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Evaluation of Contrastive Learning for Electronic Component Detection

Leandro H. de S. Silva[1,2] Agostinho Freire[1]
Bruno J. T. Fernandes[1] George O. A. Azevedo[1] and Sergio C. Oliveira[1] *

1- Universidade de Pernambuco - Escola Politécnica de Pernambuco
Rua Benfica 455, Recife/PE - Brazil

2- Instituto Federal de Educação, Ciência e Tecnologia da Paraíba (IFPB)
Rua José Antônio da Silva 300, Cajazeiras/PB - Brazil

Abstract. The rapid growth of electronic waste (e-waste) has led to an urgent need for efficient recycling processes to recover valuable materials and reduce environmental impact. Waste Printed Circuit Boards (WPCBs) constitute significant e-waste and contain valuable components and precious metals. Computer vision systems can automate the classification, disassembly, and recycling of WPCBs. However, obtaining large annotated datasets for machine learning in this domain is costly and often unavailable. This paper investigates using few-shot and supervised contrastive learning in electronic component detection. We propose a model incorporating contrastive learning components for detecting electronic components in scenarios with limited training data or annotated labels. Our experimental results show that, in limited-data scenarios, contrastive learning outperforms the original versions of Faster R-CNN object detector. This study contributes to developing efficient recycling solutions for e-waste management and resource recovery.

1 Introduction

Waste of Electrical and Electronic Equipment (WEEE) is the fastest-growing waste class [1, 2], due to factors such as reduced device lifetimes and increased consumption of these devices. It is estimated that about 30% of WEEE is composed of Printed Circuit Boards (PCBs) [1], and PCBs are the largest sources of valuable elements (precious metals), in addition to the possibility of reusing some electronic components [3]. However, the composition of PCBs is highly varied, making the recycling process quite complex [4].

Commonly, the PCB recycling process involves three steps: removal of electronic components, mechanical processing (e.g., shredding), and some chemical leaching process. Preprocessing steps, such as separating by PCB type, disassembling components, and choosing the appropriate recycling process, can increase efficiency and reduce the cost of the recycling process [4]. Computer vision systems can perform WPCB evaluation to guide automatic disassembly and recycling, classification, and separation of WEEE [5]. However, large enough labeled datasets for the PCB domain are expensive and unavailable [6].

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The central hypothesis of this work is defined as follows: a computer vision model with contrastive learning components can be used to detect electronic components in scenarios with limited available training data. So, in this work we evaluate a contrastive learning component added to the Faster R-CNN model for electronic component detection. The results indicate that contrastive learning yields better results in scenarios with limited data than the original versions of classifiers and detectors.

2 Releated works

Contrastive learning proposes a cost function that takes into account that individuals of the same class should be represented as similarly as possible, while individuals from different classes should be represented as divergently as possible, leading to larger margins of separation between classes [7].

Supervised contrastive learning, as described in SupCon [8], can be applied to supervised scenarios. In unsupervised learning, two different images belonging to the same class can be presented to the model as if they were divergent. However, in a fully supervised scenario, all image labels are known, and therefore this does not happen. Consequently, the cost function is defined as follows:

$$L^{sup} = \sum_{i \in I} L_i^{sup} = \sum_{i \in I} \frac{-1}{|P(i)|} \sum_{p \in P(i)} log \frac{exp(z_i \cdot z_{j(i)}/\tau)}{\sum_{a \in A_{(i)}} exp(z_i \cdot z_a/\tau)} \tag{1}$$

where $P(i) \equiv p \in A(i)|y_p = y_i$, meaning that $P(i)$ is a set of samples belonging to the same class. The SupCon cost function generates similar representation for individuals of the same class and distinct representation (lower similarity) for individuals of different classes. The use of SupCon outperforms the ResNet-50 and ResNet-200 models when trained with cross-entropy. Additionally, SupCon is more robust to ImageNet label corruption, and the higher the level of noise in the labels, the better the performance of SupCon compared to training with cross-entropy on the same architecture [8].

Recently, unsupervised or self-supervised training methods have been employed for object detection [9]. In this context, a similar proposal to this work is FSCE: Few-Shot Object Detection via Contrastive Proposal Encoding [10]. It is a fully supervised proposal, based on Faster R-CNN, that suggests adding a contrastive learning-based function in the model training. The first stage of FSCE is training the standard Faster R-CNN, as previously discussed, with a large database. This Faster R-CNN, called the base model, is fine-tuned by adding new classes containing a few examples in the database. In this final step, the backbone parameters are frozen, and a contrastive learning component (L_{CPE}) is added to the Faster R-CNN loss, similar to the Equation 1.

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3 Contrastive Faster-RCNN for Electronic Component Detection

3.1 FICS PCB Dataset

The FICS-PCB dataset was consists of 9,912 images of 31 PCBs captured using a DSLR camera and a digital microscope [11]. In this work, we are using only the DSLR camera images. It includes annotations for six types of components: capacitors, resistors, inductors, transistors, diodes, and integrated circuits. For our study, we used the same preprocessing and new classes split proposed in [12]: ceramic capacitor (3.140 samples), tantalum capacitor (54 samples), electrolytic capacitor (44 samples), resistor (3.006 samples), integrated circuit (653 samples), LED (67 samples), diode (33 samples), and inductor (133 samples). The class imbalance is a characteristic of the PCB's electronic component composition. Usually, an average PCB has more ceramic capacitors and resistors than other components. Figure 1 shows an image sample from the dataset.

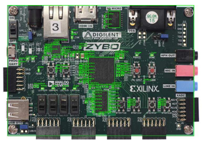

Fig. 1: Example image from the FICS-PCB dataset [11] with the corresponding annotations.

3.2 Contrastive Faster-RCNN

To evaluate the effectiveness of contrastive learning in electronic component detection, we modified the cost function of the Faster R-CNN by adding a contrastive learning component. The implementation was based on the Torchvision Faster R-CNN implementation. The modified cost function is as follows:

$$L(p_i, t_i, z_i) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*) + L_{CPE}(z_i, IOU(t_i, t_i^*)). \tag{2}$$

where L_{cls} is the standard classification component, L_{reg} is the standard regression (bounding boxes) component and L_{CPE} is the contrastive proposal enconding element. In the L_{CPE} function, z_i represents the feature vector of region i, extracted by the ROI Pooling layer. The L_{CPE} function is the supervised contrastive learning component. The only remaining element to define is the IOU weighting function, which we set as $f(u_i) = 1$ if $u_i > N_t$, and $f(u_i) = 0$ otherwise. To reduce the size of the feature vector z_i, we also used a dense layer similar to the one used in CNN for classification. However, this reduction only calculates the L_{CPE} term in the cost function. It does not require any architectural changes to the original model. Therefore, the architecture of the

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Contrastive Faster R-CNN model remains unchanged compared to the original model.

The Contrastive Faster R-CNN differs from the FSCE [10] because instead of using the TFA (two-stage fine-tuning approach) method, the model is trained in a single stage. In a typical few-shot object detection problem, there is a sufficiently large dataset for initial training, followed by the presentation of new classes with few examples. Therefore, all classes were presented simultaneously to the model in the formulation adopted for this problem.

To evaluate the Contrastive Faster R-CNN, we defined two scenarios: the first one, all classes are present and 24 PCBs were used for training and validation, and 7 PCBs were used for testing. Since the preprocessing steps include a sliding window image crop and data augmentation, each PCB image outputs several images - according to the PCB size. In the second one, only the three most numerous classes and 4 PCBs were used for training and validation. The test set is the same as the first scenario. We used the default parameters for Faster-RCNN Torchvision implementations, but specifically for the Contrastive Faster R-CNN, the number of neurons in the dense layer for feature vector reduction is 256, the Weight of L_{CPE} is 1.0, the temperature of contrastive loss is 0.2 and IOU threshold for L_{CPE}: 0.5.

4 Results

Figure 2 presents the results of Faster R-CNN and Contrastive Faster R-CNN on the test set. The model using contrastive learning has a 0.7% higher mAP than the standard version, with the largest difference in the diode class. For the integrated circuit class, the Contrastive Faster R-CNN has a higher average precision (approximately 7% higher), while for the electrolytic capacitor class, the original model has a higher average precision (approximately 12% higher). For the other classes, the average precision values are close between the two models.

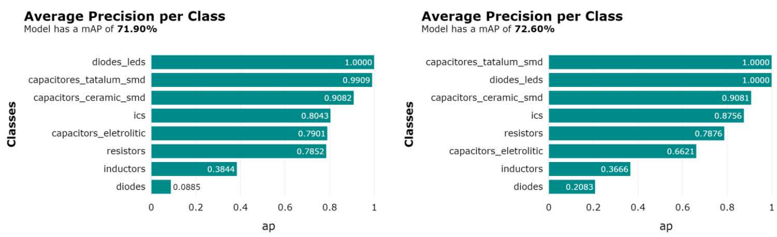

Fig. 2: Average Precision and mAP Results of Faster R-CNN and Contrastive Faster R-CNN on the FICS-PCB REMAP database.

In Figure 3 can be noted that the accuracy of the Faster R-CNN detections (49.14%) is higher than that of the contrastive learning version (47.13%).

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Regarding the class with the largest difference between the models, the Faster R-CNN correctly detects 31 diodes, while the Contrastive Faster R-CNN detects 37 diodes correctly. Removing the diode class, the Faster R-CNN and Contrastive Faster R-CNN models would have 80.9% and 80.0% mAP, respectively. In conclusion, it is not possible to establish significant differences between the models.

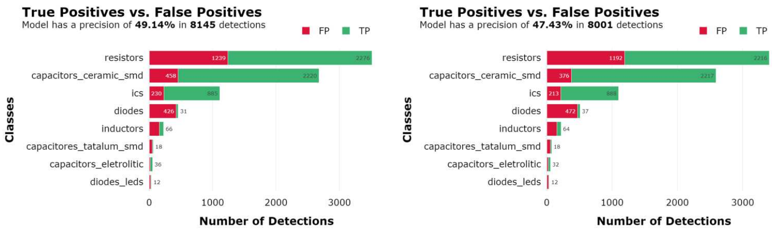

Fig. 3: Detection Evaluation Results of Faster R-CNN and Contrastive Faster R-CNN on the FICS-PCB REMAP database.

In the second scenario (only 4 PCBs and the three most numerous classes), the obtained results are shown in Figure 4, with a more significant difference between the models - 33.7% mAP for Faster R-CNN and 44.99% mAP for the version with the contrastive learning component. In all classes, the Contrastive Faster R-CNN had higher average precision.

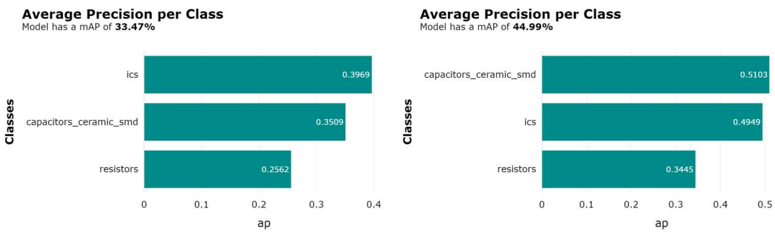

Fig. 4: Average Precision and mAP Results of Faster R-CNN and Contrastive Faster R-CNN on the FICS-PCB REMAP database reduced to 4 PCBs.

5 Conclusion

This paper evaluates using a contrastive learning component in the Faster R-CNN to detect electronic components in printed circuit boards. The contrastive Faster R-CNN performs better than the standard model when using a few-shot problem approach, resulting in an approximately 11% higher mAP. However, there is a difficulty in training the model, which requires batches with at least two objects to calculate the contrastive loss encoding (L_{CPE}) component. Although contrastive learning is beneficial in scenarios with little training data, more is needed to outperform other models when trained with an extensive dataset. If training with only a few data is possible, the difficulty of a Faster R-CNN-based object detector in this scenario can be minimized using supervised contrastive learning. The main challenge in the target application, which is detecting electronic components in PCBs for recycling, is the need for labeled data. Partial labeling of the dataset or using a semi-supervised learning approach can help address this issue.

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