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Research on Online Identification Algorithms for Discarded Circuit Board Surface-Mounted Components

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Abstract

In recent years, the rapid advancement of electronic products has significantly increased the quantity of discarded electronic products, particularly waste circuit boards, leading to issues of resource wastage and environmental pollution. Therefore, developing an efficient recycling system for circuit board surface-mounted components is crucial. However, challenges such as the wide range of component sizes, diverse types, and the similarity in characteristics of small-sized components make detection difficult. This paper uses YOLOv8 as the base network model, with YOLOv8l as the teacher model and YOLOv8n as the student model, applying the CWD knowledge distillation method to the YOLOv8n model. The study employs a combination of publicly available datasets and some self-constructed datasets as the data foundation, and conducts comparative experiments with different YOLOv8 algorithm models. The results show that the average precision of the YOLOv8 model after knowledge distillation reaches 94.8%, an improvement of 2.3% over the YOLOv8n model, with a 45.2% increase in detection speed. This indicates that the knowledge-distilled YOLOv8 model is suitable for online identification of discarded circuit board surface-mounted components in practical production environments.

Keywords

Discarded Circuit Boards; YOLOv8; Electronic Components; Knowledge Distillation.

1. Introduction

With the rapid advancement of technology and the accelerated turnover of electronic products, the quantity of discarded electronic products, particularly waste circuit boards, has surged, leading to significant issues of resource waste and environmental pollution. These waste circuit boards not only contain hazardous substances but also include a substantial amount of valuable metals such as gold, silver, and copper, whose recovery and reuse hold significant economic value. However, the complex structure and mixed materials of waste circuit boards make traditional manual processing methods inefficient, challenging, and unable to meet high environmental standards. In this context, automated identification technology is emerging as an effective solution, gradually replacing traditional methods with more efficient and reliable processing approaches.

Convolutional Neural Network-based object detection algorithms play an increasingly important role in industrial applications. These algorithms are primarily divided into two categories: two-stage detection algorithms and single-stage detection algorithms. Two-stage detection algorithms, including Faster R-CNN[1], Mask R-CNN[2], Cascade R-CNN[3], and R-FCN[4], are suited for complex scenarios and high precision applications, typically requiring more computational resources and being somewhat slower. In contrast, single-stage detection algorithms such as YOLO[5], SSD[6], RetinaNet[7], CenterNet[8], EfficientDet[9], and DETR[10] often provide faster detection speeds and are more appropriate for real-time scenarios. Among these, YOLOv8[11] stands out as an advanced algorithm in the field of object detection, demonstrating significant achievements in accuracy and

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real-time performance across various applications. YOLOv8's innovative design enables precise object detection in complex backgrounds, particularly in dynamic and rapidly changing environments, showing promising potential for automated identification of waste circuit boards.

Nevertheless, despite YOLOv8's excellent performance in object detection, challenges remain in its application to the identification of waste circuit boards. Firstly, existing YOLOv8 models may encounter issues with detection accuracy when dealing with high-density and complex structures of waste circuit boards. Secondly, real-time performance and processing speed are crucial, especially when processing large volumes of waste circuit boards, as the model's real-time capabilities directly affect the overall system efficiency and operational smoothness. Therefore, enhancing the detection accuracy and processing speed of YOLOv8 algorithms will have a positive impact on the automated identification and processing of waste electronic products.

This thesis aims to improve the YOLOv8 algorithm to address the specific requirements of online identification of waste circuit boards, proposing optimization strategies to enhance its performance. By thoroughly analyzing the challenges of YOLOv8 in this field and researching algorithmic improvements, this work will provide a more efficient and reliable solution for the effective recycling of waste electronic products and environmental protection. It is anticipated that these improvements will advance the technology for handling waste electronic products and contribute to sustainable resource utilization and environmental conservation.

2. Introduction to YOLOv8 Network Model

YOLOv8 is the latest target detection algorithm in the YOLO series released by Ultralytics. This version is divided into five different sizes of models based on the depth of the network and the width of the feature maps: YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. Among these models, YOLOv8n maintains high speed while having lower computational complexity and fewer parameters, which reduces hardware requirements for deployment.

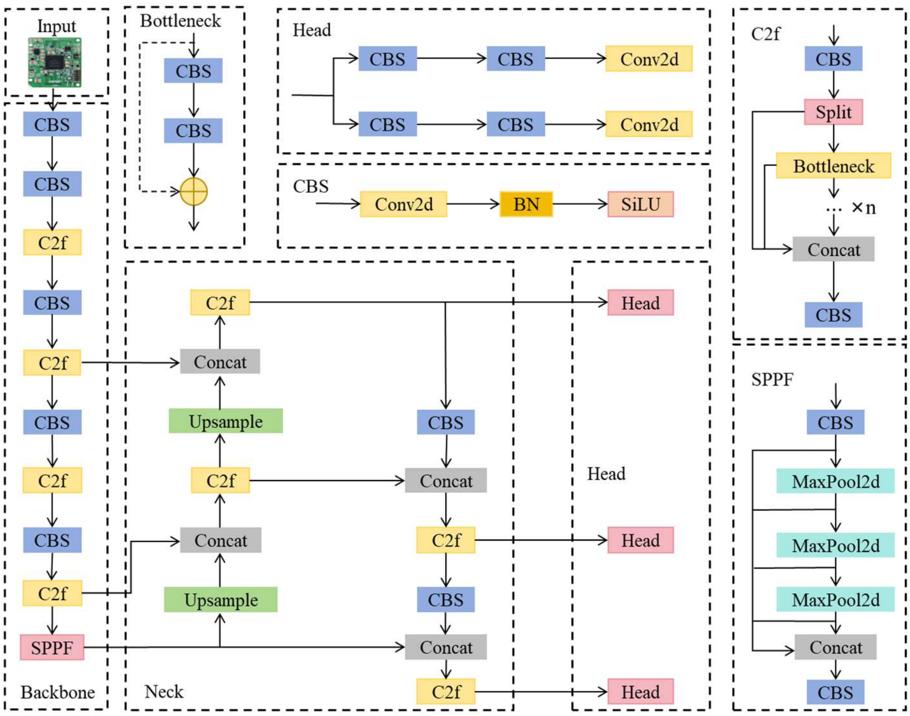

Figure 1. YOLOv8 Network Structure

YOLOv8 is an upgraded and improved version of YOLOv5, resulting in a more advanced algorithm. In the Backbone section, YOLOv5 uses CSPDarkNet as the main network, featuring C3 modules and

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SPP structures. YOLOv8 replaces the C3 modules with a more lightweight C2f module, enhancing feature extraction capabilities and reducing computational load. In the Neck section, YOLOv5 utilizes the PAN-FPN structure, which helps with the fusion of features at different scales. YOLOv8 improves upon PAN-FPN by removing the 1x1 convolution before upsampling and directly performing upsampling operations to boost performance. In the Head section, YOLOv5 employs a Coupled Head structure that handles both classification and regression tasks simultaneously. YOLOv8 introduces a Decoupled Head[12] structure that eliminates predefined anchor boxes and directly predicts the center and size of targets. This change simplifies model hyperparameters and improves detection performance for small objects by independently handling classification and regression tasks, effectively resolving inherent conflicts between these tasks and enhancing detection accuracy and convergence speed.

Regarding loss functions, YOLOv5 uses binary cross-entropy to compute classification loss and CIoU (Complete Intersection over Union) loss to measure localization accuracy. YOLOv8 adopts the VFL loss function for classification and combines DFL and CIoU loss functions for bounding box regression, improving model convergence speed and localization accuracy. These improvements make YOLOv8 excel in accuracy and small object detection while also accelerating training speed.

3. Feature-Based Knowledge Distillation Methods

Knowledge distillation involves transferring the knowledge from a high-performance but computationally intensive and complex model (the teacher) to a lighter student model to achieve model compression. To further enhance the detection accuracy of algorithms, this paper employs a channel-level knowledge distillation method, which effectively transfers the rich feature representation capabilities of the teacher model to the lightweight student model, thereby improving the student model's generalization ability and inspection performance.

Traditional feature-based knowledge distillation methods primarily rely on point-wise alignment or structural information alignment between spatial locations. However, these methods often overlook the knowledge within channels. Channel knowledge distillation allows for better utilization of knowledge within each channel and necessitates minor adjustments between the teacher and student channels. In the feature-based knowledge distillation methods discussed, this paper selects the CWD (Channel-wise Distillation) method. CWD[13] normalizes the feature activation values of each channel in a specific feature layer of the teacher and student models to obtain the corresponding probability distributions. It then minimizes the KL divergence between the probability distributions of the teacher and student channels, guiding the student network to focus more on learning regions with significant activation values in each channel during the distillation process. This approach improves the accuracy of the student model in PCB (Printed Circuit Board) chip detection tasks.

Let T and S represent the teacher and student networks, respectively, and let their activation maps be denoted as (A_T) and (A_S). The general form of the channel distillation loss is expressed as:

$$\varphi(\varphi(y^T), \left(\varphi(y^T)\right) = \varphi(\varphi(y_c^T), (\varphi(y_c^S)) \tag{1}$$

Convert the activations of the channels into a probability distribution and use a probability distance metric, such as KL divergence, to measure the difference. The formula is as follows:

$$\varphi(y^T, y^S) = \frac{T^2}{C} \sum_{c=1}^{C} \sum_{i=1}^{W \cdot H} \emptyset(y_{c,i}^T) \cdot log\left[\frac{\emptyset(y_{c,j}^T)}{\emptyset(y_{c,i}^S)}\right] \tag{2}$$

The conversion of feature values into probability distributions is done as follows:

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$$\emptyset(y_c) = \frac{\exp(\frac{y_{c,j}}{\tau})}{\sum_{i=1}^{W\cdot H}\exp(\frac{y_{c,j}}{\tau})} \tag{3}$$

Here, (c) denotes the channel index, and (i) corresponds to the spatial location within channel (c). (T) represents the distillation temperature; increasing (T) makes the probability distribution softer, indicating a focus on broader spatial regions within each channel. The channel-based knowledge distillation loss is computed as follows:

$$L_{KD} = \sum_{c=1}^{C}\sum_{i=1}^{W\cdot H}\emptyset(y_{c,j}^{T})\cdot log\frac{\emptyset(y_{c,i}^{T})}{\emptyset(y_{c,i}^{S})} \tag{4}$$

4. Experiments and Analysis

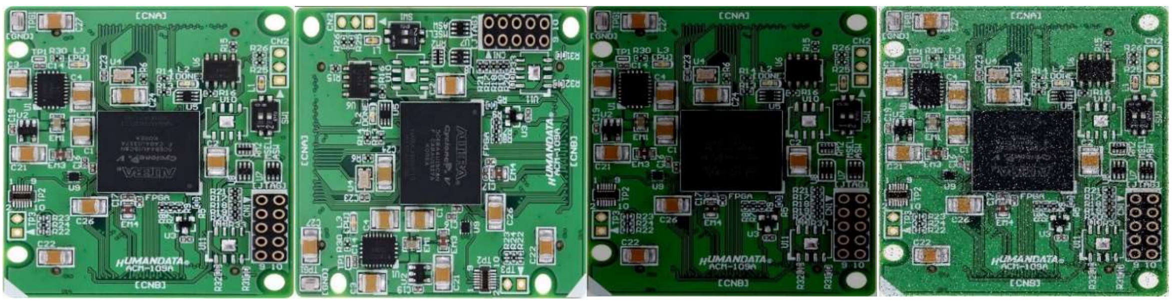
4.1 Experimental Environment

The experimental environment for this paper is configured as follows: the operating system is 64-bit Windows 11, the processor is a 13th Gen Intel(R) Core(TM) i7-13650HX@2.60 GHz, the graphics card is an NVIDIA GeForce RTX 4060, and the memory is 16GB. On the software side, the deep learning framework used is PyTorch 2.3.1, with Python as the programming language and an interpreter version of 3.8.19. During training, the parameters were set as follows: input image size was 640×640, output category was 1 (IC), batch size was set to 4, and the number of epochs was set to 200.

4.2 Experimental Dataset

Currently, there are relatively few publicly available datasets for electronic components on circuit boards, and these datasets often include a wide variety of component types. However, this experiment focuses solely on recycling high-value IC chips from discarded circuit boards. The data used in this paper primarily comes from a publicly available dataset provided by the Roboflow[14] platform, with labels modified to retain only the IC categories needed for this experiment.

Some of the datasets underwent image augmentation, including operations such as rotation, brightness adjustment, and noise addition. Figure 4 illustrates the differences between the original image (a) and the augmented images: rotation (b), brightness adjustment (c), and noise addition (d). As shown in the figure, the processed images still exhibit significant differences from the original ones.



a.Original b. Rotation c. Brightness Adjustment d. Noise

Figure 2. Dataset Augmentation Images

After applying rotations, brightness adjustments, and noise addition to the original dataset, a total of 2,096 images were generated. These images were then split into training, validation, and test sets in a 7:2:1 ratio. To maintain consistency in the experimental environment, all models used images with a size of 640×640 pixels, and all training parameters and epochs were kept the same.

4.3 Evaluation Metrics

To better assess the effectiveness of the distilled YOLOv8 model, this paper will use accuracy, recall, mean average precision, model weight size, and detection speed as evaluation metrics. However, while maintaining accuracy, greater emphasis will be placed on detection speed to select the best model for subsequent experiments. The calculation formulas are as follows:

$$P = \frac{TP}{TP+FP} \tag{5}$$

$$R = \frac{TP}{TP+FN} \tag{6}$$

$$AP = \int_0^1 P(R)dR \tag{7}$$

$$mAP = \frac{\sum_{i=1}^{n} AP_i}{n} \tag{8}$$

In the formula: TP represents the correct number of defects detected; FN indicates the number of undetected defects. FP represents the number of defect detection errors. AP stands for average accuracy; mAP represents the average accuracy; n indicates the number of categories. The smaller the Params and GFLOPs, the smaller the computational power required to represent the model, and the lower the hardware performance requirement.

4.4 Comparative Experiments

The evaluation metrics used include Precision, Recall, mAP@0.5, Params, GFLOPs, Weight size, and FPS. The distilled algorithm presented in this paper was compared with YOLOv8l and YOLOv8n algorithms under the same configuration, parameters, and dataset. The experimental results are shown in Table 1. The data indicates that the distilled YOLOv8 algorithm achieved an increase in mAP@0.5 of 1.3% and 2.3% compared to YOLOv8l and YOLOv8n, respectively, while significantly reducing both the number of parameters and the computational load. see Table 1.

Table 1. Comparative Experimental Results

Model	P/%	R/%	mAP@0.5/%	Params	GFLOPs	Weight size/MB	FPS/(f/s)
YOLOv8l	87	91.2	93.5	4.3×10^7	164.8	87.6	59.2
YOLOv8n	89.6	84.9	92.5	3.0×10^6	8.1	6.2	222.2
YOLOv8-CWD	93.1	83	94.8	3.0×10^6	8.1	6.2	322.6

From the table, it is evident that the YOLOv8 algorithm after distillation shows a significant improvement in average precision compared to YOLOv8l and YOLOv8n. Additionally, the distilled algorithm is notably faster than the original YOLOv8 models, enhancing both computation speed and detection accuracy. This suggests that the distilled YOLOv8 algorithm provides substantial benefits for subsequent tasks such as the extraction of discarded circuit board components.

4.5 Visualization Display

To provide a more convenient and intuitive demonstration of detection results, this experiment developed a PCB component detection system using C# WinForms. This system is designed to detect IC-type components. As shown in the figure, the system can connect to a camera for real-time detection. It integrates the distilled optimal model file, allowing users to either select an image or capture a photo in real time. The system then performs the detection, displays the results on the interface within a very short time, shows the corresponding coordinates, and allows for result storage for detailed subsequent analysis. This system also aims to facilitate the extraction of component elements from discarded circuit boards in collaboration with lower-level machines.

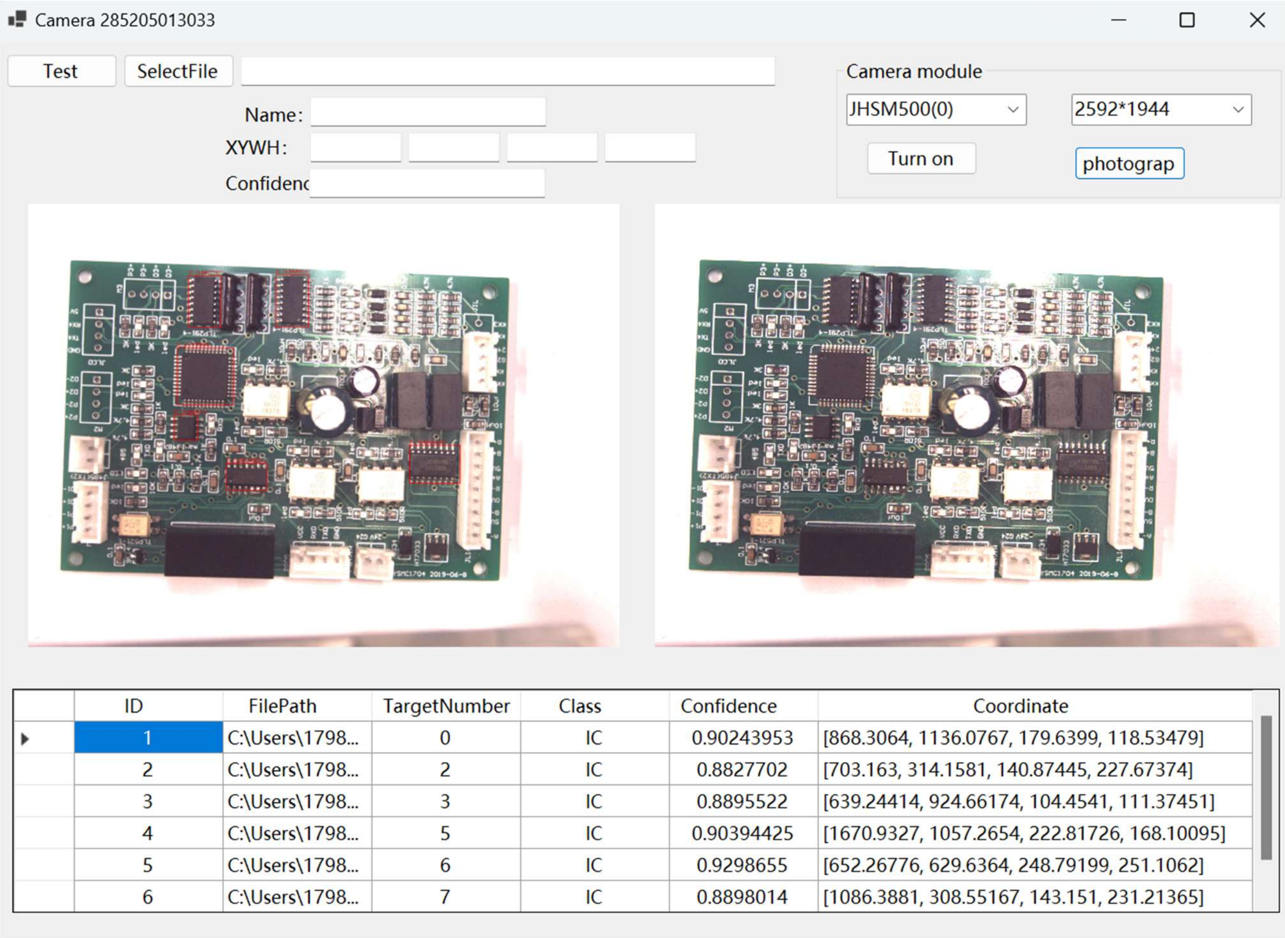


Figure 3. Interface of the Discarded Circuit Board Component Detection System

5. Conclusion

This paper addresses the precise identification of IC-type components on discarded circuit boards using the YOLOv8 algorithm as the core. We proposed a feature-based distillation method to enhance the YOLOv8 algorithm. Through a series of improvements, we achieved better detection performance. Compared to the original YOLOv8 algorithm's two models, the distilled YOLOv8 algorithm showed a 2.3% increase in mAP@0.5 and a more notable improvement in detection speed. Experimental results indicate that the distilled model performs excellently in identifying IC-type components on discarded circuit boards, improving both accuracy and detection speed. This achievement provides a better recognition effect for the subsequent removal of components from discarded circuit boards. Currently, the model has only undergone minor improvements. Future work will include recognizing other valuable components on the circuit board and implementing additional enhancements to ensure both precision and speed, aiming to improve the YOLO algorithm's ability to detect multiple targets on circuit boards.

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