Research Article

E-Commerce Logistics Inspection System Based on Artificial Intelligence Technology in the Context of Big Data

Xianhui Chen

Hunan Post and Telecommunication College, Changsha 410015, Hunan, China

Correspondence should be addressed to Xianhui Chen; 201904217319@stu.zjsru.edu.cn

Received 7 January 2022; Revised 24 January 2022; Accepted 1 February 2022; Published 11 March 2022

Academic Editor: Muhammad Arif

Copyright © 2022 Xianhui Chen. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

With the development of science and technology, the logistics industry has generally introduced information technology, and the construction of intelligent warehouse management is the development trend of the logistics industry. In order to improve the operation efficiency of intelligent warehouse and make full use of freight resources, this paper proposes an intelligent logistics inspection system based on big data. The system takes the platform data of unmanned monitoring points with multiple data sources as the research object and also uses a deep learning-based method for parcel detection and tracking in order to overcome the defects of traditional parcel detection and tracking technology. The role of the system is to obtain the parcel flow data of each unmanned monitoring point and then upload these important data to the scheduling system of the warehouse to realize the intelligent management of the warehouse.

1. Introduction

With the continuous development of the market economy, society’s demand for logistics has deepened, and the development of the logistics industry has made a great contribution to the growth of the national economy [1]. Along with the rapid development of Internet technology and E-commerce, the development of modern logistics has generated a new situation. At the same time, however, the express industry has also added many challenges, such as a high rate of empty warehouses and low warehouse operating efficiency and service quality [2]. The main reason behind this is the lack of an advanced warehouse management model, the low level of information technology, and the relatively immature technology of warehouse management information systems. At present, intelligent storage technology is developing rapidly [3]. This is mainly reflected in the continuous intelligence and networking of storage facilities, automation and standardization of equipment operation, interconnection of storage systems with other systems, and the use of big data to achieve the integration and utilization of storage resources. Among them, the application of warehousing information technology is developing most rapidly [4]. Warehouse information technology is mainly through intelligent technology that makes the use of storage resources and warehouse operation process transparent and digital. With the industrial upgrading of the express industry, intelligent warehousing is the future direction of development. Warehouses are divided into types of warehouses according to their function. Sorting warehouses are warehouses where parcels of different sizes and destinations are sorted, and they are transfer stations where goods are sorted and distributed. For this reason, we need to use communication or intelligent technology to monitor and digitally manage the operation of the sorting warehouse, mainly by establishing a tracking and counting system for different types of parcels and then integrating the statistical data and monitoring information into the management terminal system of the sorting warehouse. The design of an intelligent and efficient parcel detection and counting system is of great importance for the intelligent management of the sorting warehouse [5, 6].

The sorting warehouse has a number of conveyor lanes, which are driven by motors running on conveyor belts. The
conveyor aisles are divided into main and subtrunk aisles, where parcels meet or are diverted at the intersection of the conveyor aisles. The conveyor channels of the sorting warehouse are abstracted into a transmission network, and the flow of parcels inside the transmission network now needs to be monitored to facilitate the management of the sorting warehouse. At present, the system solutions for monitoring the flow of parcels in the transmission network are based on Radio Frequency Identification (RFID) technology and laser scanning-based detection statistics system solutions [7].

RFID technology is a noncontact and non-line-of-sight capture technology. It is based on the principle of using radio waves for rapid information exchange and storage. The general RFID system consists of three parts [8, 9]: the reader, the electronic tag, and the data management. But at this stage of RFID technology parcel tracking detection system scheme, there are many problems; first of all, flow through the transmission network monitoring point of the parcel volume size change is relatively large, the electronic tag attached to the outer surface of the parcel makes the electronic tag cannot always be very close to the reader, will produce missed detection of the parcel. And the electronic label production cost is relatively high, and it is the ordinary barcode label dozens of times. Therefore, the implementation ability of this program is not high.

The implementation of a parcel tracking and monitoring system based on online laser scanning requires equipment to generate a special laser and receive a laser response above the transmission channel at the monitoring point [10]. A barcode label with a reflective laser is attached to the outer surface of the parcel, the parcel flows through the laser’s irradiated area reflecting the laser, and the laser receiving response device accepts the information to upload the data to the warehouse management system. The system is simple and easy to implement but requires human involvement to ensure the accuracy of the monitoring system, as the solution relies on laser communication; once the laser communication is interrupted, there will be problems, such as the barcode that reflects the laser being obscured or the parcel being flipped in transit with the label side on the back side of the laser receiving equipment; there will be many parcels that miss statistics. Therefore, the implementation of the scheme will have serious shortcomings, requiring manual involvement in adjusting the state of the parcels on the transmission channel, demanding high conditions on-site, and not being very intelligent.

To this end, we use computer vision technology [11] and intelligent technology [12] to implement a tracking, detection, and counting system for different types of parcels. Deep learning-based target detection and machine vision-based multitarget tracking are used in the design of the parcel tracking and counting system to improve the statistical accuracy of the parcel tracking and counting system [13]. The system is practical and easy to use and has important production applications as it can store real-time site monitoring data for a period of time. The remaining paper is arranged in the following way.

Section 2 presents the related work and literature review. Many concepts are also defined in Section 2. Section 3 presents the methods used for the target detection and the design of the logistic inspection system on the basis of big data and deep learning. In Section 4, the experiments are carried out, and their results are analyzed in a comparative manner. Finally, the conclusions of the paper are presented in Section 5.

2. Related Work

2.1. Target Detection. The role of target detection is to the extraction of targets of interest from video surveillance or continuous images, and it is the basis for subsequent tracking and recognition of targets of interest [14]. Target detection is the segmentation of uninteresting backgrounds as well as foreground targets of interest, and it can be divided into background-based modelling and foreground-based modelling methods [15], depending on the object to be processed. The background modelling approach is based on processing the background, creating a time-dependent background model, and indirectly segmenting the foreground by comparing the background models of images in different time sequences to obtain the foreground region for tracking targets [16]. The foreground-based modelling approach directly models the region of the image where the target is located, extracts features such as greyscale and texture, and designs a suitable classifier to classify and detect it [17].

The method based on background modelling is to first establish the overall model and the background model of successive frames, then compare the overall model of the current frame with the background model of the current frame, and determine whether each pixel in the current frame belongs to the motion foreground by the threshold method. The foreground region is then divided, and the tracking target is obtained by operations such as expansion or erosion of the graph and finding the edges of the region. The background modelling method generally involves the initialization of the background model, the maintenance of the model, and the detection and segmentation of the foreground, and the general process is shown in Figure 1. N indicates the number of video frames used for background model initialization, and background initialization refers to the initialization of the image background to build the model.

The target-based modelling approach includes two stages: offline training and online detection. (1) Offline training phase: the key to this process is feature representation and then classifier training to obtain the classifier model. (2) Online detection stage: after scanning the test samples with sliding windows at multiple scales, the same feature representation method as in the previous stage is used to build the apparent model, and then the classifier model trained in the previous stage is used to classify them. Based on the classification results, we determine whether each window is a foreground target and finally output the specific area location of the target to be detected.
The advantages of foreground target-based modeling methods over background-based modeling methods are that they are not constrained by the scene, have a relatively wide range of applications, and do not require resegmentation of the detection results. The key to target-based modeling is the efficiency and accuracy of the feature representation and the construction of a suitable classifier. Feature representation is the process of mapping pixels in an image to distinguishable dimensional data. According to current research, there are two main approaches to image feature representation, namely, manually designed-based and learning-based feature representation methods.

2.2. Target Tracking. With the development of motion target tracking algorithms, these tracking methods can be divided into three main categories: traditional classical tracking methods, correlation filtering methods, and deep learning methods. The traditional classical tracking methods are divided into generative and discriminative methods, with the generative methods being represented by Kalman filtering, Camshift tracking, and optical flow tracking; all of them are slow. The discriminative class of methods is represented by tracking learning and detection (TLD). The difference between discriminative and generative methods is the inclusion of a classifier, which is trained using machine learning to distinguish between foreground and background.

The relevant filtering class methods are represented by Minimum Output Sum of Squared Error filter (MOSSE) [18], Discriminative Scale Space Tracker (DSST) [19], and so on. The core idea of the correlation filter class is to train a filter template that performs a correlation operation with the eigenvalues of the image. Only the response of the operation with the tracked region is maximized, and from the maximum position of the response, the central position of the tracked target can be determined, and the predicted position result is then used to update the parameters of the filter for the next prediction.

The deep learning category is represented by Detect and Track (D&T). This method is a standard method used to solve the video standard approach to the target detection problem. Our goal is to use convolutional neural networks for both detection and tracking by simultaneously directly inferring tracklet over multiple frames. This method uses detection and tracking-based loss to train an end-to-end fully convolutional architecture, which is also known as a joint detection and tracking method. The input to the network consists of successive frames of images that are first passed through a convolutional network backbone to generate convolutional features that are shared in the detection and tracking tasks. Local displacements at different feature scales are estimated by calculating the convolutional correlation values between the feature responses of adjacent frames of the images. In addition to these features, this method uses an ROI pooling layer to classify and regress preselected rectangular boxes (BOX) and an ROI tracking layer to regress BOX transformations (translations, scales, and aspect ratios) across frames. The latter part of the algorithm’s architecture is composed of a fully convolved ROI pooling layer and an ROI tracking layer and can be trained end-to-end for object detection and tracking. Finally, in order to infer the trajectory of the object in the video, this method connects the detection based on tracking small segments.

2.3. Overall Design of the System. The design of a detection and tracking system for logistics is based on a multitarget monitoring and tracking process with continuous frame images. The main design of the system can be divided into the design of target detection and the design of target tracking or target detection combined with target tracking. The acquisition of continuous frame images requires the secondary development of the industrial camera. The target detection module needs to be designed with a suitable deep learning model, balancing detection speed with detection accuracy. In the design of target tracking, not only can tracking algorithms be considered, but also hardware detection methods can be considered to obtain the motion state of the moving target. The overall platform design of the system should consider data exchange between modules, data storage and data query, real-time detection display, and so on. The block diagram of the system is shown in Figure 2.

The logistics detection and tracking system based on artificial intelligence technology designed in this paper is divided into eight main parts.

2.3.1. Camera Module. This module is responsible for the parameter setting of the camera and the acquisition of images or video control. The secondary development of the camera is required for camera module and the driver modification and camera use according to actual needs,
facilitating the access of various brands of cameras to the system and improving the scalability of the system.

2.3.2. Encoder Module. This module is mainly responsible for the communication and information processing between the system and the encoder. It obtains the pulse data from the encoder by writing a query program, converts it into displacement information, and thus obtains the movement status of the parcel on the transmission channel.

2.3.3. Interface Operation and Display Module. This module mainly displays the real-time detection image results and the running time of the target detection module and also allows you to query the history data of parcel detection and so on by querying the interface layout.

2.3.4. System Settings Archive Module. This module is where the system runs after setting reasonable parameters and stores these reasonable parameters in order to avoid setting reasonable parameters again after the system has been restarted. To avoid setting reasonable parameters again after system restart, the archived data is loaded directly.

2.3.5. Parcel Data Storage Module. This module is mainly to store the number of parcels recorded during the operation of the system, the record is mainly the number of parcels at a certain moment, convenient for the subsequent historical data query, but it is also to avoid the loss of data brought about by the system power failure.

2.3.6. Recognition and Detection Module for Parcels. The image is analyzed and detected by deep learning target detection counting to obtain the position information of the target in the image, and then the data is transmitted to the tracking module.

2.3.7. Parcel Motion Tracking Module. This module aims to analyze the motion information of the moving target and realize the tracking process of the target.

3. Methods

This section is intended to describe the different types of methods. The first method is based on deep learning, which is used to detect the target. Secondly, the methods of motion target tracking are presented. Lastly, in the context of big data, the design of a logistic inspection system was proposed.

3.1. Deep Learning-Based Target Detection

3.1.1. YOLOv3 Model Principles. The YOLO family of target detection models is the more commonly used target detection method at this stage, and the YOLOv3 model [20] can be improved and compressed by synthesizing some deep
3.1.2. Improved Target Detection Based on the YOLOv3 Model. Extensive experiments have been conducted to demonstrate that adding Spatial Pyramid Pooling (SSP) [21] to some basic classification networks improves detection accuracy. The model network for SSP is shown in Figure 4.

For example, using the ZF-5, Convert-5, Overfeat-5, and Overfeat-7 base detection networks, the classification networks with SSP were tested on the dataset Image Net 2012, and the detection metrics top-1 and top-5 error rates were reduced compared to the base detection networks without SSP. In the case of deep learning networks for target detection tasks, where different scales of feature maps are processed and where the input image resolution and aspect ratio of the detected objects vary, the addition of SPP can improve the detection accuracy with minimal changes to the original detection network structure. YOLOv3 has significantly improved the detection accuracy of the YOLO series of modules. In order to enrich the deep network features, the SPP module is added to the YOLOv3 network. The added SPP module consists mainly of 4 parallel pooling layers with \( 1 \times 1, 5 \times 5, 9 \times 9, \) and \( 13 \times 13 \) convolution kernels. A feature pyramid pooling layer is added between the previous layers 5 and 6 of the first detection header layer in YOLOv3 to become YOLOv3-SPP, as shown in Figure 5.

YOLOv3 has 3 scales of detection head layers, similar to YOLOv3-SPP, and the SPP module is added between the 5th convolutional layer and the 6th convolutional layer in front of each scale of the detection head layer in the YOLOv3 network structure, adding a total of 3 SPP modules. The model with three SPP modules in YOLOv3 is called YOLOv3-SPP3, which has been experimentally demonstrated to further improve the detection accuracy and can complete the real-time detection of parcels.

3.2. Motion Target Tracking Methods. Motion target tracking is the construction of corresponding matching relationships between successive images based on relevant features such as target shape texture, color, position, and speed. Its general processing flow is shown in Figure 6. N in the diagram indicates the initial image frame to be tracked, as the tracking process is performed on the target object in chronological order. The process is to manually calibrate or detect the target in the initial frame to obtain the initial target state and then use feature modelling and statistical modelling to complete the apparent modelling. The process is mainly to obtain the initial target state by manual calibration or target detection of the initial frame and then to complete the apparent modelling using feature modelling and statistical modelling.

The tracking method in this paper combines the idea of real-time measurement with the direct measurement of the parcel’s motion state instead of the prediction of the parcel’s motion state. Firstly, the parcels in consecutive frame images are also identified and detected, and then an external rectangle-based IOU matching method is used. A matching result greater than a threshold value indicates that the parcel inside the rectangle has been detected. Otherwise, the parcel inside the rectangle is a newly appeared parcel. Each time the matched rectangle is placed in the cache, these rectangles are then moved according to the measured parcel movement distance, and the result is used as the input reference object for the next match. The point of the method is that the rectangular box will appear to change each time it is matched, and this paper will replace the old with the new, continuously replacing and updating until the end of the trace. This method adapts to a certain extent to the constant changes of the wrapped external rectangle. The detailed implementation is shown in Figure 7.

3.3. Design of a Logistics Inspection System in the Context of Big Data. When designing a big data logistics warehouse security intelligent monitoring and detection system, the system server can be designed using a relational distributed database for the background database. This type of database can store a large amount of information about people, equipment, and abnormal behavioral characteristics. We use the SSM framework to develop and design a monitoring and control information management platform for logistics warehouses. The logistics warehouse monitoring information management platform representation layer is divided into client and Web server side; the client is responsible for receiving and responding to the user’s request.

Figure 8 shows the logistics detection management diagram under big data monitoring. In the logistics monitoring and management system, the first step is to apply the YOLO detection algorithm based on this paper with the
improved tracking algorithm for target detection localization and target tracking. Then real-time logistics parcels are classified, and finally, the data aggregation and monitoring of the whole logistics system are completed.

4. Experimental Results and Analysis

In this section, the different types of experiments are carried out for comparison purposes. The results of the experiments are achieved for target recognition, tracking detection, and practical storage applications. These results are thoroughly analyzed.

4.1. Experimental Results for Target Recognition and Tracking Detection. For this time, a comparison experiment of the three methods was done, first preparing the same detection data, that is, the same consecutive frame images. The tests were then carried out on the same computer. More than 2000 consecutive frames were detected, and the results of one of the frames based on the tracking algorithm of this paper are shown in Figure 9.

The results of the comparison are shown in Table 1, judged by indicators such as recognition accuracy and the number of frames recognized.

From the detection results, it can be seen that the tracking results in this paper have the highest accuracy and the fastest recognition. The Kalman filter-based tracking method relies on the recognition results of the YOLOv3 recognition module, which affects the quasialcuaracy of the tracking results. The DSST filter-based tracking method, on the other hand, creates multiple correlation filters in the process of multiple parcel tracking and the computational speed of tracking is slower. This paper is designed to track directly using measured parcel movement data. The tracking method in this paper is not only accurate but also
computationally fast and meets the real-time application requirements of logistics detection.

4.2. Experimental Results for Practical Storage Applications. The entire system was tested on a picking line in a company's warehouse after the design was completed, and the specific test periods and results are shown in Tables 2 and 3.

This paper collects test data for two time periods: one is the afternoon time period when there is more parcel traffic and the other is the time period when there is less parcel traffic. Each row of data is the number of parcels flowing through the monitoring point in 10 minutes. The results show that the overall accuracy rate is lower for the time period with more parcel traffic than for the time period with less parcel traffic. The main reason for the above phenomenon is the number of packages. This has a greater impact on parcel detection and identification, reducing the number of correctly identified packages. This has a greater impact on parcel detection and recognition, reducing the number of correct identifications. The data in both tables show that the output of the system is more accurate.
Figure 7: The logistics parcel tracking method in this paper.

Figure 8: Logistics detection management diagram under big data monitoring.
Figure 9: Results of a frame detection based on the tracking algorithm in this paper.

Table 1: Results of the three methods of tracing.

| Tracking method                  | Number of actual parcels (pcs) | Number of packages tracked (pcs) | Correct rate (%) | FPS/frame |
|---------------------------------|---------------------------------|---------------------------------|------------------|-----------|
| Kalman filter-based tracking    | 141                             | 160                             | 87               | 10        |
| DSST-based filter tracking      | 141                             | 148                             | 95               | 2         |
| Measurement tracking for this paper | 141                         | 143                             | 98               | 14        |

Table 2: Statistical results of the overall testing of the system for a particular afternoon time period.

| Serial number | Actual parcel/pc | Software count/pc | Accuracy rate/|%
|---------------|------------------|-------------------|--------------|
| 1             | 1500             | 1415              | 94.33        |
| 2             | 1400             | 1347              | 96.21        |
| 3             | 1000             | 959               | 95.90        |
| 4             | 1400             | 1357              | 96.93        |
| 5             | 1200             | 1152              | 96.00        |
| 6             | 1400             | 1296              | 92.57        |
| 7             | 800              | 775               | 96.87        |
| 8             | 700              | 666               | 95.14        |
| 9             | 1200             | 1153              | 96.08        |
| 10            | 1400             | 1318              | 94.14        |
| 11            | 1100             | 1050              | 95.45        |
| 12            | 555              | 523               | 94.23        |
| Total         | 13655            | 13011             | 95.28        |

Table 3: Statistical results of the overall testing of the system for a particular morning time period.

| Serial number | Actual parcel/pc | Software count/pc | Accuracy rate/|
|---------------|------------------|-------------------|--------------|
| 1             | 700              | 703               | 99.57        |
| 2             | 500              | 515               | 97.00        |
| 3             | 500              | 519               | 96.20        |
| 4             | 600              | 608               | 98.67        |
| 5             | 700              | 679               | 97.00        |
| 6             | 296              | 293               | 98.99        |
| Total         | 3296             | 3317              | 99.36        |
5. Conclusion
This study focused on the detection of big data and parcel tracking in a company's sorting warehouse. Initially, the analysis was carried out for the model and network structures of YOLOv3 target detection. Additionally, the detection principle and improvement methods of the model were also analyzed. In addition, a tracking scheme was designed to directly measure the parcel movement distance combined with deep learning target detection. Finally, the research presented an intelligent storage management scheme based on big data. Further, the experimental results verified that the proposed method can be applied to the actual logistics identification tracking process and has a certain application value.

Data Availability
The datasets used during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest
The author declares that he has no conflicts of interest.

Acknowledgments
The corresponding author upon reasonable request.

Data Availability
The datasets used during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest
The author declares that he has no conflicts of interest.

Acknowledgments
This work was supported by the project Research and Practice on Talent Training Mode of “Post Certificate Course Integration” of E-Commerce Specialty in Higher Vocational Colleges under “1 + X” Certificate System (Project no. XJXX21A054).

References
[1] E. Szaruga and E. Zaloga, “Global network economy society: information needs on the ethical framework and trust in transportation and logistics business among users of the google search engine,” European Research Studies, vol. 24, no. 2B, pp. 835–849, 2021.
[2] J. Miki, D. M. Herold, K. Pilch, M. Ćwikliki, and S. Kummer, “Understanding disruptive technology transitions in the global logistics industry: the role of ecosystems,” Review of International Business and Strategy, vol. 31, no. 1, pp. 62–79, 2021.
[3] P. Kolarovszki and J. Vaculík, “Intelligent storage system based on automatic identification,” Transport and Telecommunication Journal, vol. 15, no. 3, pp. 185–195, 2014.
[4] A. P. Pandian, “Artificial intelligence application in smart warehousing environment for automated logistics,” Journal of Artificial Intelligence, vol. 1, no. 02, pp. 63–72, 2019.
[5] C. K. M. Lee, Y. Lv, K. K. H. Ng, W. Ho, and K. L. Choy, “Design and application of Internet of things-based warehouse management system for smart logistics,” International Journal of Production Research, vol. 56, no. 8, pp. 2753–2768, 2018.
[6] J. Pei, K. Zhong, J. Li, X. Jiyuan, and W. Xinyi, “ECNN: evaluating a cluster-neural network model for city innovation capability,” Neural Computing & Applications, 2021.
[7] V. Hinkka and J. Täsiälä, “RFID tracking implementation model for the technical trade and construction supply chains,” Automation in Construction, vol. 35, pp. 405–414, 2013.
[8] P. Yang, “PRLS-INVES: a general experimental investigation strategy for high accuracy and precision in passive RFID location systems,” IEEE Internet of Things Journal, vol. 2, no. 2, pp. 159–167, 2014.
[9] I. Abad, C. Cerrada, J. A. Cerrada, R. Heradio, and E. Valero, “Managing RFID sensors networks with a general purpose RFID middleware,” Sensors, vol. 12, no. 6, pp. 7719–7737, 2012.
[10] M. Golparvar-Fard, J. Bohn, J. Teizer, S. Savarese, and F. Peñamora, “Evaluation of image-based modeling and laser scanning accuracy for emerging automated performance monitoring techniques,” Automation in Construction, vol. 20, no. 8, pp. 1143–1155, 2011.
[11] S. S. Abosuliman and A. O. Almagrabi, “Computer vision assisted human computer interaction for logistics management using deep learning,” Computers & Electrical Engineering, vol. 96, Article ID 107555, 2021.
[12] M. Yang, M. Mahmood, X. Zhou, S. Shafaq, and L. Zahid, “Design and implementation of cloud platform for intelligent logistics in the trend of intellectualization,” China Communications, vol. 14, no. 10, pp. 180–191, 2017.
[13] S. Hossain and D. Lee, “Deep learning-based real-time multiple-object detection and tracking from aerial imagery via A flying robot with GPU-based embedded devices,” Sensors, vol. 19, no. 15, p. 3371, 2019.
[14] P. Schröder, T. T. Schmidt, and F. Blankenburg, “Neural basis of somatosensory target detection independent of uncertainty, relevance, and reports,” Elife, vol. 8, Article ID e43410, 2019.
[15] J. Hu, X. Zhi, W. Zhang, L. Ren, and L. Bruzzone, “Salient ship detection via background prior and foreground constraint in remote sensing images,” Remote Sensing, vol. 12, no. 20, p. 3370, 2020.
[16] Y. Pang, Y. Wu, C. Wu, and M. Zhang, “Salient object detection via effective background prior and novel graph,” Multimedia Tools and Applications, vol. 79, no. 35, pp. 25679–25695, 2020.
[17] D. Liang, J. Pan, H. Sun, and H. Zhou, “Spatio-temporal attention model for foreground detection in cross-scene surveillance videos,” Sensors, vol. 19, no. 23, p. 5142, 2019.
[18] I. Ullah, M. Fayaz, and D. Kim, “Improving accuracy of the kalman filter algorithm in dynamic conditions using ANN-based learning module,” Symmetry, vol. 11, no. 1, p. 94, 2019.
[19] C. Wang, Y. Xu, H. Liu, and X. Jing, “Retrogression of correlation filters for discriminative visual object tracking,” Journal of Electronic Imaging, vol. 27, no. 6, Article ID 063010, 2018.
[20] A. Farhadi and J. Redmon, “Yolov3: an incremental improvement,” in Proceedings of the Computer Vision and Pattern Recognition, pp. 1804–2767, Springer, Salt Lake City, UT, USA, June 2018.
[21] Z. Huang, J. Wang, X. Fu, T. Yu, Y. Guo, and R. Wang, “DC-SPP-YOLO: dense connection and spatial pyramid pooling based YOLO for object detection,” Information Sciences, vol. 522, pp. 241–258, 2020.