prior box. r represents the image resolution of the clustering input. $u(0,r)$ represents the size range of the recognition device. There are a total of three groups and nine prior boxes in YOLOv4 used in the study. These three sets of prior boxes can detect and recognize devices of different sizes, including large, medium, and small, as set. To avoid the phenomenon of undetectable size, the study only selected one detection head, which means that all devices are placed on a certain layer for detection, to avoid undetectable situations. Meanwhile, to prevent situations where the device volume is too small and cannot be detected, the study added IK-means on the basis of K-means clustering. This enables clustering of all nodes in the network and sets two thresholds, Sun et al. utilized YOLO algorithm for effective detection of targets at multiple scales to improve the accuracy of different picking devices [20]. This allows for scale division of devices of different sizes. Through the detection of three sets of prior boxes, a total of nine prior boxes were obtained. Two threshold values were set to annotate the size of the object boxes, and rectangular annotation boxes were defined. The size of this annotation box is defined using the length of the diagonal, and the specific definition formula can be represented by Formula (7).

$$Diag(j) = \sqrt{(a_j^w)^2 + (a_j^h)^2} \tag{7}$$

In Formula (7), $(a_j^w)^2 + (a_j^h)^2$ represents a rectangular annotation box. $j = 1, 2, \cdots, m$, . m represents the total amount of all annotation boxes. $Diag(j)$ represents the diagonal length corresponding to the annotation box. w represents width. h represents height. After obtaining the length of the diagonal, clustering algorithms can be used to cluster the diagonal and obtain different detection box cluster centers. After calculating the cluster center, it can be utilized for determining the threshold that needs to be set for the research. The calculation of threshold can be represented by Formula (8).

$$\begin{cases} Th_1 = (C_1 + C_2)/2 \\ Th_2 = (C_2 + C_3)/2 \end{cases} \tag{8}$$

In Formula (8), $C = (C_1, C_2, C_3)$ represents the cluster center. Th_1 and Th_2 represent threshold 1 and threshold 2. The flowchart of using K-means combined with IK-means clustering is shown in Fig. 3.

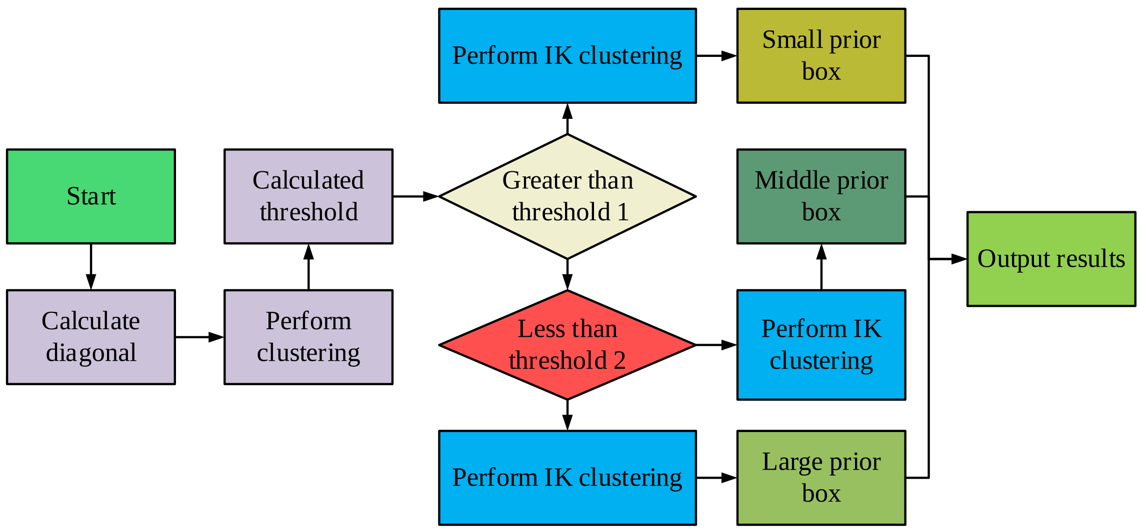


Fig. 3. Flowchart of K-means combined with IK-means clustering.

To further ensure the high detection accuracy of the model, attention modules were introduced into the backbone network of the model. The addition of attention modules could enhance the learning efficiency and detection and recognition accuracy of the model for data information. Meanwhile, to reduce the impact of dimensionality reduction on the attention module channels, the study eliminated the dimensionality reduction effect by performing lightweight operations on the attention module. The attention module at this point can be represented by Formula (9).

$$W(k) = \begin{bmatrix} w^{1,1} & \cdots & w^{1,k} & 0 & \cdots & 0 \\ 0 & w^{2,2} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \cdots & w^{C,C-k+1} & \cdots & 0 & w^{c,c} \end{bmatrix} \tag{9}$$

In Formula (9), k serves as the size of the convolution kernel in the module. C represents the number of channels for inputting feature maps in the module. At this point, the shared weight values of all channels can be represented by Formula (10).

$$w_i = \sigma(\sum_{j=1}^{k} w_i^j y_i^j), y_i^j \in \Omega_i^k \tag{10}$$

In Formula (10), σ represents the activation function. y_i represents weight. Ω_i^k represents the k domain channels in the y_i weight. The schematic diagram of the attention module structure is showcased in Fig. 4.

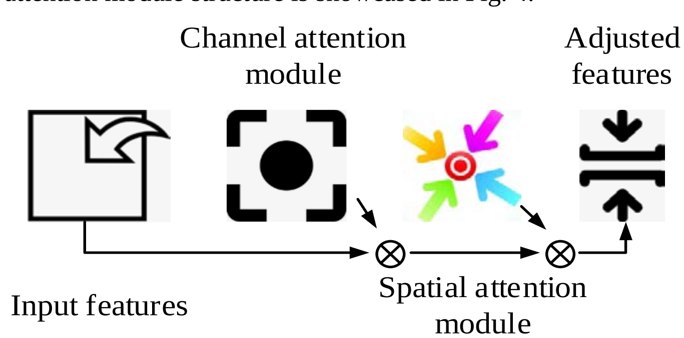


Fig. 4. Schematic diagram of the structure of the attention module.

In summary, the IoT information training room equipment detection on the ground of the improved YOLOV4 algorithm first improved the prior boxes using K-means clustering, then added attention modules to the backbone network and removed the SPP structure in the YOLOV4 network. The flowchart of the device detection and recognition system in the improved YOLOV4 algorithm device management system is shown in Fig. 5.

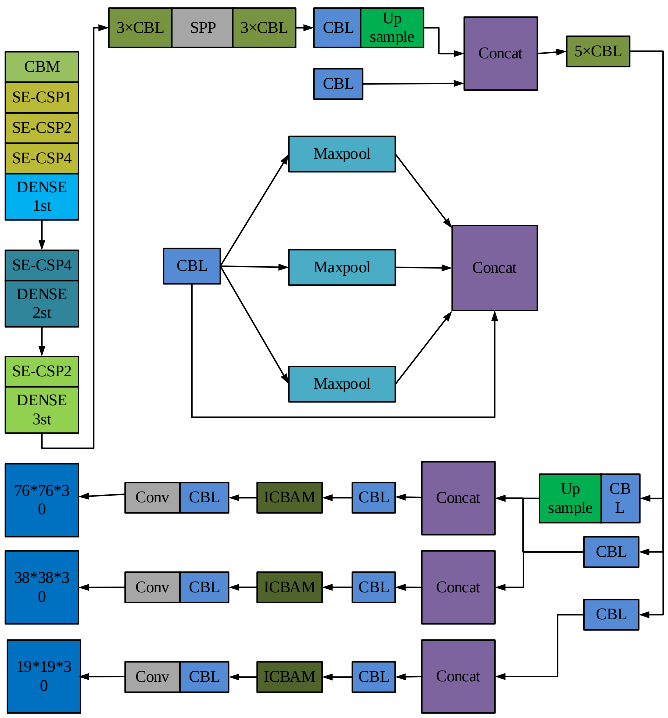


Fig. 5. Flowchart of equipment detection and identification system in equipment management system with improved YOLOV4 algorithm.

On the ground of the analysis in Fig. 5, after the model training is completed, it is necessary to use mAP in the target domain as an evaluation indicator. mAP can be represented by Formula (11).

$$mAP = \frac{1}{N}\sum_{i=0}^{N-1} AP_i \tag{11}$$

In Formula (11), N represents the category of the detected target, with a value of 3. AP_i represents the AP value corresponding to the three types of detection targets.

IV. Performance Analysis of Equipment Management System Model on the Ground of Improved YOLOV4 Algorithm

To verify the performance of the IoT information training room equipment detection management system model on the ground of the improved YOLOV4 algorithm, this study compared the YOLOV4 algorithm and Single Shot Multibox Detector (SSD) with the improved YOLOV4 algorithm as comparative methods. This is to verify the performance of the IoT information TREMS on the ground of the improved YOLOV4 algorithm in equipment detection and recognition.

A. Performance Analysis of Equipment Inspection Management System Model

To verify the performance of the equipment management system model in the IoT information training room in equipment detection and recognition, the performance of the model was analyzed. It takes the loss value during the training process of the system model as one of the indicators to judge the performance of the model. The comparison results of function loss values for three methods in device detection and recognition are shown in Fig. 6.

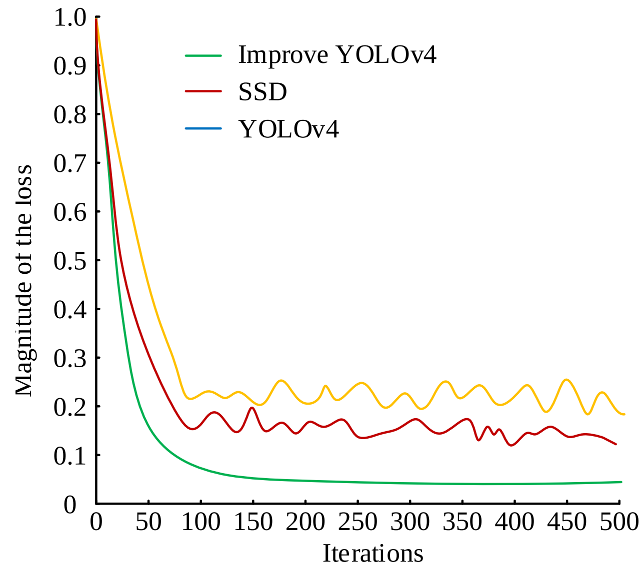
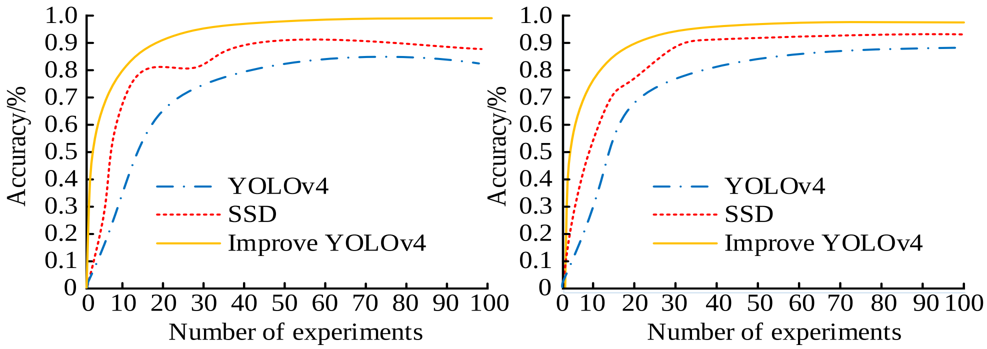


Fig. 6. Comparison results of function loss values among three methods for device detection and recognition.

Fig. 6 showcases that the loss value of improved YOLOv4 tends to stabilize after 146 iterations, with a loss value of 0.16. The loss value of SSD slows down after 98 iterations, but does not tend to stabilize. Instead, it remains fluctuating, with a loss value of 0.25. The loss value of YOLOv4 slows down after 95 iterations, but does not tend to stabilize, with a loss value of 0.31. This indicates that the smaller the difference between the predicted and actual values in the processing of device data, the more accurate the predicted results of the device management system model constructed in the study. To verify the performance of the model in device image detection and recognition, the accuracy and recall of recognition were studied as validation indicators. The comparison results of recognition accuracy and recall of the three methods are showcased in Fig. 7.

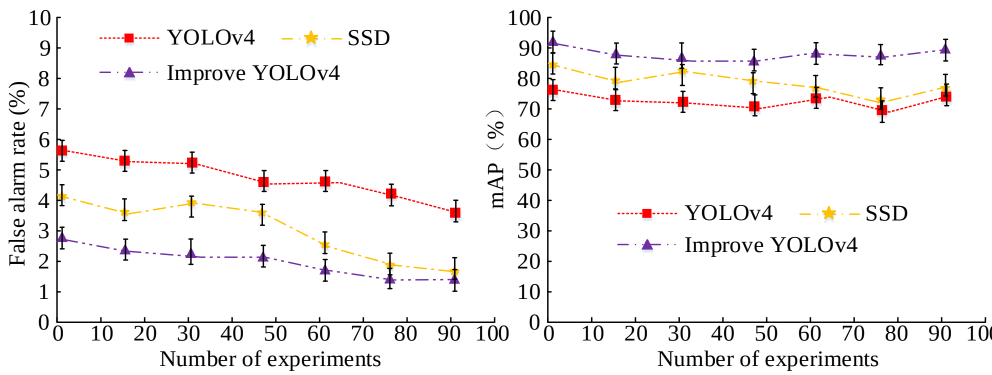
Fig. 7(a) shows that there is a certain difference in the accuracy of device recognition among the three methods. The improved YOLOv4 has a device recognition accuracy of 95.71%, SSD has a device recognition accuracy of 88.64%, and YOLOv4 has a device recognition accuracy of 81.52%. Fig. 7(b) shows that among the three methods, the improved YOLOv4 has the highest recall rate for device recognition data, which is 92.83%. The recall rate of SSD is 88.31%, and the recall rate of YOLOv4 is 82.9%. This indicates that the improved YOLOv4 system model constructed in the study has stronger robustness in data detection. To verify the recognition performance of the system model on devices, the study used device recognition false alarm rate and mAP as indicators. The comparison results of the false alarm rate and mAP for device recognition using three methods are shown in Fig. 8.

Fig. 8(a) shows that during the equipment detection and recognition process in the IoT information training room, the improved YOLOv4 has a false alarm rate of 2.15%. The device detection and recognition false alarm rate of SSD is 3.95%, and the device detection and recognition false alarm rate of YOLOv4 is 5.26%. Fig. 8(b) shows that the improved device detection and recognition mAP for YOLOv4, SSD, and YOLOv4 are 91.66%, 82.39%, and 78.24%, respectively. This indicates that the system model constructed in the study can significantly reduce errors in equipment detection and recognition processes, and improve detection performance. To further validate the system model, the quantity of floating-point operations per second and the number of frames transmitted per second of the image were used as indicators for performance validation. As shown in Fig. 9, the comparison results of three methods on the quantity of operations and the quantity of transmitted frames are presented.



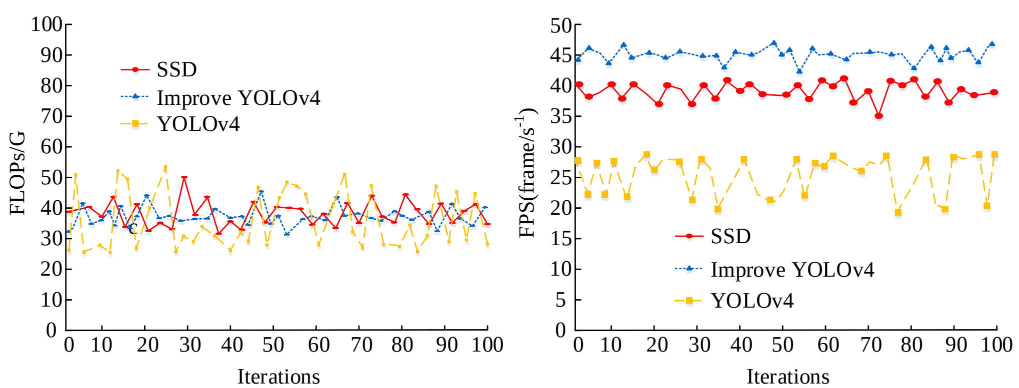
(a) Accuracy of different methods (b) Recall rates for different methods

Fig. 7. Comparison results of recognition accuracy and recall of three methods.



(a) Device recognition false alarm rate using different methods (b) Comparison results of mAP using different methods

Fig. 8. Comparison of false alarm rates and mAP results of three methods for device recognition.



(a) Comparison results of floating-point operations for device detection and recognition using different methods (b) Comparison results of transmission frame rates for device detection and recognition using different methods

Fig. 9. Comparison results of three methods on the number of operations and transmission frame rate.

Fig. 9(a) shows that there is a certain difference in the number of floating-point operations per second among the three methods when detecting devices in the IoT information training room. The budget for improving YOLOv4, SSD, and YOLOv4 is 42.36, 36.25, and 31.83, respectively. Fig. 9(b) shows that the transmission frame rate plays a crucial role in image monitoring and recognition. The improved YOLOv4 has a detection and recognition transmission frame rate of 43.59 for device images, while SSD and YOLOv4 have a detection and recognition transmission frame rate of 38.17 and 24.93 for device images, respectively. This indicates that the management system model has better performance and stronger adaptability in the recognition process of device images.

B. Application Performance Analysis of Equipment Inspection Management System Model

To verify the application performance of the IoT information technology TREMS in equipment detection, a study was conducted to compare the clustering results of equipment detection and recognition data, and the clustering effect was used as the validation indicator. The comparison results of K-means and system model clustering performance are shown in Fig. 10.

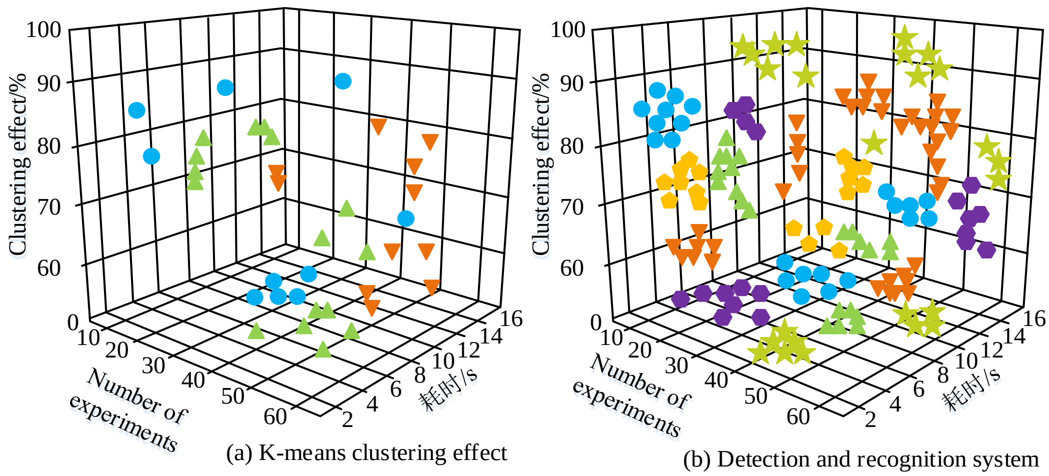
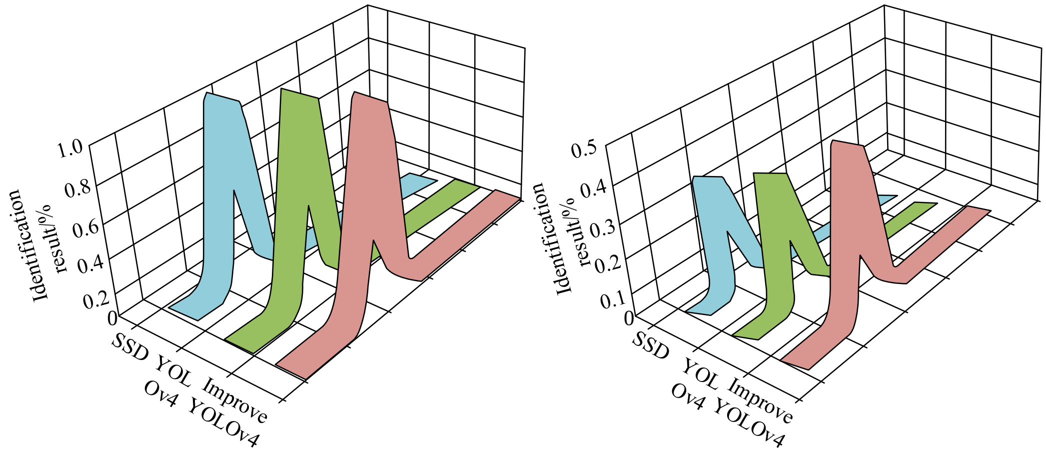


Fig. 10. Comparison of clustering performance between K-means method and system model.

Fig. 10(a) shows that in the K-means clustering results, a total of three types of device information were found, taking a total of 12.8 seconds. Through analysis, it was found that the clustering method did not have a good overall recognition effect on the equipment in the IoT information training room. Fig. 10(b) shows that during the detection and recognition process of IoT information training room equipment in the system model, a total of 6 types of equipment were identified, which is much higher than the clustering results of K-means. Simultaneously detecting and recognizing takes 9.5 seconds. This indicates that the IoT information training room equipment detection management system constructed through research has a better effect on data clustering and can improve the performance of equipment detection and recognition. To further validate the performance of the system model, environmental conditions were studied as validation indicators. The device detection and recognition performance of the system model was validated in bright and dim environments, as showcased in Fig. 11, which showcases the detection and recognition outcomes of three methods in two different environments.

Fig. 11(a) shows that in a brightly lit environment, all three methods have good performance in detecting and recognizing devices. The improved YOLOv4 achieved a recognition result of 97.05%, SSD achieved a recognition result of 92.46%, while YOLOv4 achieved a relatively poor recognition result of 87.69%. Fig. 11(b) shows that in a dim environment, the detection and recognition outcomes of the three methods on the device are significantly affected. The recognition results of improved YOLOv4, SSD, and YOLOv4 were 46.95%, 38.31%, and 31.28%, respectively. Through comparison, it was found that the detection capability of the equipment management system model has significant advantages compared to the comparative methods. For further verifying the application performance of the system model, the recognition scalability of the system model was analyzed. As shown in Fig. 12, three methods were applied to analyze the clustering ability in device detection and recognition. The curve in the figure represents the iterative process of clustering, the graph on the right shows the clustering model, and the orange in the figure represents the clustering center.

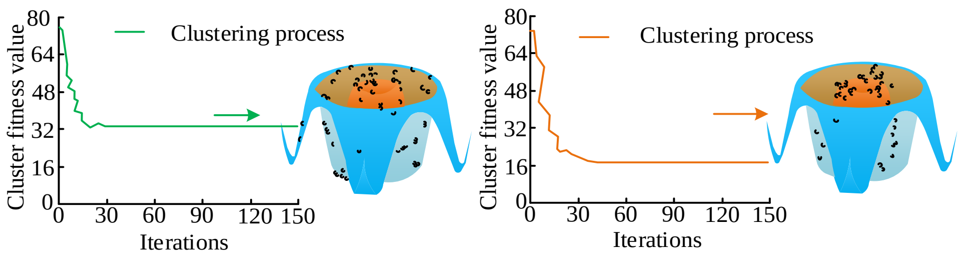
Fig. 12(a) shows that the YOLOv4 method stopped clustering analysis of the data after 31 iterations, and the entire clustering process was relatively scattered, with fewer trajectory points in the orange position. Fig. 12(b) shows that the SSD method stopped analyzing the clustering data after 52 iterations. Fig. 12(c) shows that the improved YOLOv4 method stopped analyzing clustering data at 49 iterations, but it had the most trajectories in the orange region, with only four trajectories outside the orange region. This indicates that the improved YOLOv4 method has a more stable applicability performance in clustering data.



(a) The detection and recognition results of three methods in bright environments

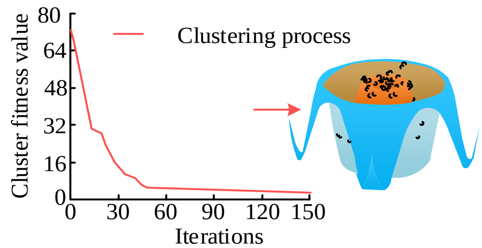
(b) The detection and recognition results of three methods in dim environments

Fig. 11. Three methods for detecting and identifying equipment in two different environments.



(a) YOLOv4 scalability and adaptability performance

(b) SSA scalability and adaptability performance



(c) Improving YOLOv4 scalability and adaptability performance

Fig. 12. Application analysis of three methods for clustering ability in equipment detection and recognition.

V. Discussion

In the research on the management system of the IoT information technology training room based on the improved YOLOV4 detection and recognition algorithm, there may be challenges such as difficulties in data collection, algorithm optimization, hardware and equipment limitations, data security and privacy issues, and difficulties in verifying practical application scenarios. These challenges may affect the progress of the research and the accuracy of the results, which requires researchers to continuously improve and optimize the research methodology to ensure that the final research results can be effectively applied and verified. Through related research, it is found that the potential future directions of research mainly include algorithm optimization, multi-target detection, behavior recognition, multi-sensor fusion, scenario-oriented optimization, system integration and deployment, and privacy protection and data security. These directions will help to further enhance the intelligence level of the management system of the IoT informatized training room and improve the management efficiency and security.

VI. Conclusion

To enhance the management ability of the IoT information training room management system, a study was conducted on the equipment management system of the training room. It proposed a system model for equipment detection and management in IoT information training rooms on the ground of an improved YOLOV4 algorithm. The results showed that the system model identified a total of six types of devices in the detection and recognition process of IoT information training room equipment, with a detection and recognition time of 9.5 seconds. In bright environments, the improved YOLOv4 achieved a recognition result of 97.05%, while in dim environments, the improved YOLOv4 achieved recognition results of 46.95%, and its adaptability was significantly better than the comparison method. This indicates that the system has high accuracy and robustness in device detection and recognition, and can meet the needs of users for device management. Meanwhile, the system can perform real-time detection and identification of equipment in the training room, thereby improving the ability of equipment management and effective utilization. However, there are still certain shortcomings in the research, and there is still room for optimization of equipment detection and recognition algorithms in the IoT information training room. By optimizing the algorithm, the performance of detection and recognition could be further enhanced, providing more data support for training room managers.

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