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Computer Vision System for Multi-Robot Construction Waste Management: Integrating Cloud and Edge Computing

Zeli Wang [1], Xincong Yang [2,*], Xianghan Zheng [3], Daoyin Huang [4] and Binfei Jiang [4]

1 Department of Management Science and Engineering, East China University of Science and Technology, Shanghai 200030, China
2 School of Civil and Environmental Engineering, Harbin Institute of Technology, Shenzhen 518055, China
3 College of Computer and Data Science, Fuzhou University, Fuzhou 350108, China
4 Putian Digital Group Co., Ltd., Putian 351100, China
* Correspondence: yangxincong@hit.edu.cn

Abstract: Sorting is an important construction waste management tool to increase recycling rates and reduce pollution. Previous studies have used robots to improve the efficiency of construction waste recycling. However, in large construction sites, it is difficult for a single robot to accomplish the task quickly, and multiple robots working together are a better option. Most construction waste recycling robotic systems are developed based on a client-server framework, which means that all robots need to be continuously connected to their respective cloud servers. Such systems are low in robustness in complex environments and waste a lot of computational resources. Therefore, in this paper, we propose a pixel-level automatic construction waste recognition platform with high robustness and low computational resource requirements by combining multiple computer vision technologies with edge computing and cloud computing platforms. Experiments show that the computing platform proposed in this study can achieve a recognition speed of 23.3 fps and a recognition accuracy of 90.81% at the edge computing platform without the help of network and cloud servers. This is 23 times faster than the algorithm used in previous research. Meanwhile, the computing platform proposed in this study achieves 93.2% instance segmentation accuracy on the cloud server side. Notably, this system allows multiple robots to operate simultaneously at the same construction site using only a single server without compromising efficiency, which significantly reduces costs and promotes the adoption of automated construction waste recycling robots.

Keywords: construction waste management; waste recycling; multi-robot; computer vision; edge computing; cloud computing

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1. Introduction

The construction industry has played an important role in the economic activities of many countries. In China, the 2019 government report shows that the total gross output value of the construction industry exceeded 3 trillion US dollars in 2018 [1]. Meanwhile, the output value of the construction industry in the United States exceeded 6 trillion US dollars last year [2]. Frequent construction activities inevitably produce a large amount of construction and demolition waste (CDW), which has a lot of negative effects on the natural environment. CDW refers to the residual and damaged products and materials generated by construction, renovation, demolition, and other building activities, including a significant proportion of metals, plastics, wood, and other materials, especially during the construction process [3,4]. Worldwide, government reports indicate that construction waste accounts for a large proportion of all waste generated [5,6]. Currently, most of the CDW mixed with different objects end up in landfills for disposal, which is wasteful and results in contamination [7]. The landfilled CDW causes greenhouse gas emissions, air pollution, harm to human health, and other adverse effects [8]. In order to reduce the impact of construction activities on the environment, it is important to implement the "3Rs" strategy of reuse, recycling, and reduction during construction and demolition [9].

Although the problem of low recycling rate and reuse rates has captivated the attention of Chinese researchers since the early 1990s, waste management in the construction industry has not substantially improved [10,11]. Similar situations have occurred in Hong Kong and Europe. Although government policy encourages builders to classify and reuse CDW to reduce the amount of CDW that is directly landfilled, reports after many years of policy implementation indicate that these policies have had little effect [12–14]. Therefore, it is essential to develop robots for CDW recycling. Wang et al. proposed robotic prototypes for CDW recognition and picking in 2018 and 2020 [15,16]. Researchers used a crawler robot to patrol the entire construction site and used computer vision algorithms to recognize CDW. Therefore, the robot can automatically collect and classify CDW. However, the current robots used for construction waste recycling have some design flaws and are difficult to cope with in real conditions on actual construction sites. Using a single robot to patrol a huge construction site is extremely inefficient, and the robot has to deal with difficult-to-traverse terrain on the construction site, such as stairs, elevators, and pontoons, which can lead to mechanical failures and even safety accidents. Therefore, multi-robot collaboration is necessary on real construction sites. The entire workflow of automated CDW handling at construction sites involves patrolling the area, identifying CDW, picking it up, storing it in designated containers, and transporting it for further processing. Among these steps, computer vision plays a pivotal role in accurately identifying target objects and guiding the robotic arm's operations.

However, most of the previous computer vision-based CDW recognition methods are based on dedicated servers for complex computations, which means that the image data captured by the camera need to be uploaded to the server in real time [17]. Such methods have four main drawbacks: (1) real-time data transmission is extremely dependent on the network environment, but the chaotic environment of the construction site leads to a lot of weak signal zones, which means that the system has a reliability problem; (2) when there is no construction waste in front of the robot, which is most of the time, the computational power requirement of the system is low. Occupying servers all the time leads to a lot of computational power being wasted; (3) in a multi-robot collaborative CDW collection scenario, it is extremely costly to equip each robot with a dedicated server, which hinders the popularization of automated CDW recovery methods; (4) construction wastes from different construction sites have different characteristics, and the previous CDW recognition platforms neither included most common CDW types nor provided modules for expanding target CDW, which reduced the universality of the platforms.

In order to provide highly accurate, reliable, and cost-effective solutions, this paper introduces cloud computing and edge computing technologies into the field of robotic construction waste recycling. Cloud computing is a technology that shares computer storage and computing power, which is conducive to providing resources to multiple users on demand [18]. Through cloud computing, we can greatly improve the computing power of terminal equipment and thus reduce costs [19]. However, like most of the cloud computing systems, construction waste collection robots that rely on cloud computing are facing the problems of response time and network burden. Different from cloud computing, edge computing is a distributed computing paradigm that brings computation and data storage closer to the location where it is needed, in order to improve response times and save bandwidth [20]. Edge computing has played an important role in areas with large amounts of data and high network latency, such as traffic management and ocean monitoring [21].

The computer vision platform developed in this research is based on edge computing, cloud computing, and computer vision technologies, and combines the advantages of different technologies to provide an advanced target recognition approach for multi-robot collaborative construction waste collection. Using this approach, this study developed a multi-robot collaborative platform for construction waste recycling. The platform operates efficiently with only a single server without compromising the performance of individual robots. This advantage is primarily attributed to the efficient utilization of computational resources and the rational allocation of tasks within the system. In the platform design, the edge computing module is responsible for high-frequency tasks, such as real-time object detection and basic path planning, thereby reducing reliance on the cloud server. The cloud server, in turn, focuses on high-precision instance segmentation and object recognition. This division of labor and collaborative architecture enables multiple robots to perform efficiently on the same server, even in complex construction site environments. In order to verify this research, we evaluated the effectiveness of the construction waste recognition platform by field experiments. We selected small pieces of construction waste made of plastic and metal as our test because their diverse and irregular shapes represent the complexity of construction waste, making them suitable test cases to evaluate the effectiveness of our recognition platform. The results show that by optimizing the system structure and algorithms, the proposed platform is able to achieve the fast recognition of target construction waste on the edge platform and accurate target identification at the pixel level on the cloud computing platform. This platform is able to reduce the overall cost of a multi-robot collaborative construction waste recycling system while improving its robustness. We also provide modules that facilitate the rapid training of personalized recognition models based on different construction site conditions.

The rest of this paper is organized as follows. The next section reviews previous studies and the latest technologies for construction automation, edge computing and cloud computing. The following section introduces the system architecture and algorithms, after which, experiments and evaluations of this research are illustrated. Then, conclusions of this study and future works are drawn in the final section.

2. Related Studies

2.1. Construction Waste Management

At present, although the correct and efficient disposal of waste is the consensus of all industries, the method of waste disposal in the construction industry is not satisfactory. In the UK, resource efficiency has attracted much attention, especially CDW management, which is an important part of sustainable strategies. Therefore, Ghaffar et al. investigated relevant organizations through questionnaires and interviews, pointing out that attention should be paid to exploring and investing in new technologies [22]. In addition, this study also reveals that 44% of respondents thought that CDW treatment on the construction site needed improvement. Similarly, a study from China also contends that scientific research institutions should be encouraged to increase special technology investment to build a CDW recycling technology system and explore the key technologies of waste recycling [23].

Many studies have focused on specific CDW processing methods. Barbudo et al. claim that many CDWs were not handled properly, so they put forward several suggestions for the treatment of CDW [24]. In their comments, it is mentioned that in order to ensure the effectiveness of the waste management strategy and minimize the amount of CDW transported to the landfill, reasonable steps should be taken to dismantle and classify the waste. Another study uses big data, feature analysis, evolutionary mining, and model-building methods to improve CDW management [25]. Through these technical methods, real-time monitoring and intelligent control of the whole process of construction waste are realized in order to improve the utilization rate of construction waste.

Previous research also applied robots to CDW management. Computer vision has been widely used in the classification of construction waste [26]. Recently, through the combination of computer vision and robots, researchers have achieved automatic sorting of construction waste. Previous studies have tried to implement automated sorting in waste sorting plants, such as the ZenRobotics (ZenRobotics, Vantaa, Finland) sorting system [27]. The system scans the CDW on the conveyor belt, identifies the type of CDW through a computer vision system, and then uses a robotic arm to sort out useful CDW. Davis et al. used a convolutional neural network to classify the construction waste in the waste bin at the construction site into seven categories, and experiments show that the system has 94% accuracy [28]. Asadi et al. introduced a vision-based mobile robot system for automatic pickup and placement of objects on the construction site. The system is composed of a manipulator, an unmanned ground vehicle, and stereo cameras. The success rate in the grasping test is 90%, and the system can be used for CDW pickup [29]. Wang et al. developed an on-site CDW collecting robot [15]. The robot combines simultaneous localization and mapping (SLAM) and instance segmentation technologies to achieve accurate CDW picking. Similarly, Chen et al. developed a construction site CDW recycling robot prototype using SLAM technology and 3D object grasping technology [30].

However, current research has not yet solved the problems of high cost and high dependence on the network, which leads to low feasibility of applications on construction sites. Similarly, the robot developed by Asadi et al. uses a laptop equipped with GTX 960m GPU (Nvidia, Santa Clara, CA, USA), while Wang et al. use a server equipped with GTX1080 GPU (Nvidia, Santa Clara, CA, USA). High-precision artificial intelligence algorithms are inseparable from the computing power of GPU. When more complex algorithms need to be applied on construction sites, the robot will be equipped with a better GPU. Therefore, such robots face similar dilemmas. First of all, the price of GPU greatly increases the cost of CDW recycling robots and hinders their application and promotion of it. Secondly, the strategy of relying on cloud servers to run artificial intelligence algorithms makes it difficult for such robots to adapt to the environment of the construction site and wastes a lot of computing resources. Thus, how to effectively reduce costs and improve reliability is one of the key research directions for construction waste recycling robots.

2.2. Edge Computing and Cloud Computing Techniques

Cloud computing has received widespread attention in many industries. Since its birth in 2007, cloud computing has replaced grid computing and has attracted attention from industry and academia [31]. Cloud computing is a technology that provides resources and services on demand, while mobile cloud computing uses mobile devices to access remote services through the cloud, enabling users to obtain storage space, programs, etc., from cloud providers when the device is limited [32].

In the construction industry, there is research on applying cloud computing to design, construction, supply chain management, and so on [33]. Researchers separate the data and activities of public and private clouds by placing insensitive programs in the public cloud and storing private data in the private cloud. Rawai et al. believe that the excellent communication and information exchange capabilities of cloud computing can lead to better green construction management and strengthen the collaboration of project stakeholders [34]. Over the past decade, cloud computing has been extensively studied in the fields of waste management, safety management, energy management, project management informatics, and supply chain management [35]. However, the defects of cloud computing, such as low security, high latency, and high network requirements, restrict the development of cloud computing.

In order to make up for the shortcomings of cloud computing and also benefit from the development of mobile computing and the Internet of Things (IoT), edge computing technology places a large number of computing and storage resources at the edge of the Internet, which is close to mobile devices or sensors [36]. Edge computing can improve the response speed, privacy, scalability, and robustness of the system. At the same time, the widespread use of 5G in recent years has further promoted the development of mobile edge cloud computing [37]. By optimizing deep learning methods and deploying edge deep learning frameworks, edge computing technology has been applied in areas such as the Internet of Vehicles, smart manufacturing, smart homes, and smart cities [38]. Fan et al. proved that systems that integrate deep neural networks with cloud computing, edge computing, and can increase the overall work efficiency of the intelligent manufacturing industry by 20% and increase the application of deep neural networks by 15% [39]. In the construction industry, Lv et al. use machine learning, collaborative computing, and other technologies to improve the computing capabilities of mobile edge computing systems and provide a certain technical foundation for edge computing in smart cities [40].

In general, a large number of studies have applied cloud computing technology, providing a wealth of technical means for the design, construction, and management of the construction industry. However, the application of edge computing in the construction industry has not received enough attention. We believe that the low cost, high efficiency, and low hardware requirements of edge computing can provide great support for the future development of smart construction. At the same time, previous studies have shown that edge platforms usually do not have strong computing capabilities. In order to apply edge and cloud computing to construction waste recycling robots, this research needs to redesign the robot system and optimize the algorithms.

3. Intelligent Construction Waste Collection System

To achieve lower computing costs and energy, this research focuses on developing an edge-cloud combined target recognition system for construction waste recycling.

3.1. System Architecture

The construction waste collection platform mainly includes a mobile module, an environment perception module, a computing module, and a pickup module, as shown in Figure 1. Among them, the mobile module is mainly composed of motors, wheels, and batteries, while the movement of the trolley is controlled by the corresponding drive module. The environment perception module contains a lidar module and an RGB camera to perceive the surrounding obstacle information and target information. The computing module is divided into cloud computing and edge computing. Cloud computing uses a server with TITAN XP, and the edge computing platform is Jetson NX (Nvidia, Santa Clara, CA, USA). We chose the UR3 robotic arm for the picking system because its degree of freedom and accuracy met the requirements.

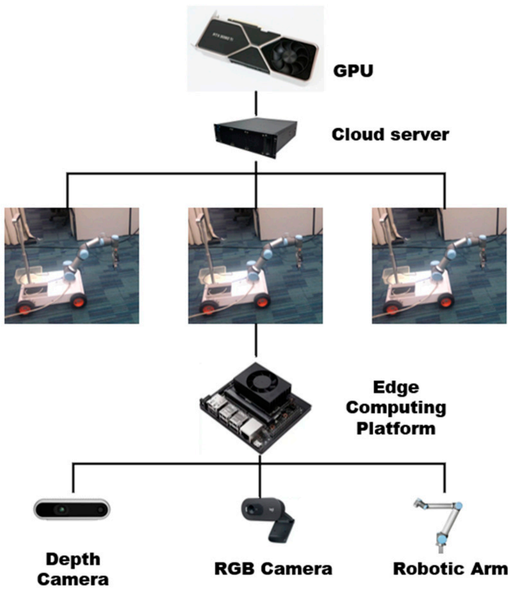


Figure 1. System architecture of construction waste collection platform.

On the robot, we use wired connections to complete the interaction between systems, which is low-cost and reliable. The interaction between the edge platform and the cloud computing platform usually uses the network to connect, and the previous construction waste pickup robot uses Wi-Fi for interaction. However, ensuring comprehensive Wi-Fi coverage across the entire construction site is impractical. The development of 5G technology provides a better choice for data interaction. Fifth-generation technology has the advantages of low latency and high speed [41]. Therefore, the construction waste pickup platform uses 5G to transmit data with the cloud computing platform.

3.2. Scheduling of Edge Computing and Cloud Computing

Since different algorithms require different computing resources, the ability to assemble different algorithms into a suitable system is the advantage of the construction waste collection platform that combines cloud computing and edge computing technology. Previous studies have found that the complete use of remote cloud computing systems to run computer vision algorithms is heavily dependent on the fluency of network communication. When the network is not smooth, the construction waste collection robot cannot stop moving and misses the target object in time. Similarly, when the network delay is too high, the first object pickup will fail due to the error between the RGB image used for recognition and the current position of the robot. Although the error can be successfully made up during the second pickup, it is ultimately time-inefficient. Therefore, applying the target recognition algorithm to the car can greatly reduce the occurrence of such errors. Due to the limited computing resources that Jetson NX can provide, the construction waste collection platform needs to use a target recognition algorithm that requires fewer computing resources and is sufficiently accurate. Unlike edge computing systems, cloud computing platforms have sufficient computing resources to run instance segmentation algorithms at a faster speed. The use of cloud computing platforms at an appropriate time can reduce the construction waste collection platform's network requirements, and can also ensure the accuracy of target object pickup.

The computer vision platform proposed in this study integrates edge computing and cloud computing to optimize the efficiency of construction waste discovery and ensure the accuracy of target pose recognition. The edge computing platform utilizes lightweight and fast computer vision algorithms for real-time target detection to ensure fast processing directly in the field. When a target is recognized, the robot transmits image data to the cloud computing platform. The cloud computing platform then performs instance segmentation algorithms that provide detailed information about the object type, location, and orientation. This collaboration between edge computing and cloud computing ensures that computationally demanding tasks are handled by the cloud, while real-time responsiveness is supported by the edge platform. The workflow of edge computing in collaboration with cloud computing is shown in Figure 2.

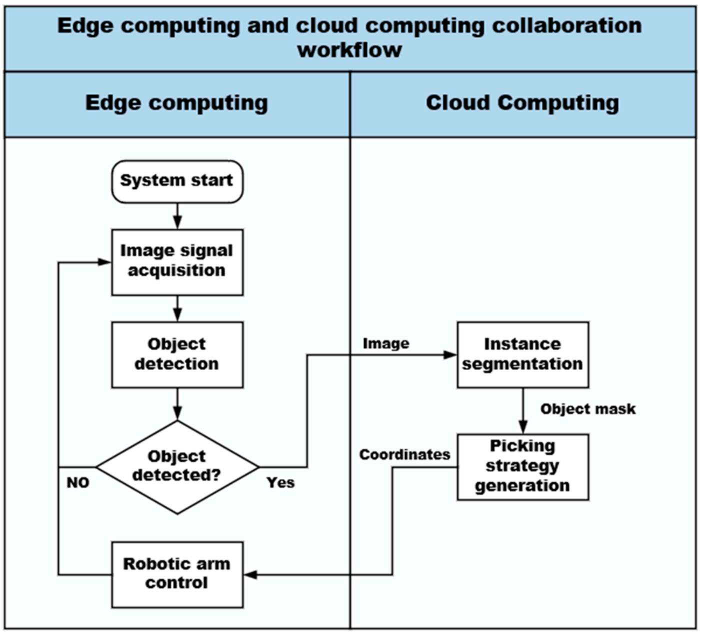


Figure 2. Construction waste collection platform workflow.

3.3. Computer Vision Algorithm

3.3.1. Algorithm Introduction

The classic target detection algorithms include target recognition and instance segmentation. In order to quickly identify target objects during the journey, an efficient target algorithm needs to be first deployed. Classical object recognition algorithms include faster R-CNN, SSD, and YOLO [42–45]. Among them, faster R-CNN is the best in accuracy, and YOLO requires fewer computing resources. In order to meet the needs of real-time recognition, we need an algorithm that not only meets a certain recognition rate but also quickly recognizes objects on the move. Therefore, we chose YOLO as the preliminary object recognition algorithm.

The YOLO algorithm only contains a single CNN model, which means that it is an end-to-end target detection model [43]. In YOLO, the image is first resized to 448 × 448, and then processed by the CNN network to output the result. In the CNN network, the picture is divided into multiple grids according to S × S, and each grid is used as the center point to detect the target and give bounding boxes borders and confidence values. At the same time, each grid also needs to predict the probability that it belongs to a certain category and use this information to generate a class probability map. In this study, a new generation of YOLO algorithm was used, and its structure is shown in Figure 3. CBM (Convolution + Batch Normalization + Mish) is used for feature extraction, CSP (Cross-Stage Partial Network) enhances gradient flow and reduces computation, and CBL (Convolution + Batch Normalization + Leaky ReLU) balances efficiency and non-linearity for detection tasks. By modifying the CNN network, YOLO not only surpassed the faster RCNN in the COCO data set test but also showed great advantages in processing speed. This research also introduces Yolo-tiny for the construction waste collection platform, which greatly accelerates processing speed while ensuring certain accuracy [46].

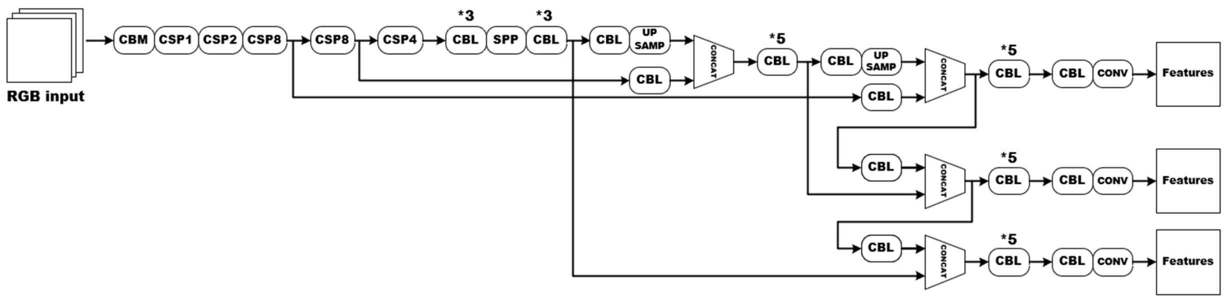


Figure 3. YOLO algorithm.

To speed up the processing speed as much as possible, we applied NVIDIA's TensorRT technology to the target recognition algorithm [47]. Meanwhile, we have also optimized the input image. As we mentioned earlier, the YOLO algorithms will resize the input image, which is 832 × 832 in this case. However, the data collected by the RGB camera are 1280 × 960, which means that the program needs to fill the image with blanks (become 1280 × 1280) before conducting resize processing. Therefore, after we weighed the accuracy and speed, we modified the resize process to output a 640 × 480 image. The results of these optimizations have been verified in experiments.

This platform also includes an instance segmentation algorithm named YOLACT, which can determine the posture of the construction waste in real time [48]. YOLACT abandoned part of the accuracy and used multiple templates to process the entire image. Among them, different templates have different sensitivity to objects. For example, some templates are responsible for detecting the contours of objects, and some are responsible for distinguishing the background. Since the template does not depend on the number of categories, a few templates can predict a large number of objects. After that, YOLACT combines the template mask with the prediction results of the CNN network, then crops and obtains the appropriate results.

3.3.2. Datasets Establishment Strategies

The first step is to collect RGB image data. Since there are no data set for construction waste, we used the data from the previous study on construction waste collection robots [13]. The data set contains a variety of different lighting environments, backgrounds, and types of target objects; the position information of the target object is stored by COCO data set format [49]. A part of the RGB images is shown in Figure 4.

Figure 4. A part of the data set.

In order to train the computer vision model, the data needs to be processed manually. However, the instance segmentation algorithm and the target recognition algorithm require different data formats, which causes the users of the platform to do repeated work. Therefore, we have developed a data conversion program for the platform to read mask information and generate bounding box information automatically, as shown in Figure 5. Thus, the data set established according to the COCO data set format can be implemented in two different algorithms.

```
Program start
Read target classes
For each image:
  For each polygon:
    Read polygon endpoints p[n]
    Read polygon classname A
    Initialise ymin,ymax,xmin,xmax
    from p[0] to p[n]
      ymin = minimum value of p[i].y
      xmin = minimum value of p[i].x
      ymax = maximum value of p[i].y
      xmax = maximum value of p[i].x
    Generate object infomation [A,(xmin,ymin),(xmax,ymax)]
    Store information
```

Figure 5. Pseudocode of data format conversion.

At the same time, to reduce the pressure of data collection and increase the scale of data sets as much as possible, we have integrated a data augmentation algorithm into the construction waste collection platform. After the user enters a small amount of data, the platform can automatically increase the size of the data set by tenfold. Through this process, we can improve the recognition accuracy of computer vision algorithms. The algorithm is developed based on the IMGAUG algorithm, which changes the brightness, contrast, sharpness, and noise of the original image and considers the changes in the image under motion blur, as shown in Figure 6 [50]. At the same time, since the data augmentation does not change the actual position of the object, the platform will automatically generate the position information of the target object. The pseudocode is shown in Figure 7.

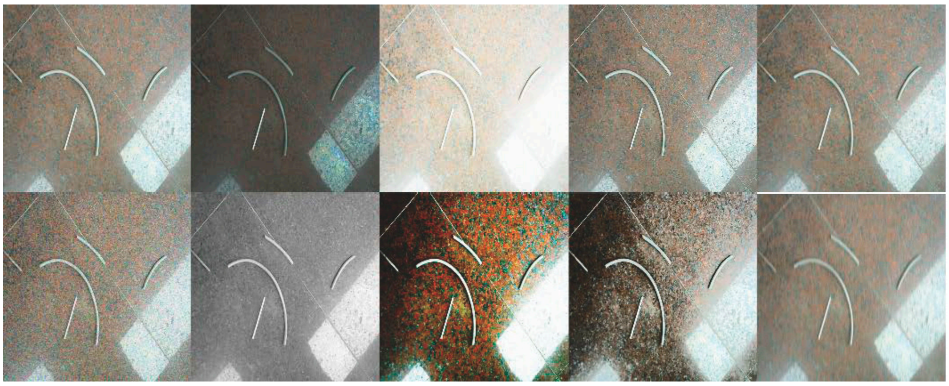


Figure 6. Data augmentation result.

```
Program start
Read target dataset
For each image:
  Processing Brightness reduction
  Processing Brightness increase
  Processing GaussianBlur
  Processing MotionBlur
  Processing HistogramEqualization
  Processing SigmoidContrast
  Processing Grayscale
  Processing AdditiveGaussianNoise
  Processing CoarseDropout
  Processing Sharpen(slightly)
  Processing Sharpen(severely)
  Save new images separately
  Read object infomation
  Modify object information
  Save new object information separately
```

Figure 7. Pseudocode of data augmentation.

The method introduced in this chapter provides a low-cost method for platform users to obtain an image data set that can be used in the construction waste collection robot platform. Through this method, builders can easily create data sets for personalized needs; the workflow is shown in Figure 8.

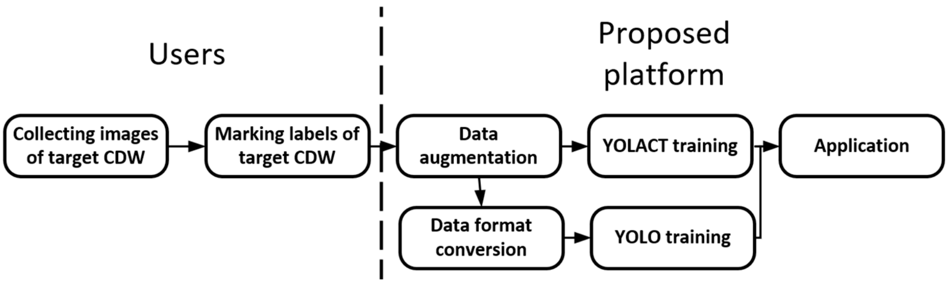


Figure 8. Workflow of computer vision system in construction waste collection platform.

4. Experimental Results and Discussion

To evaluate the computer vision framework proposed in this study, we conducted extensive experiments. These experiments were designed to validate the robustness of edge computing and cloud computing platforms in performing object detection and instance segmentation tasks, which are critical for enabling robotic automation. Specifically, we tested various models, input image resolutions, and hyperparameter configurations to ensure the system's adaptability, and reliability under different conditions.

The proposed computer vision framework was evaluated on an experimental platform comprising an edge computing module, a cloud server equipped with a discrete GPU, and a tracked robot. The structure of the robot is shown in Figure 9. The detailed configuration of these components is described in the System Architecture section.

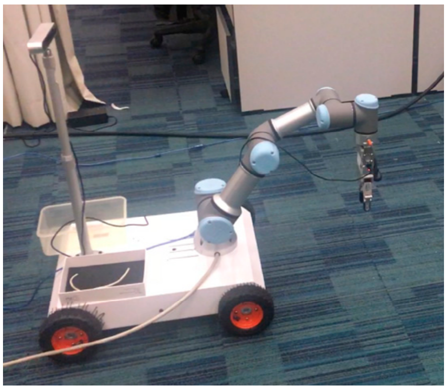


Figure 9. Construction waste collecting robot.

4.1. Edge Computing

In this study, we chose YOLO-Tiny as the target recognition algorithm and deployed it in the edge computing system. Its accuracy needs to be reasonably evaluated. In this section, we compare the results of YOLO-Tiny with YOLO to fully demonstrate the performance of the algorithm in the construction waste collection platform. After training with the same parameters and images, we applied the model to Jetson NX. Figure 10 shows the performance of the two algorithms in the test set, respectively. We found that although the accuracy of YOLO-Tiny has declined, it still maintained a high level. This means that the algorithm had a higher probability of identifying the target object. Although there were deviations in the judgment of the object position, it is enough to determine whether there is a target object.

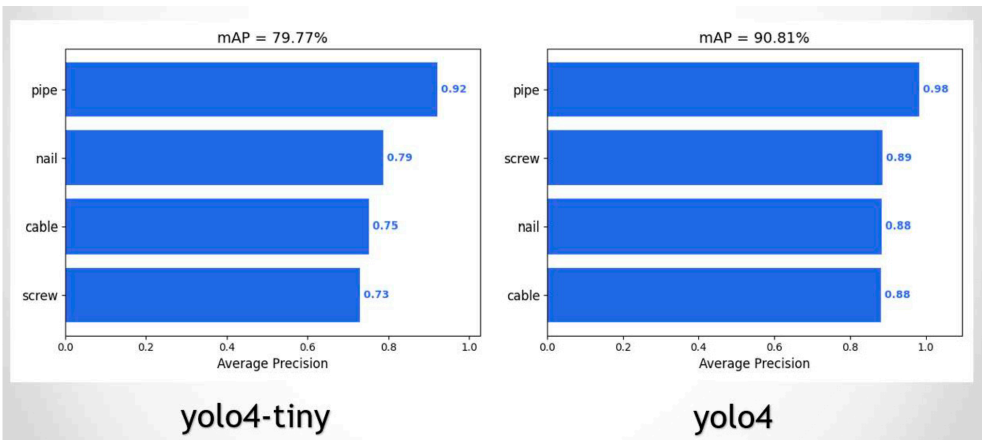
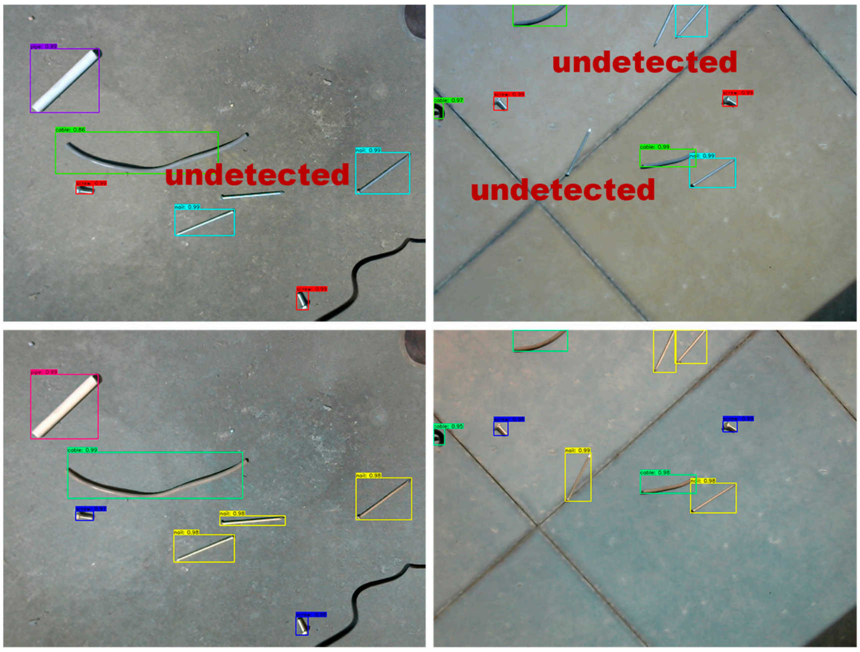


Figure 10. Comparison of accuracy between YOLO-Tiny and YOLO.

A subsequent evaluation found that YOLO-Tiny would have missed detection in scenes with many targets, as shown in Figure 11, and this situation would disappear after some objects were picked up.



YOLO-Tiny

YOLO

Figure 11. Missed detection problem of YOLO-Tiny.

Regarding the most important issue of processing speed, this study separately tested the number of images that can be analyzed per second on the NX platform for the two algorithms, expressed in the form of fps. The results show that YOLO-Tiny has a great advantage in processing speed on the Jetson NX platform. As shown in Table 1, it can reach 13.4 fps after optimization by TensorRT technology. However, this still does not satisfy the needs of construction waste collection robots.

Table 1. Comparison of processing speed (fps).

	YOLO-Tiny	YOLO	Faster R-CNN
No TensorRT	4.8	1.42	1
With TensorRT	13.4	RAM Run out	RAM Run out

Therefore, we optimized the YOLO-Tiny algorithm, and the results show that its processing speed increased by more than 70%, and reached the requirement of real-time target recognition, as shown in Table 2.

Table 2. The processing speed of YOLO-Tiny after improvement (fps).

	YOLO-Tiny-Revised
No TensorRT	5.3
With TensorRT	23.3

4.2. Cloud Computing

In the cloud computing platform, we mainly evaluated the accuracy of recognition and estimated the required data flow. YOLACT's performance is different under different input sizes, thresholds, and models, so we evaluated the performance in a variety of situations, as shown in Table 3. The results show that YOLACT can achieve the highest accuracy of 93.20% with a threshold = 0.5 after 180,000 training iterations in 540 epochs. The instance segmentation and bounding box results are shown in Figure 12.

Table 3. Evaluation result of YOLACT in different situation.

Model	mAP	All	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
Input = 500												
730_130000	box	74.82	94.31	93.64	93.03	91.79	89.11	84.93	78.13	65.89	45.75	11.58
	Mask	49.57	90.28	87.16	81.54	73.36	62.52	47.08	31.52	16.40	5.87	0.01
786_140000	box	75.00	94.37	93.96	92.91	91.43	89.18	85.52	78.58	67.17	45.07	11.77
	Mask	49.40	90.34	87.56	81.34	73.17	61.80	46.29	31.30	16.26	5.96	0.01
842_150000	box	75.03	94.35	93.71	92.83	91.39	88.95	85.36	78.82	67.16	45.16	12.53
	Mask	49.41	90.37	87.55	81.21	73.12	61.71	46.58	31.49	16.48	5.46	0.01
Input = 700												
540_160000	box	74.59	95.18	94.21	93.11	92.18	89.80	85.19	77.16	65.12	43.12	10.81
	Mask	54.86	93.20	91.66	87.48	80.73	71.47	57.14	37.35	19.73	9.66	0.21
574_170000	box	74.64	94.90	94.38	92.83	91.98	89.17	84.91	77.35	67.28	43.92	9.63
	Mask	54.75	93.11	90.62	86.79	81.10	71.11	56.50	37.09	20.56	10.45	0.13
608_180000	box	75.09	94.55	93.78	93.63	91.89	89.66	85.62	77.40	66.73	46.14	11.51
	Mask	55.2	92.81	91.36	87.25	81.03	72.52	58.38	38.82	20.70	8.78	0.34

Figure 12. Instance segmentation results of YOLACT.

In the evaluation, we arranged 20 target objects in an area of about 50 square meters, and the robot took about 4 min to complete patrolling work. In this case, the construction waste recycling robot for nails and screws needed to upload 7200 images at a rate of 30 images per second, while the construction waste collection platform developed by this research only needed to upload 20 images to complete the task, which greatly reduced the burden of cloud servers and networks.

4.3. Recognition Platform

The previous experiments and comprehensive experiments show that the proposed platform can correctly decide whether to use an edge computing platform or to invoke cloud computing resources depending on the actual situation. The edge computing platform can analyze the video data stream captured by the camera in real time and detect the presence of a construction waste target around 0.04 s. After the robot stops moving, the video frames are uploaded to the cloud server, and pixel-accurate coordinates of the target are obtained within 0.5 s (depending on the network latency and whether queuing is required).

4.4. Discussion

The experimental results illustrate the robustness and efficiency of the proposed platform under various conditions. The successful implementation of YOLO-Tiny on the edge computing platform demonstrates its ability to perform real-time target detection at 23.3 fps with minimal computational resources. This finding is particularly significant for construction sites where network connectivity may be inconsistent, highlighting the system's suitability for environments with limited infrastructure.

Moreover, the use of YOLACT on the cloud platform achieves a high instance segmentation accuracy of 93.2%, ensuring precise identification and localization of construction waste. This level of precision is crucial for enabling the robotic arm to perform accurate picking and sorting tasks.

By effectively combining edge and cloud computing, the platform achieves a balance between speed and accuracy, overcoming the limitations of systems that rely exclusively on either approach.

From a practical application perspective, the platform's ability to support multiple robots with a single server significantly reduces costs while maintaining high performance. This cost-effectiveness is a key factor in promoting the adoption of automated construction waste recycling solutions, particularly in large-scale construction projects. Furthermore, the system's modular design and data augmentation capabilities allow for easy customization to adapt to different types of construction waste and site-specific requirements, further enhancing its versatility and scalability.

However, there are still some shortcomings in this study that need to be improved: (1) the types of construction waste included in the image database were not complete enough. In the future, the data set will be further expanded to increase the versatility of the computer vision model; (2) limited by the computing power of the edge platform, the accuracy of the algorithms used on the edge computing platform was not high. In the future, the neural network structure will be further optimized to improve the accuracy of the algorithm.

5. Conclusions

This study presents a novel multi-robot collaborative platform for construction waste recycling, integrating edge and cloud computing technologies. By leveraging edge computing for real-time object detection and cloud computing for high-precision instance segmentation, the proposed system achieves an optimal balance between speed and accuracy, making it highly robust and cost-effective for deployment in complex construction environments. Compared with the traditional approach of equipping each robot with a separate server, this approach not only reduces the equipment acquisition cost but also reduces the waste of network bandwidth and computing resources, thereby significantly reducing the deployment and operation costs of the overall system. This cost-effective solution provides a practical technical foundation for the large-scale promotion and application of automated construction waste recycling robots, especially in scenarios with limited resources but high task requirements, such as large construction sites.

Edge computing reduces latency and bandwidth usage but has limited computational power, while cloud computing offers scalability but depends on stable networks and incurs high costs. This study combines both paradigms, assigning real-time detection to edge computing and high-accuracy tasks like instance segmentation to cloud computing, achieving efficiency, cost-effectiveness, and robustness in complex environments. On the edge platform, the optimized YOLO-Tiny algorithm with TensorRT achieves 23.3 fps, 23 times faster than Faster R-CNN, without significant accuracy loss. On the cloud platform, YOLACT processes images with a maximum accuracy of 93.20%, validated through extensive testing and evaluation.

The platform developed in this research was also designed with automated data augmentation and conversion algorithms. Users only needed to process less image data to use this platform. These algorithms reduce the longest time-consuming work process of the Computer Vision Technology Center. In practical applications, it can greatly increase builders' willingness of use, increase the number of construction waste recycling, and reduce environmental pollution.

In future work, the functions of the construction waste recognition platform, especially the recognition accuracy under different lighting conditions, weather, and construction environments, will be more fully evaluated. At the same time, we will focus on improving the small-sample target recognition algorithm, which will reduce the difficulty of image data collection and processing for a large variety of construction waste. In addition, the structure of the neural network algorithm will be further studied in order to improve accuracy and reduce computational complexity.

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