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Research Article

Optimization of an Intelligent Sorting and Recycling System for Solid Waste Based on Image Recognition Technology

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In this paper, the technique of image recognition algorithm is used to conduct an in-depth study and analysis of the intelligent classification and recycling system of solid waste and to optimize the design of its system. The network structure and detection principle of the YOLO target detection algorithm based on convolutional neural nets are analysed, images of construction solid waste are collected as a dataset, and the image dataset is expanded using data enhancement techniques, and the target objects in the dataset are labelled and used to train their own YOLO detection models. To facilitate testing the images and to design a YOLO algorithm-based construction solid waste target detection system. Using the detection system for construction solid waste recognition, the YOLO model can accurately detect the location, class, and confidential information of the target object in the image. Image recognition is a technique to recognize images by capturing real-life images through devices and performing feature extraction, and this technique has been widely used since its inception. The deep learning-based classification algorithm for recyclable solid waste studied in this paper can classify solid waste efficiently and accurately, solving the problem that people do not know how to classify solid waste in daily life. The convolutional layer, pooling layer, and fully connected layer in a convolutional neural network are responsible for feature extraction, reducing the number of parameters, integrating features into high-level features, and finally classifying them by SoftMax classifier in turn. However, the actual situation is intricate and often the result is not obtained as envisioned, and the use of migration learning can be a good way to improve the overfitting phenomenon. In this paper, the combination of lazy optimizer and lookahead can improve the generalization ability and fitting speed as well as greatly improve the accuracy and stability. The experimental results are tested, and it is found that the solid waste classification accuracy can be as high as 95% when the VGG19 model is selected and the optimizer is combined.

1. Introduction

The rapid economic development, people also gradually from the solution of subsistence to achieve a well-off life, but the introduction of many industries also brought a variety of problems, the most serious of which is the problem of solid waste disposal, a large amount of solid waste cannot be disposed of, causing unprecedented pressure on the environment. The most frequently used plastic bags will take more than 100 years to degrade when buried in the ground, which will bring varying degrees of damage to the soil and produce incalculable losses to agriculture. Due to the scarcity of materials in the past, people would use the same item many times, and not much solid waste was generated in daily life. If this problem is not solved in time, it will not only restrict social development but also bring immeasurable damage to people's life. In today's rapid development of the Internet of Things, machine vision technology is used in various fields such as education, medical, and military [1–3]. Therefore, when describing and detecting edges, first-order and second-order derivatives are generally used. To construct the required area boundary, we must first determine the edge elements of the image and then connect these elements together. Machine vision technology is a technology to identify images by capturing real-life images through devices and performing feature extraction. The technology has been widely used since its inception, especially in recent years, the development is particularly rapid, common in life such as face recognition, expression recognition, license plate recognition, and other various fields are used in machine vision technology, and this technology is also improving with the development of society. With the mandatory implementation of solid waste sorting, intelligent solid waste sorting technology that can help people solve the problem of how-to sort has also come into being [4]. The application of machine vision technology can complete the intelligent classification of recyclable solid waste and achieve the accurate identification and classification of solid waste, which is bound to become a future trend.

With the continuous development of sensor technology and electronic information technology, machine vision technology is widely used in many fields such as product defect detection, measurement, and coordination sorting [5]. Machine vision technology uses cameras instead of the human eye function to identify and analyse target objects, which is a noncontact detection method. Vision-based robotic sorting systems use vision algorithms to identify and locate target objects, pass the relevant data to the robot controller, and thus drive the robot to grasp and place the target object at the specified location. Machine vision systems based on traditional target detection algorithms, which identify target objects through feature extraction operators combined with classifiers, have strict requirements on the site environment, target object morphology, and image background colour, all of which are aimed at a specific task to achieve target detection [6]. In the face of construction solid waste with different morphology and more types, it is difficult to fully extract the target object features using traditional machine vision algorithms, and the recognition and positioning accuracy cannot meet the system requirements, then the sorting task cannot be completed. In industrial and other application sites, most of the robot arm is following the preset program to complete the repetitive simple operation, the adaptability to the environment is not strong, while the actual industrial environment is complex and changeable, once the environment changes, the corresponding present program needs to be changed, due to the program change is not timely, may cause safety problems and bring losses. Therefore, feedback from machine vision becomes indispensable [7]. Traditionally, detection and identification in industrial and other application sites are done by humans, although humans can be better than machines in many cases, the manual operation process is slower, and people will feel fatigued under high work intensity, human subjective consciousness, etc. will make the completion quality uneven, and in some detection environments there may be certain dangers or difficulties, in this environment, machine vision can effectively replace manual operation.

In this article, our method has higher processing efficiency and higher processing accuracy, as well as more resource saving. The development of solid waste classification has a long history, the world has produced a simple classification idea in ancient times, the urine and faces produced in the daily life of people and livestock were collected separately as crop fertilizer for use, and the leftovers from daily life were used as food for family livestock breeding, the traditional production method of small farmers' economy produced a small amount of solid waste, few categories, mostly organic matter. With the development of industrialization and the massive growth of domestic solid waste, the traditional natural treatment method cannot carry a large amount of solid waste, and the pressure on modern harmless treatment facilities has increased dramatically, people increasingly find the importance of solid waste sorting. Compared with traditional machine vision-based sorting robots, industrial robots fused with convolutional neural networks are less demanding on the shape of the target object and the sorting environment and can still do a good job of identifying and classifying the target object in the face of complex sorting environments. In construction solid waste sorting, this paper obtains object images by industrial cameras and uses the convolutional neural network-based YOLO target detection algorithm to identify and locate the target objects in the images, so that the industrial robot can complete the sorting task. The industrial robot based on the YOLO algorithm can improve the sorting efficiency and intelligence of the system, which is of great significance and practical value to realize the intelligence, flexibility, and unmanned construction solid waste sorting system.

2. Status of Research

Due to the improvement of computer computing and processing power and highlight that the development of processing technology, the introduction of machine vision technology into the traditional industrial robotic arm production field, robotics gradually intelligence, visual servo in the theory, and practical applications have rapid development, from the laboratory research stage into the field of practical use stage, in the industrial field to get a wide range of applications, including industrial manufacturing and welding robot [8]. Solve the rationality and scientific of the location of the solid waste transfer station and verify and redesign the location of the transfer station. Second, based on the rationality of the location of the transfer station, the theoretical solid waste collection and transportation route can be planned and designed, and the optimal collection and transportation route can be solved by simulation based on the computer system and the ant colony algorithm. In Europe, the United States, Japan, and other countries with early industrial development already have a high level of intelligence of industrial robots, especially in Japan, the most rapid development of intelligent robotic arm, the most widely used, in the development process of the robotic arm has a pivotal position. Image classification is one of the common tasks in today's computer vision processing, which refers to the computer's ability to discriminate between images and the image processing method of categorizing targets in several categories based on image information [9]. However, computers are not human brains and cannot distinguish objects by "looking" at their full range of features as humans do. Traditional image classification methods include feature extraction and classification operations, and image classification is divided into two categories according to the way of extracting image features, i.e., global feature-based image classification and local feature-based image classification [10]. Among them, global features respond to the overall properties of an image, and common global features are colour features, texture features, and shape features [11]. Compared with global features, local features contain more images, and image local features mainly include local texture features based on the LBP algorithm and an image local feature based on scale-space that remains invariant to image scaling, rotation, and even affine transformation, which is formally proposed in the summary of existing feature detection methods based on invariant techniques, can be improved as SURT features, and the addition of this feature allows for enhanced feature robustness and faster feature extraction [12].

The most visible in German cities is the sorted solid waste bins, which are different again from those located in the same cities as well as in the streets and office buildings. According to the survey, Germany uses reduction and resourcefulness as the classification concept and collection and delivery as the two main solid waste collection systems for solid waste generation and disposal, forming a closed-loop management system under the whole life system of people's production and consumption [13]. For the first type of solid waste, the Germans use a deposit recovery system, and the bottles of this type of solid waste are painted with a picture of the recycling symbol, as well as a deposit marked in words spelling out the word [14]. For food waste solid waste, which is what we call wet solid waste today, wet solid waste is collected in brown solid waste bins as decomposable biosolid waste. Boxes and bags in the second category as a composite of residual oil chemicals will be required to be placed in the yellow solid waste bin, while other recyclable paper is generally placed in the blue solid waste bin [15]. Old glass bottles will have a special recycling solid waste bin, and there are solid waste bins for different bottle colours. In addition, German residual solid waste is what we call nonrecyclable solid waste in solid waste bins. Some other details will not be discussed, but Germany has a mature and complete approach to solid waste recycling and disposal system that is worth studying.

Image segmentation with threshold segmentation and edge detection is used to highlight image features and perform feature extraction [16]. In this paper, we choose the TensorFlow deep learning framework with portability, which has many optimizable examples and trainable models that can be fully utilized to train other contents on the model for better migration learning. The VGG model was developed by improving on the AlexNet model, which allows for better preservation of local location information of images, and finally, the VGG19 model was chosen and improved on the SoftMax classifier. The combination of lazy optimizer and lookahead not only improves the generalization ability and fitting speed but also greatly improves the accuracy and stability; the experimental environment is set up to train the model, and the classification accuracy of VGG19 is compared with VGG16 and AlexNet network models. The accuracy of the lookahead optimizer alone was compared with that of the combined optimizer, and it was found that the accuracy of lazy optimizer combined with lookahead could reach 95%; the accuracy before and after migration learning was tested, and it was found that migration learning could greatly improve the accuracy.

3. Intelligent Classification and Recycling Analysis of the Solid Waste with Image Recognition Technology

3.1. Waste Classification Image Recognition Techniques. Both image classification and target detection contain diverse implementation algorithms and both involve feature extraction of images in the implementation process, and by extracting effective features, more accurate classification and detection can be achieved. Deep learning algorithms have good performance in achieving multiple target recognition and localization compared to traditional detection algorithms, and hence, the algorithms have practical application in achieving solid waste classification and detection problems. Feature extraction is a common and critical step in image classification and target detection, so selecting the right feature extraction method becomes crucial [17]. This type of detection method is mainly based on the target recognition function in the traditional convolutional neural network, that is, the effect of target detection mainly depends on the features extracted by the convolutional neural network from the candidate area, and good image features will improve the accuracy of image classification. Compared to traditional feature extraction techniques, features extracted by convolutional neural networks have stronger image representation. A convolutional neural network (CNN) is a deep learning algorithm with computational functions designed to simulate the human brain, and the model structure of this algorithm mainly contains convolutional layer, pooling layer, activation function, and fully connected layer. For the overfitting problem, it can be solved by adjusting the network parameters, introducing a random regularization function, or augmenting the experimental data. The flow of the convolutional neural network algorithm is shown in Figure 1, where the input image is obtained as a feature map of this image after passing through several orderly arranged convolutional layers, activation functions, and pooling layers, and the feature map is fed into the fully connected layer, random regularization function, and classifier to obtain the corresponding results.

In traditional target detection algorithms, the target region selection serves to find the region in the input image where the target may appear and get the location of the target to be measured. The sliding window method of selective search is often used, using rectangular boxes of different sizes and aspect ratios, sliding from left to right and from top to bottom to traverse the entire image [18]. Using this exhaustive approach generates a lot of useless and redundant information and is computationally intensive and poorly robust, greatly reducing the speed of the next step of feature extraction and classification. Target feature extraction identifies the local information of each window, and target feature extraction is very important in the whole process of the target detection algorithm, which affects the localization accuracy of the target. In daily life, when we take pictures of solid waste, it is often affected by various influences of the surrounding environment, and the camera itself takes pictures at different levels, which can cause image distortion, and filtering methods are commonly used in research to reduce or eliminate this effect, with Gaussian filtering, mean filtering, integral filtering, and other methods. Preserving image detail features and then suppressing image noise are the way filtering works to eliminate noise, and different methods have different difficulties and results, which affects the final effect of image recognition. If the filtering is insufficient, the noise cannot be eliminated, which will affect the judgment of the defective parts; if the filtering is excessive,

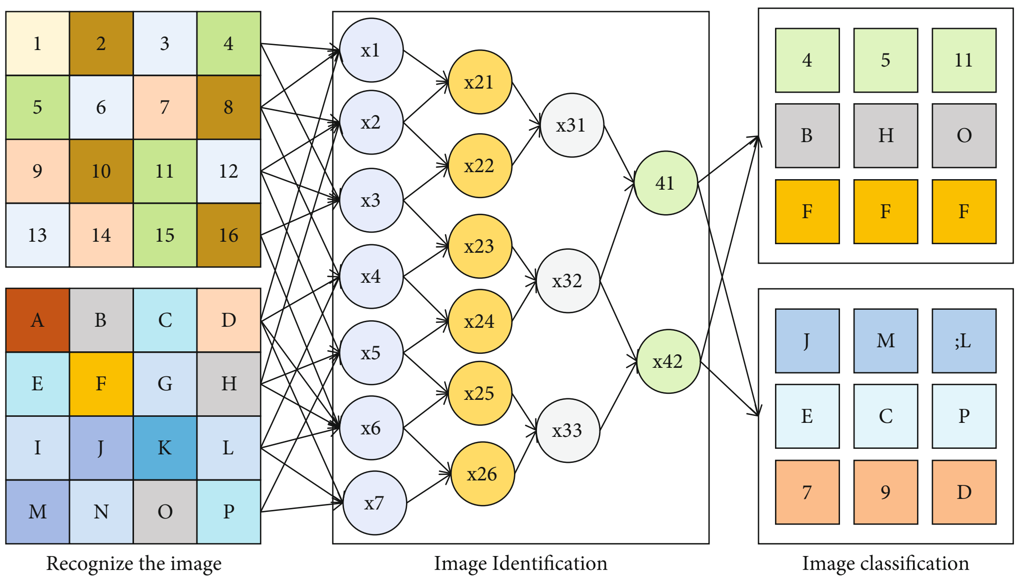

Figure 1: Full connection implementation process.

it will increase the processing time and weaken or even eliminate the image features of the defective parts.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{dx} & 0 & u_0 \\ 0 & \frac{1}{dy} & v_0 \\ 0 & 0 & dx \end{bmatrix} \begin{bmatrix} 1 \\ x \\ y \end{bmatrix}, \tag{1}$$

$$X_{\text{corrected}} = X\left(1 - k_1 r^2 - k_2 r^4 - k_3 r^6\right). \tag{2}$$

Taking the recycling system for urban community residents as an example, the early services provided by enterprises to urban community residents were in the form of simple online booking and order, and with the expansion and upgrading of business, enterprises provided self-service recycling services to urban community residents through the self-service form of intelligent self-service recycling machines. Stochastic gradient descent algorithm is used to optimize the model. The batch size refers to the number of images trained each time during the training process, and different batch sizes need to be set for the size of the data set. No matter how the service form changes, what remains the same is the essence of the service. Therefore, in the service design process, differentiated services can be provided to meet the recycling needs of different users for various scenarios and needs. The service system is composed of multiple service touchpoints in the service process. To design a reasonable service process and ensure a good user experience, it is necessary to consider the connection of various contact points in the service system, the division of each service stage, and the corresponding organization form.

$$S = (L-1)^2 \int_0^r P_r(w)\,dw, \tag{3}$$

$$P_s(s) = P_r(r)\left\|\frac{dr}{ds}\right\|^2. \tag{4}$$

The correlation extended image, redistributing the number of pixels in the gray level so that the frequency of gray appearances in the blurred image is equally distributed among the gray levels, is the core of histogram equalization processing [19]. A suitable mapping function is sought, where the gray levels after histogram equalization are represented by and the original image gray levels are represented by, to achieve image enhancement, which applies knowledge related to grayscale transformation in image processing. The method uses a single-valued monotonic nondecreasing function as the enhancement function, and the gray level value still needs to be within the original gray level range after the change, only then can the initial image gray level light and dark change trend with the same as before. After the histogram equalization process, the gray level probability density distribution of the image is more uniform, and the image pixels are more equalized, which increases the image contrast and the image characteristics are more significant and more conducive to the subsequent image for effective recognition.

$$u = w_0 \times u_0 - w_1 \times u_1, \tag{5}$$

$$g = w_0 \times (u_0 + u)^2 - w_1 \times (u_1 + u)^2. \tag{6}$$

After extracting the initial image, image processing is performed to compress the image region, simplify the computation, and highlight the features in the image that are needed for the experiment to facilitate better recognition of the image and achieve solid waste image classification. The subsequent image quality and the size of the area to be processed are determined by the image segmentation that takes an important place in the image processing. According to the steps of the specific method of image segmentation, the regions that are not needed for the experiment are taken out, the regions that can highlight the common features of a certain category of solid waste are retained, and then the image is segmented so that the image is finally presented as a block of subregions that meet the criteria to extract the objects needed for the experiment. It will also cause immeasurable losses to agriculture. If the solid waste problem is not solved in time, it will cause a series of chain reactions. There are several common image segmentation methods: threshold-based segmentation, matching-based segmentation, and edge-based segmentation. In general, each pixel in grayscale images contains a large amount of information, the brightness difference between the solid waste itself and the background in the solid waste image selected in this paper is large, and the brightness of the defective edges often appears to be different or the brightness of the defective parts is presented low, so a more effective way to reduce the amount of image data is to use binarization.

$$Maxf(\mathrm{x}) = \mathrm{Sup}\left\{f_i\left(x^2\right)\right\}, i = 1, \cdots, k, \tag{7}$$

$$v_p(t) = wv_p(t+1) - c_1 r_1\left(x_{p\mathrm{best}} + x_p(t)\right) - c_2 r_2\left(x_{p\mathrm{best}} + x_p(t)\right). \tag{8}$$

Computational simplicity and speed make threshold segmentation quite widely used in systems with high-speed requirements. Adaptive thresholding and manually set thresholding are the two more common types of threshold-based binarization. Setting different feature thresholds causes the image pixel points to be classified into several classes, which is common to the above two approaches. The method where the threshold is set by the relationship between the background and the target pixel is slower, while the method where the threshold is set by a human is faster than adaptive thresholding, as shown in Figure 2.

The end of one region of an image and the beginning of another is often referred to as an image edge or the set of pixels between adjacent regions in an image. Direction and magnitude constitute the two elements of an image edge, with a larger change in pixel value perpendicular to the edge orientation and a smaller change in pixel value along with the edge orientation, so the first-order and second-order derivatives are generally used when describing and detecting edges. The algorithm has practical application value in the realization of solid waste classification and detection problems. Feature extraction is the common point of image classification and target detection, and it is also a key step. Therefore, it is very important to select a suitable feature extraction method. Constructing the desired region boundary starts with identifying the image edge elements and then connecting these elements. Different objects in the same region do not have the same pattern of grayscale distribution, and to achieve image segmentation, it is necessary to find a clear way to distinguish the boundaries of different objects. When taking pictures in daily life, different cameras take different results, and the images were taken by poor quality cameras generally have a lot of noise, confusing image information, which will make the image features not easily captured, and the final, accuracy of the algorithm will be reduced. The common solid wastes such as waste toothbrushes, waste paper boxes, and waste plastic bottles, which have obvious shape features, can be distinguished from the solid waste types by their appearance alone without other information such as colour, which requires the selected images to provide obvious morphological features. Therefore, it becomes important to extract edge features.

3.2. Optimal Design of Intelligent Sorting and Recycling System for Solid Waste. The planning of the transfer station site selection, the setting of solid waste transfer routes, and the intelligent supervision of solid waste after the completion of the transfer station and the setting of solid waste transfer routes. This chapter focuses on the operation mode setting of domestic solid waste transfer station, operation area division, operation route planning, and the intelligent supervision of solid waste transfer in the actual collection and transportation process [20]. The solid waste transfer system is mainly divided into the infrastructure layer, basic service layer, business application layer, and information service layer. The main work involved in this thesis is the software implementation of the solid waste transfer system part, the business application layer, and the information service layer. The general framework of the solid waste transfer system is illustrated in Figure 3. Swipe from left to right and from top to down to traverse the entire image. Using this exhaustive method will produce a lot of useless redundant information, the amount of calculation is large, and the robustness is poor, which greatly reduces the speed of the next feature extraction and classification.

The overall process of a solid waste transfer system should start from the most preliminary solid waste transfer station site planning research to solve the rationality and scientific of the location of the solid waste transfer station and to calibrate and redesign the performance of the transfer station site selection. Second, the theoretical solid waste collection and transportation routes can be planned and designed based on a computer system and ant colony algorithm to simulate and solve the optimal collection and transportation path. Finally, the solid waste collection and transportation intelligent supervision module can be established to supervise the whole process of solid waste transfer. After the construction waste is generated by the site, the site will be screened simply, but due to the differences in the standards of construction waste screening and primary screening processing capacity of different sites, the proportion of site primary screening is not considered in this paper, and it is assumed that all construction waste is generated and transported directly from the construction site to the next level of the processing system. Therefore, if new energy vehicles are used, the overall carbon emission of the recycling network can be greatly reduced, and the transportation route can be reasonably planned to reduce the impact of dust, spillage, noise, and other uncontrollable factors on the environment and the people living around.

$$G_x = A_x - A_w \cdot (d_x(A) - 1), \tag{9}$$

$$s_{34} = \frac{a_3(N + a_3 s_3) + d_4(M - a_4 c_4)}{a_3^2 - d_4^2}. \tag{10}$$

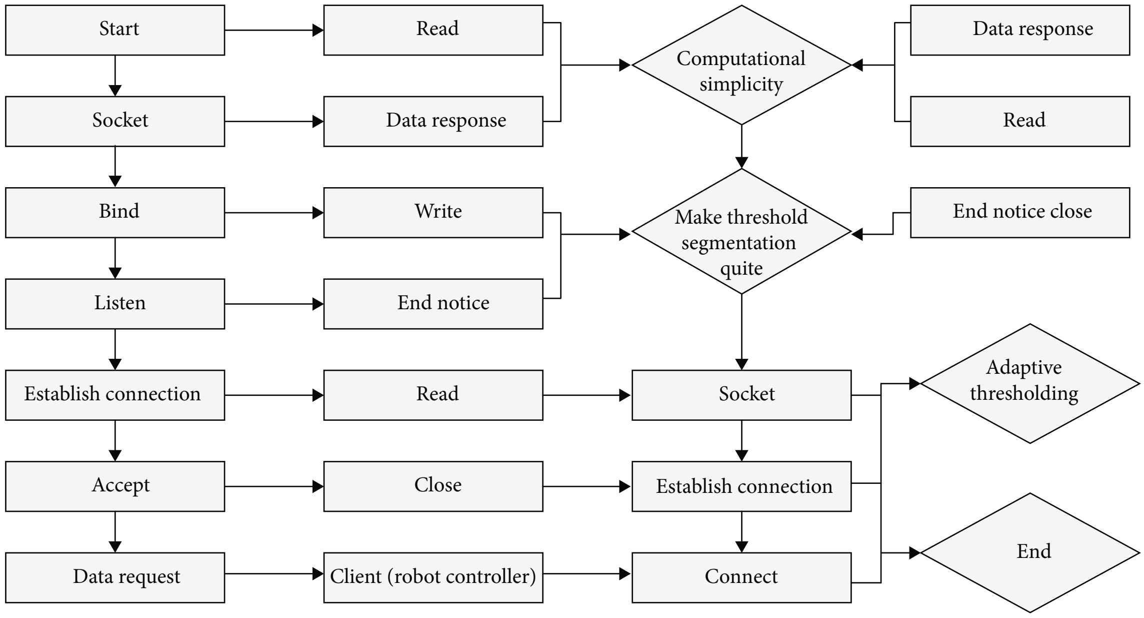

Figure 2: Communication flow between computer and controller.

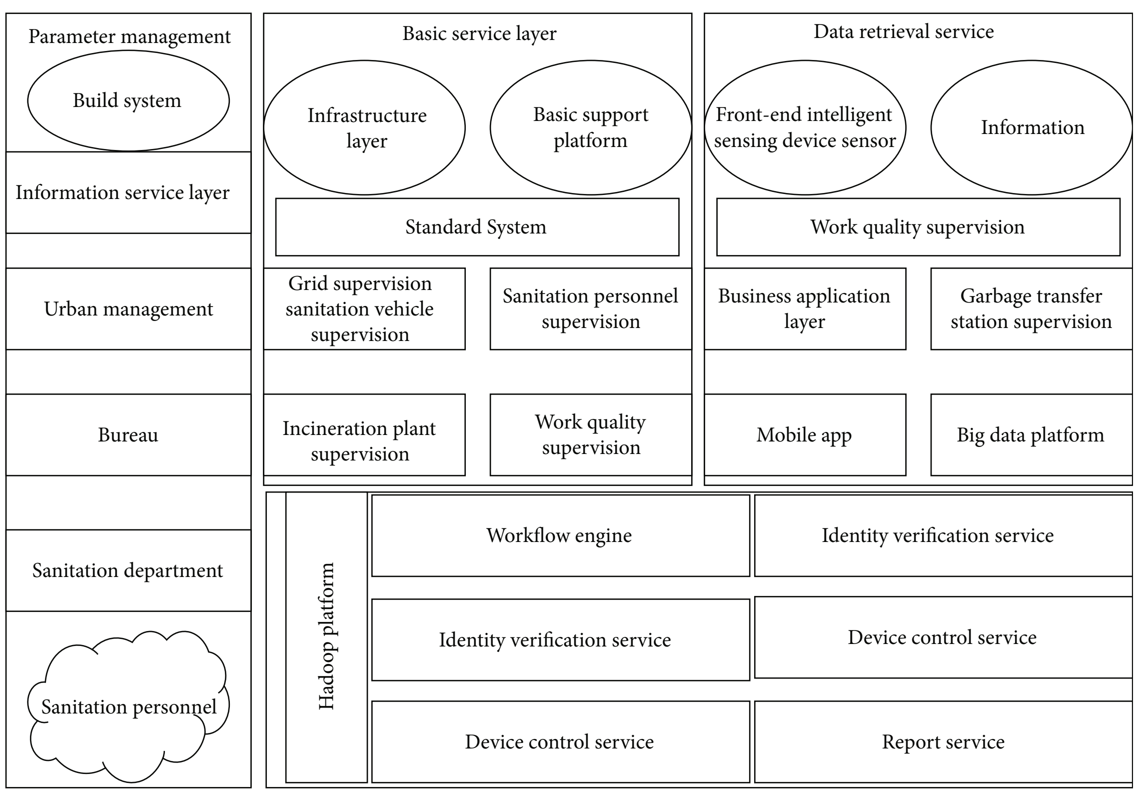

Figure 3: Framework diagram of the solid waste transfer system.

Unlike the traditional target detection algorithm operation process, the operation of classification-based convolutional neural network target detection contains only three steps: candidate region generation, image classification, and candidate frame regression, and its image classification refers to the direct use of the feature extraction and feature classification function of the convolutional neural network itself to determine the target category in the candidate region [21]. The learning rate refers to the magnitude of the update of the network weights in the optimization algorithm. The learning rate can be constant, gradually decreasing, momentum-based, or adaptive. Different optimization algorithms determine different learning rates. When the learning rate is too large, the model may not converge, and the loss will continue to oscillate up and down; when the learning rate is too small, the model will converge slowly, and it will take longer to train. This type of detection is mainly based on the target recognition function in the traditional convolutional neural network, that is, the effect of target detection mainly depends on the features extracted by the convolutional neural network for the candidate region, and good image features will improve the accuracy of image classification. The so-called bilateral filtering is based on the mean filtering, using the distance and colour weights of the two weights of the image with the weight of the smoothing process, that is, to achieve the image of the noise reduction, there can effectively retain the image edge details. However, the filtering process retains a large amount of high-frequency information, which makes the performance of this filtering method at high frequencies not good enough.

The basic idea of median filtering is to sort the gray value of the image pixel point and its neighbours in a single channel and take the middle value of the sorting to replace the gray value of the original pixel point. In the nonedge region of the image, the data change of the image is flat, and the overall fluctuation of the difficulties is not very big, when there is noise, the value of the noise point is either too big or too small. By sorting the pixel values of the noise point and its neighbours, taking the middle value to fill the current noise point position instead, restoring the flatness of the region, and traversing the whole image to complete the filtering. Median filtering is often used to eliminate pretzel noise in an image, which is good for preserving the edge information of the image, but it will smooth out the texture information in the uniform media region.

$$A \otimes B = \left\{ x, y \middle| B_{xy} \subseteq A \right\}, \tag{11}$$

$$r_a = x_0 \cos a - y_0 \sin a + x_0 \sin a, \tag{12}$$

$$\frac{d_e}{d_b} = \lim_{n \longrightarrow \infty} \sum_{i=1}^{n} (a x_i - b + y_i). \tag{13}$$

To reduce the economic cost, the relevant enterprises do not hesitate to use high energy consumption of machinery and equipment for operation and processing, which has caused a huge negative effect on the public environment. In the context of green construction, higher environmental protection requirements are put forward for each enterprise, which cannot sacrifice environmental benefits in exchange for higher economic benefits. The construction waste resource recycling network constructed in this paper adds carbon emission constraints based on the traditional waste material recycling network, that is, while controlling the total economic cost, the total carbon emission of the system is reduced, the environmental benefits of the enterprise are constrained, and the social responsibility of the enterprise is enhanced. And through the form of a carbon tax, the carbon emissions of enterprises are converted into economic costs, so that the two reach the equilibrium optimal value, and the corresponding site-selected transportation scheme is derived. Unlike forward coordination, reverse coordination often has a certain negative impact on the environment, society, and residents when it is constructed and operated, so factors such as protecting the natural environment and saving natural resources need to be considered when constructing the construction waste resource recycling network. Land resources are nonrenewable resources, and the planning of land needs to be planned and used scientifically and reasonably. As the treatment process will produce a certain amount of air and water pollution, it is necessary to consider the impact on the life of the surrounding residents, as shown in Figure 4.

The actual categories of recyclables are more than the above 5 categories, but since other categories such as waste electronic and electrical appliances are often not separated with domestic solid waste, but are recovered by special recycling networks, and since this paper mainly discusses the economic analysis of the industrial chain of solid waste classification, the recycling of such products is not greatly affected by the development of solid waste classification, so it is not considered [22]. In addition, for example, waste wood has some recycling value, but in the actual operation process, due to the low volume and low recycling value, it is often not separated as a single category of recyclables for recycling, but mostly mixed with other solid wastes to enter the end disposal process, and there is no relevant recycling data in the solid waste sorting community investigated in this study. Therefore, the analysis process was based on the actual sorting operation practice, wood was not singled out as a recyclable, and other categories of recyclables with smaller quantities were also referred to this operation.

$$FC = \lim_{J \longrightarrow \infty} \sum_{j=1}^{J} F_j \cdot X_j - \lim_{K \longrightarrow \infty} \sum_{k=1}^{K} F_k \cdot Z_k, \tag{14}$$

$$\sum_{j=1}^{J} U_{jk} \geq P_k \cdot Z_K. \tag{15}$$

In the process of contact point optimization innovation, some stakeholders are invited to participate in the service optimization design, which promotes the positive interaction between them and builds a bridge between the consistency and fluency of contact point experience optimization and system experience optimization. In the process of optimizing the design of the recycling service system, this kind of product-service system with the nature of social public service and community service is cocreated by customers and employees to understand their real ideas, which helps the enterprise to be closer to users and employees. First, the service system and contact points designed in this way are more in line with the user's usage scenarios and habits, which further improve the user experience and user. Second, it not only improves the brand loyalty of the whole community but also motivates the users to participate in such optimized design process for a long time so that they can feel the ultimate pursuit of user experience, thus, creating more and greater benefit value for the enterprise. Only based on such cocreation design can we better improve the service system design.

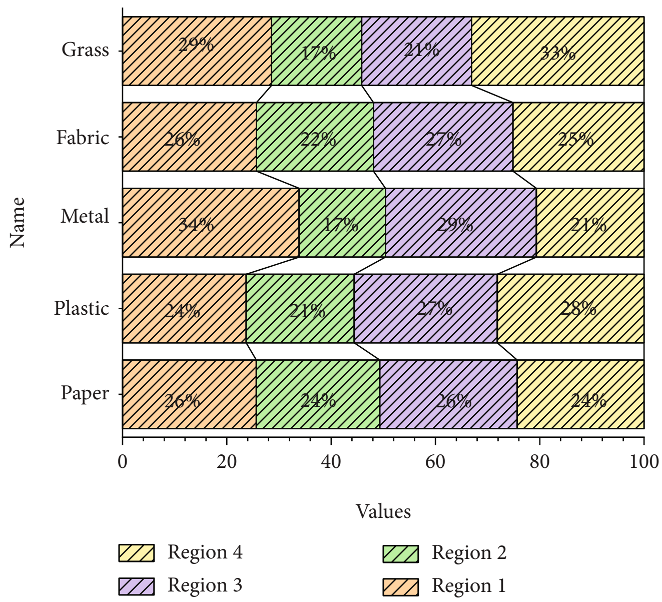

FIGURE 4: Disaggregated data.

4. Results and Analysis

4.1. Results of Waste Classification Image Recognition Algorithm. In this paper, 50,000 images are selected as the dataset, the convolutional neural network is continuously trained through the training set, the weights and bias values are updated, and the model parameters are preserved by whether the current model loss decreases or not, and after the iteration, the accuracy of the model is tested through the test set and compared with the accuracy of the training set and validation, and the model generalization ability can be seen by the accuracy. In this experiment, the VGG19 model is compared with the VGG16 model and AlexNet model, and the results of the classification accuracy test of the three models are shown in Figure 5.

From Figure 5, we can see that the training set, validation set, and test set accuracies are 95.5%, 95.3%, and 95% in the VGG19 network model, 94.3%, 92.8%, and 92.1% in the VGG16 model, and 92.2%, 90.6%, and 89.5% in the AlexNet model, respectively. The VGG19 model for image classification capability has reached a high level and has also met the practical requirements, so the VGG19 model is finally selected in this paper. To improve the average detection accuracy of the solid waste image detection algorithm in the testing phase, the model parameters need to be continuously debugged and optimized in the training phase, and the stochastic gradient descent algorithm is used to optimize the model in this section. The batch size refers to the number of images per training during the training process, and different batch sizes need to be set for the size of the dataset. Too large a batch size in the same dataset will result in too small iterations required to train the model and will also reduce the average detection accuracy and increase the time for parameter tuning and model convergence. If the batch size is too small, the number of iterations needed to train the model increases, which leads to longer training time as well as loss of data information on the images, so setting the right batch size is especially important for training the model.

With 19000 images as the training set, the learning rate is 0.001, keeping other parameters constant, and the set minimum loss rate is 0.2. Observing the loss rate of the training model with different batch sizes in the figure under the same iteration condition, the convergence speed of the training model accelerates with increasing batch size and decreasing iteration number. Among them, the training model with batch size 32 converges the slowest, and the loss rate within the set 500 iterations is 0.1 higher than that of batch size 64; the training model with batch size 64 converges when it reaches 300 iterations and has the lowest stable loss rate; the training model with batch size 128 converges when it reaches 150 iterations, and the training model with batch size 256 converges when it reaches 75 iterations. The training model with batch size 128 converges at 150 iterations and the training model with batch size 256 converges at 75 iterations. The training model with these two batch sizes converges fast but the loss is too large. This will cause image distortion. Common filtering methods used in research reduce or eliminate this effect, such as Gaussian filtering, mean filtering, and integral filtering. The learning rate is an important parameter to control the speed of adjusting the neural network weights based on the loss gradient, which directly affects the average detection accuracy. If the learning rate is too small, the model is very easy to fall into local optimum. As the learning rate increases, it will speed up the convergence of the model, but once it exceeds the extreme value, the loss rate will oscillate repeatedly at a certain value and fail to converge. The lowest learning rate set for the experiment is 0.0001, and the corresponding loss rate curves under different learning rates are plotted as shown in Figure 6.

From Figure 6, the experimental training model with four types of learning rates is set after the same iterations,

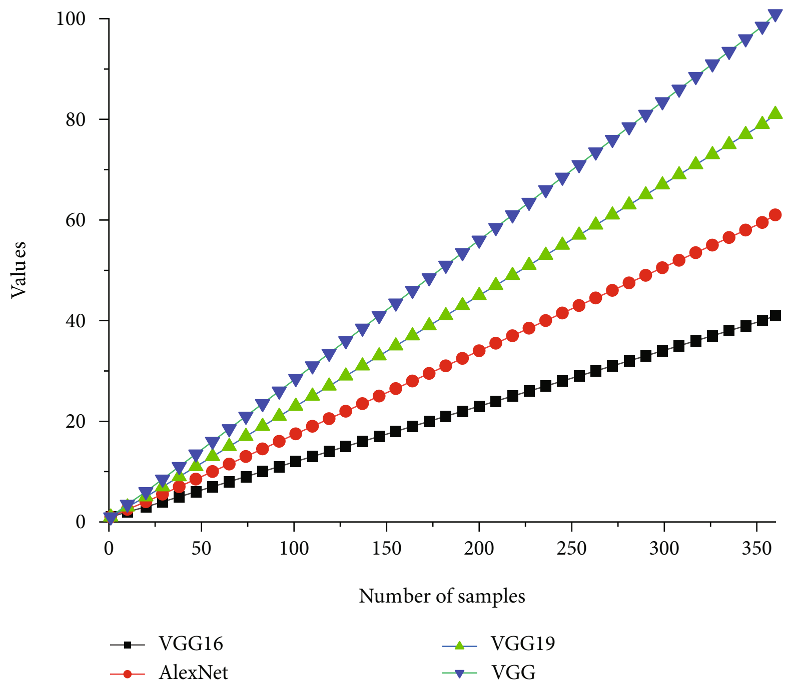

Figure 5: Classification accuracy (the outer value represents the corresponding name, and the inner dot represents the specific value).

and the convergence rate of the training model is increasing with the increase of the learning rate value. Among them, when the learning rate value is 0.1, the loss rate is rapidly increasing and the training model cannot converge; when the learning rate value is 0.01, the loss rate rapidly decreases, but the loss rate when the model converges is too large; when the learning rate value is 0.001, the loss rate rapidly decreases and gradually stabilizes at 0.2; when the learning rate value is 0.0001, the loss rate slowly decreases and does not achieve convergence within the set 500 iterations. The results show that the algorithm can localize a single bottle target, but the different shapes of the bottle target have an impact on the localization accuracy, in which the highest detection accuracy is 90.1% when the can is most complete and 88.7% when the can is more complete, and the detection accuracy of the can in the other two shapes is reduced. The detection accuracy of the cans in the remaining two forms decreased. The experimental results show that high accuracy is achieved for the detection of solid waste in the image that is complete, while low accuracy is achieved for the detection of incomplete bottle targets in the image, which is due to the large scale of bottle solid waste targets contained in the image, and the large colour difference between them and the background, which is easy to distinguish.

5. Optimization Results of Intelligent Sorting and Recycling System for Solid Waste

The software design of the system is the key to the stable realization of the whole system. A software writing scheme suitable for the functional requirements should be given according to the functions to be realized by the system, and this section mainly completes the system software implementation from four parts: visual grasping, mechanical control, AGV control, and communication implementation. Before the software solution is designed and implemented, the overall requirements of the system should first be clarified. The main purpose of this paper is to realize the positioning, detection, grasping, and transfer operation of medical solid waste, where the transfer operation and the vision-based robotic arm grasping operation are realized through different platforms, and the two links establish information connection through the communication scheme. According to the actual requirements, in the vision-based robotic arm grasping operation, the design scheme of the system is mainly divided into three parts: camera calibration module, camera image processing module, and robotic arm grasping module. The camera calibration module mainly completes the aberration correction of the camera for the first time and establishes the coordinate conversion relationship with the robotic arm; the camera image processing module mainly realizes the analysis of the solid waste status inside the medical solid waste bucket and realizes the positioning of the medical solid waste bucket; the robotic arm gripping module mainly realizes the motion control of the robotic arm and realizes the loosening and closing through the control output to complete the accurate gripping task, as shown in Figure 7.

From the abovementioned mode, the linear motion is mainly adapted to the situation that requires the motion trajectory of the stored point playback to be straight; the joint motion is faster and more efficient; and the gate-type movement is mainly applied to the case of grasping suction and discharge, etc., which needs to avoid certain obstacles. According to the specific method steps of image segmentation, take out the areas that are not needed for the experiment, reserve the areas that can highlight the common characteristics of a certain type of solid waste, and then segment the image. The main

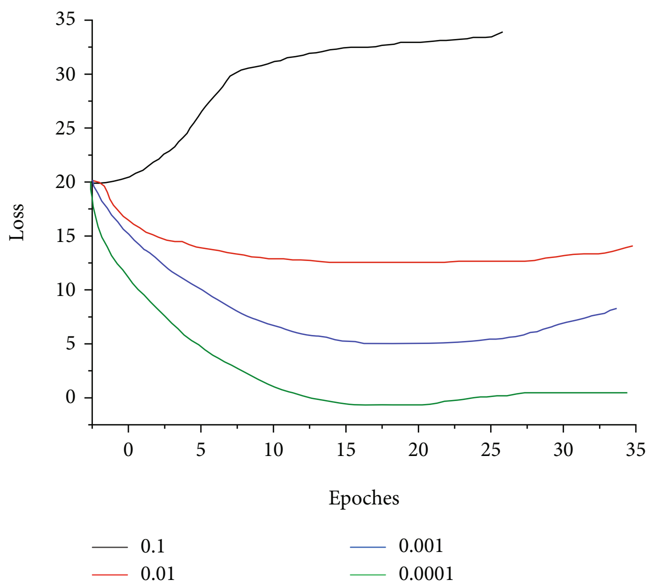

Figure 6: Model loss results with different learning rates.

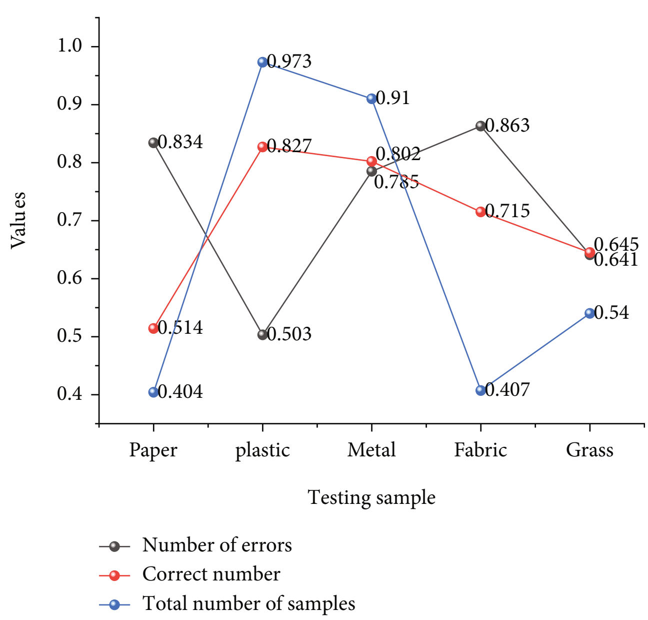

Figure 7: System classification test results.

purpose of this system for the application of the robotic arm is to achieve visually assisted completion of medical solid waste barrel grasping, medical solid waste barrel in the grasping process must be in a horizontal-vertical state, to prevent the pollution of the environment and personal injury caused by the dumping of medical waste, and the fixture designed in this paper is to grasp from the top-down, therefore, the control of the robotic arm in the grasping scheme for medical solid waste barrel. The scheme mainly uses the gate type movement control mode. First, according to the created map information, the path planning is carried out for the arrival route of the target navigation point, the path planning is the optimal distance scheme to reach the target point, and the drive wheel drive is

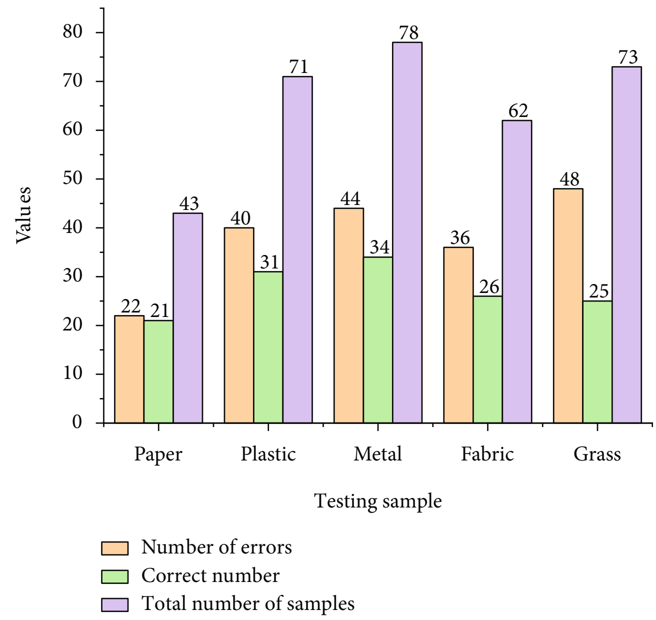

Figure 8: Cost results, in the figure, the values under different types are represented.

completed according to the planned path, and at the same time, according to the LIDAR real-time environment detection, the current path is judged whether there is an obstacle, and if there is no obstacle in the current detection range, the drive wheel drive realizes navigation; if the obstacle is detected in the current path. If an obstacle is detected in the current path, the path is planned again from the current position to the target point position until it reaches the target navigation point, as shown in Figure 8.

From the calculation results, it can be seen that hazardous solid waste has the highest collection and transfer cost per ton, mainly due to the low volume of generation; recyclables have a higher collection and transfer cost than other solid waste, mainly due to the construction of a large number of recycling stations and recruitment of personnel; food waste has the lowest collection and transfer cost, mainly due to the low investment in fixed assets and disposal in the area making the transportation distance shorter and the transportation. The cost of food waste collection and transfer is the lowest, mainly due to the low investment in fixed assets and disposal in the district, which makes the transportation distance shorter and the transportation cost lower. The collection and transfer link are mainly to transport the sorted solid waste to the next stage of disposal, only the spatial location of solid waste and other materials is changed, and the output is also recyclables, hazardous solid waste, food waste, and other solid waste 4 types of solid waste, of which recyclables are also sorted simply, and are roughly divided into waste paper, waste plastic, waste metal, waste plants, and waste in the recycling station.

6. Conclusion

A dataset of common recyclable bottle solid waste images was constructed by acquiring 5000 images and augmenting them to 20,000 images using various data enhancement methods.

The 19000 images in the dataset were used as the training set and 1000 images as the test set, which provided the data basis for the validation experiments of the improved Faster RCNN network model. Our method can only be used for this type of processing for the time being. The model mainly focuses on adjusting the size of the convolution kernel and the structure of the convolution layer, enhancing the image characterization ability, introducing the random regularization function, reducing the feature dimension, weakening the overfitting phenomenon, and realizing the fast extraction of image features. To achieve accurate localization of bottle targets to be detected in solid waste images of different sizes, the anchor parameter is designed, a suitable candidate window for bottle target detection is selected, and the candidate frame regression method is designed to improve the accuracy of bottle target detection. For the classification of bottle targets in images, a multilabel classification function is used to properly classify them, and more accurate classification results are obtained. The two parameters of batch size and learning rate are optimized. The algorithm in this paper is compared and analysed with similar algorithms, and the test results show that the algorithm achieves 90.6% accuracy for locating bottle targets in images, 92.6% accuracy for classifying bottle targets in images, and 6.6 FPS detection speed, which verifies the effectiveness of the algorithm in this paper for detecting common recyclable bottle solid waste.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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