

Based On YOLOV8 Intelligent Trash Can Garbage Classification Detection Algorithm

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Abstract: Since 2019, China has begun to vigorously implement a garbage sorting system across the country, with Shanghai being the first city to fully implement garbage sorting. For example, residents do not have a strong sense of classification and lack of classification knowledge, resulting in low classification accuracy. The management of the wharf is relatively loose, and the garbage collection, transportation and treatment links sometimes fail to strictly distinguish between various types of garbage, which affects the classification effect. Waste collection facilities are rudimentary, and sorting labels may not be uniform and oversimplified, which is not conducive to fine sorting. Therefore, it is urgent to solve the problem of garbage classification and become an urgent problem for all countries to study. The problem of sorting valuable garbage after garbage collection. The rapid development of deep learning provides the technical demand for intelligence. In this paper, the YOLOV8 algorithm is used to train the garbage classification model, and about 10,000 custom garbage datasets with 4 categories are used to classify food waste, hazardous waste, recyclable waste and other waste. In this paper, methods such as Os, pandas, and numpy are used in Python programming. For model deployment, models can be deployed using trained weight files and configuration files, and models can be integrated into tools such as OpenCV, TensorFlow, etc., for real-time detection or integration into other applications.

Keywords: Convolutional neural network, small object detection, YOLOV.

1. Introduction

At present, in the face of the challenge of rapid growth of domestic waste, China has realized the importance of garbage classification to improve the efficiency of garbage disposal, and has launched a series of policy measures to promote the development of garbage classification. Since 2017, the state has begun to pilot the implementation of the domestic waste classification system in 46 cities, and gradually extended it to cities above the prefecture level across the country. Although the policy level has attached great importance to and actively promoted, in the actual implementation process, the garbage classification work still faces a series of problems. On the one hand, public awareness and waste sorting practices are uneven, and some residents are unable to actively participate in waste sorting due to lack of knowledge. In this context, as an emerging technology product, intelligent sorting trash cans try to automatically complete garbage sorting through AI recognition technology, reduce the burden of labor, and improve sorting efficiency. However, there are still problems in the application of such products, such as excessive size, high cost, classification accuracy and efficiency need to be improved, which limits their wide application in real life. Therefore, in the future, the research focus in the field of intelligent waste classification will be to continuously optimize the accuracy and efficiency of the classification algorithm, and develop intelligent waste classification solutions that are more suitable for China's national conditions, economical and practical, and easy to promote, so as to meet the huge and complex domestic waste treatment needs in China0.

2. The Overall Design of The YOLO8 Algorithm

Predict the location and category of objects in an image with a single forward propagation. The algorithm may adopt an anchor-free design, an updated backbone network structure, and a cascade and pyramid mechanism, aiming to improve the detection accuracy, especially the detection ability of small targets, while continuing to maintain real-time performance. While optimizing speed and accuracy, YOLO8 realizes end-to-end learning from the original image to bounding box coordinates and class probability, which further strengthens its real-time object detection performance with limited computing resources[2]. The biggest innovation of the YOLO series is the expansion of the high-efficiency layer aggregation network, E-ELAN and composite model reduction, model scaling, reparameterization network, and label matching, through the construction of three models to achieve accurate detection of small target objects, as shown in Figure 1.

3. Convolutional Neural Networks

Integrative neural networks are a type of deep learning model specifically designed to process data with grid-like structures (such as images, videos, speech signals, etc.), especially for computer vision tasks. Drawing on the concept of the receptive field of neurons in the biological visual system, CNN can efficiently extract multi-level spatial features from input data through the characteristics of local connection and weight sharing[3]. A typical convolutional neural network (CFN) is mainly composed of a human layer, a convolutional layer, a pooling layer, a fully connected layer, and an output layer, as shown in Figure 2.

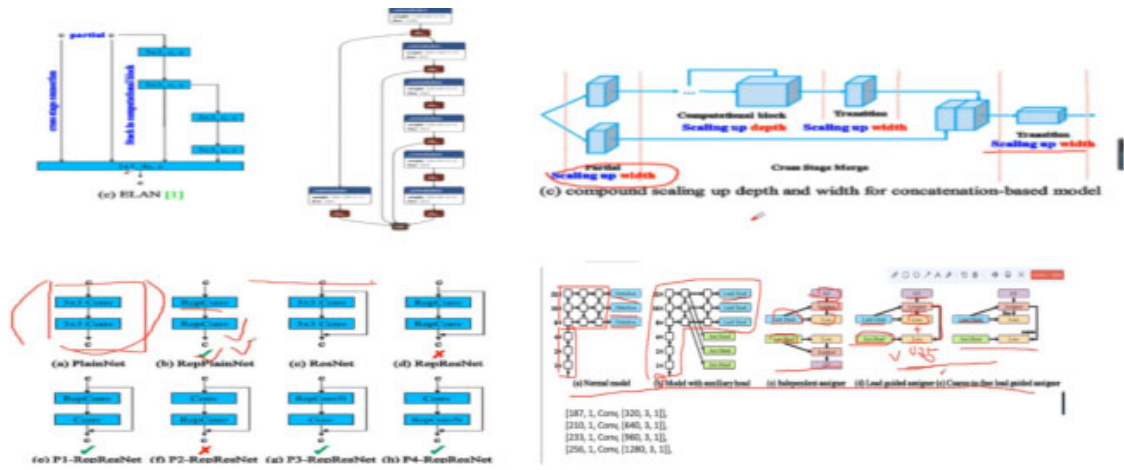


Figure 1 The overall design of the YOLO8 algorithm

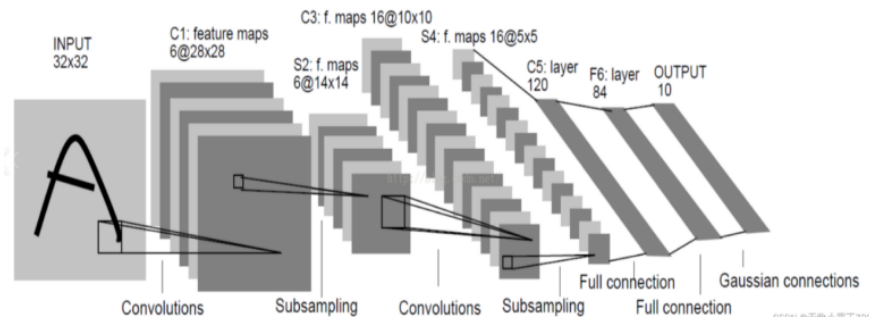


Figure 2 Neural network model

3.1. Convolutional layers

Convolutional layers are the core components of convolutional neural networks, which can adaptively learn and capture local spatial structure information in the image, such as textures, edges, and shape features, by sliding and applying a learnable convolutional kernel (filter) to the input image. The convolutional kernel shares the same parameters on the whole image, and this weight sharing feature ensures that the model has a certain invariance to the change of the position of the target feature in the input data, that is, the translation invariance, and greatly reduces the number of

parameters and the amount of computation required by the model, so as to improve the learning and inference efficiency of the model, which is especially suitable for processing data with spatial structure such as images. A weight matrix, the convolution kernel, progressively "scans" over the two-dimensional input data. While the convolutional kernel "slides", it calculates the product of the weight matrix and the scanned data matrix[4], and then summarizes the results into an output pixel. Using the 3x3 convolution kernel as shown in Figure 3, the size of the convoluted image is (width-2)*(height-2) without padding.

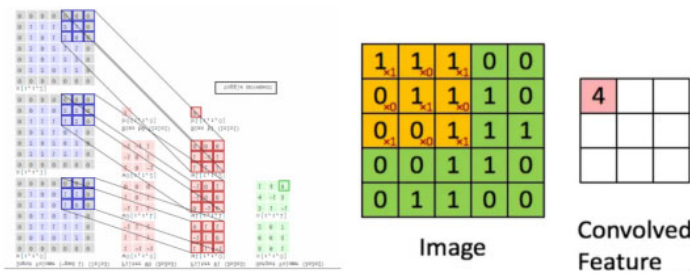


Figure 3 Convolutional layer algorithm

3.2. Pooling layer

The function of the pooling layer is to select the features extracted from the convolutional layer, and the common pooling operations include maximum pooling and average pooling, and the pooling layer is calculated by sliding the matrix window of $n \times n$ size, similar to the convolutional layer,

except that instead of doing cross-correlation operations, it is to find the maximum value and average value in the matrix of $n \times n$ size. The pooling window size is typically 2x2 or 3x3 in steps of 1 or 2, as shown in Figure 4, and can also be set on a case-by-case basis. In a convolutional neural network, as shown in the figure, the maximum pooling and average pooling operations are performed on the feature map.



Figure 4. Pooling layer algorithm

3.3. Fully connected layer

The pooling layer is generally followed by a fully connected layer, the fully connected layer converts all the feature matrices of the pooling layer into a one-dimensional feature large vector, the fully connected layer is generally

placed at the end of the convolutional neural network structure, which is used to classify the picture, and when it comes to the fully connected layer, our neural network is ready to output the result, as shown in Figure 5, the vector of the penultimate column is the data of the fully connected layer.

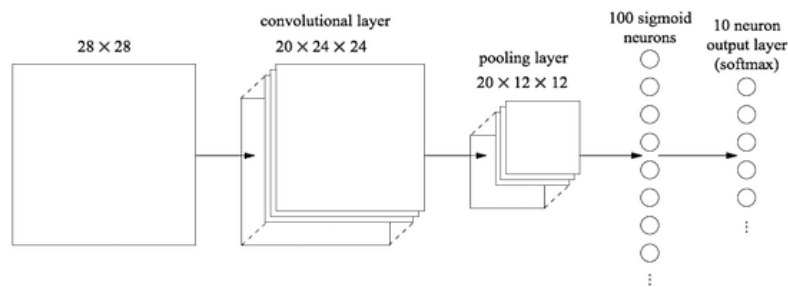


Figure 5. Fully connected layer

4. YOLOv8 Algorithm

Yolo v8 mainly involves: backbone uses C2f module, the detection head uses anchor-free + Decoupled-head, the loss function uses the combination of classified BCE, regression CIOU + VFL (new items), the box matching strategy is changed from static matching to Task-Aligned Assigner matching mode, the last 10 epochs close Mosaic operation, and the total number of epochs trained from 300 to 500[5][6].

4.1. Image acquisition

In the process of constructing the dataset, waste samples from different background environments and life scenarios were deliberately included, including but not limited to the practical application scenarios of waste classification such as

family life, office space, and public areas. This cross-channel and multi-source data integration method helps the model to improve its universality and ability to cope with unknown scenarios when dealing with various complex waste classification problems.

At present, the size of our dataset has reached about 400 samples, and the amount of garbage in each category is relatively balanced, aiming to maintain the balance of the dataset, so that the model can pay equal attention to each category in the training process, so as to effectively improve the classification accuracy of various types of garbage. Overall, the well-designed dataset and training process aim to nurture an intelligent system that can stably and accurately perform garbage sorting tasks under various conditions.

Table 1. Image acquisition

RECYCLABLE GARBAGE	FOOD WASTE	TOXIC AND HAZARDOUS WASTE	OTHER GARBAGE
PAPER PLASTICS METAL GLASS FABRIC WASTE	VEGETABLE LEAVES FRUIT PEELS FISH BONES, MEAT BONES TEA RESIDUES HUSK MELON PEEL	USED BATTERIES EXPIRED MEDICINES CHEMICAL CONTAINERS	DISPOSABLE DIAPERS TOILET PAPER TOWELS NAPKIN CIGARETTE BUTTS BROKEN CERAMICS WORN-OUT POTTERY

In this study, data augmentation techniques were used to

enhance the diversity and complexity of the initial dataset.

Specifically, by performing random brightness adjustments and horizontal or vertical flipping operations on the original image, different lighting conditions in real life and the representation of junk objects in different viewing angles were simulated[7]. This kind of data augmentation method effectively expands the size of the dataset without collecting additional physical samples, and also improves the

generalization performance of the model on unseen data. In other words, through data enrichment, the model is exposed to more varied and richer scenarios in the training process, so that it can make more accurate and flexible garbage classification judgments for various complex situations in practical applications, as shown in Figure 6.

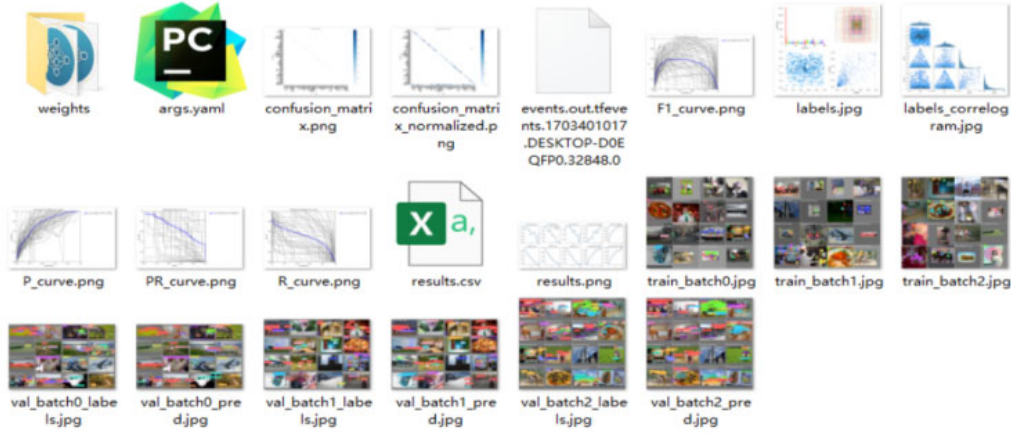


Figure 6. Image acquisition

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4.2. YOLOv8 model training

In the model training stage, we carried out 30 rounds of

iterative optimization, so that the model continuously learned and adjusted internal weights and parameters, so as to continuously improve the recognition and classification performance on the training dataset. In the end, the model showed strong practical performance. Through the detailed confusion matrix and ROC curve analysis, as shown in Figure 7, we can confirm that the YOLOv8S model has achieved significant results in object recognition tasks[8]. The confusion matrix data shows that the model is particularly prominent in correctly identifying the target class (true example) and excluding the non-target class (true negative example), while incorrectly judging the non-target class as the target class (false positive example) and omitting the target class (false negative example) is rare[9]. This means that the model can accurately distinguish between recyclable garbage, kitchen waste, hazardous waste or other garbage in the garbage sorting task, and minimize the misclassification, which strongly supports the practical application needs of intelligent garbage classification.

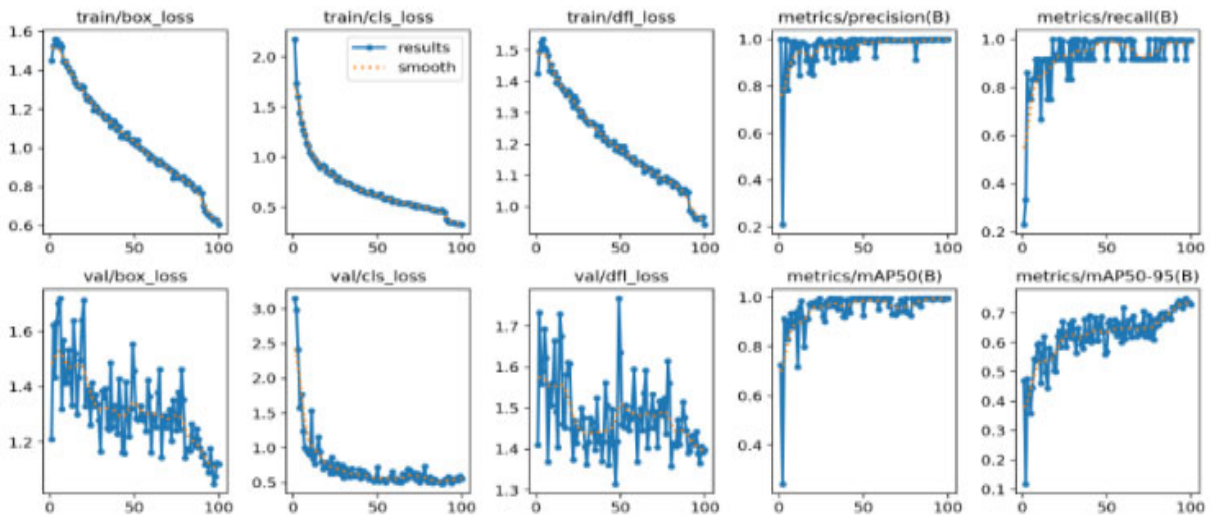


Figure 7. Model training

5. Conclusion

This paper focuses on the research of object detection technology, which is crucial in the field of computer vision, and first expounds the latest development trend of object detection technology, especially emphasizing the core challenge of small object detection. In this paper, the application of convolutional neural networks in object detection is analyzed in detail when reviewing the basic chapters, focusing on the YOLO8 algorithm, which is a milestone achievement in the field of object detection and lays a solid foundation for subsequent research.

In this paper, we make a detailed analysis of the current YOLOv8 object detection algorithm. The design and optimization of YOLOv8 is the focus of this paper, especially to solve the problem of small target detection, and several innovative strategies are proposed. Specifically, by integrating a deformable convolution module into the backbone network to broaden the receptive field of the detection point on the feature map, the capture of small target features is strengthened, so as to significantly improve the detection performance of small targets while maintaining the efficiency of training and inference, and also promote the detection accuracy of large and medium-sized targets.

References

- [1] Guo Wei. Ethical thinking on the problem of municipal solid waste in China [D]. Hunan University of Science and Technology, 2019.
- [2] Dong Ziyuan. Design and implementation of garbage classification system based on deep learning[D]. University of Chinese Academy of Sciences (Shenyang Institute of Computing Technology, Chinese Academy of Sciences), 202
- [3] Chen Xianchang. Research on deep learning algorithm and application based on convolutional neural network [D]. Zhejiang Gongshang University, 2014.
- [4] ZHOU Yueqi. Research on vehicle compaction line detection method based on convolutional neural network YOLO [D]. Zhejiang Academy of Science and Technology, 2020.
- [5] Wang Lin. Research on improved object detection algorithm based on YOLO [D]. Jiangnan University, 2020. North University of China Dissertation 67
- [6] Li Jinyu, Chen Xiaolei, Zhang Aihua, et al. Review of garbage classification methods based on deep learning[J]. Computer Engineering, 2022:1-9.
- [7] Zhang Wei. Garbage detection and classification based on YOLO neural network [J]. Electronic Science and Technology, 2022, 35(10), 45-50.
- [8] Zhang Xujuan. Research on deep learning model of garbage classification based on image recognition [D]. Lanzhou: Northwest Normal University, 2021.
- [9] Shao Wenjie. Research on garbage detection method based on deep convolutional neural network [D]. Nanjing: Nanjing University of Posts and Telecommunications, 2022.
- [10] Su Zhe. Research on image classification method of domestic waste based on deep learning [D]. Lanzhou: Northwest Normal University, 2021.