

Application of Deep Transfer Learning in Electronic Connector Recognition and Inspection

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Abstract: As a key component for device interconnection, the quality inspection of electronic connectors has become a core link in the production process. This article is based on deep transfer learning to build a connector recognition and detection hardware system. Using a layered design approach, the five layer architecture of "data layer preprocessing layer transfer learning detection layer post-processing layer application layer" is analyzed, and a small sample connector defect detection method that integrates data augmentation is proposed, which has high application value.

Keywords: Electronic connectors; Deep learning; Transfer learning; Machine vision; Identification and detection.

1. Introduction

In the context of the transformation of the electronic manufacturing industry towards intelligence, electronic connectors, as key components for device interconnection, have become a core link in the production process for quality inspection. Electronic connectors have the characteristics of a wide variety of models, fine structure, and high assembly density. Common identification and detection tasks include model classification, pin offset, shell damage, and other defect detection. With the popularization of customized production models, new types of connectors continue to emerge, and traditional detection methods face severe challenges [1-3].

Traditional inspection methods are primarily divided into manual inspection and rule-based machine vision inspection. Manual inspection relies on the experience of operators, resulting in issues such as low efficiency, strong subjectivity, and susceptibility to fatigue, making it difficult to meet the demands of large-scale automated production. Rule-based machine vision inspection achieves detection by setting manual rules such as grayscale thresholds and edge features, but it is sensitive to lighting variations and background interference. Additionally, adapting to new connector models requires redesigning rules, leading to poor flexibility.

In recent years, deep learning technology has achieved breakthrough progress in the field of object detection due to its powerful automatic feature extraction capability. Representative algorithms such as Faster R-CNN and YOLO have been widely applied in general scenarios. However, these methods require a large number of annotated samples for model training, while the collection of electronic connector samples is constrained by production cycles, confidentiality agreements, and other factors. The annotation

process also requires professional personnel, making it difficult to construct large-scale annotated datasets. Few-

shot transfer learning, which transfers knowledge learned from the source domain to the target domain with scarce samples, provides an effective solution to this problem. Its application in electronic connector recognition and detection can reduce sample dependency, improve detection efficiency, and hold significant theoretical and engineering value for advancing intelligent quality control in the electronic connector industry [4-6].

2. Design of Electronic Connector Identification and Inspection Hardware System

By analyzing the structure and function of electronic connectors, hardware system design and platform construction of machine vision systems can be carried out. The layout of the digital manufacturing platform includes hardware selection such as machine vision industrial cameras, light sources, and lens units, and the construction of an image acquisition system. The specific hardware structure of the electronic connector visual inspection system, as shown in Figure 1 and Figure 2, mainly consists of three industrial cameras, a light source, an industrial computer, a workbench, a feeding sorting device, a removal device, and visual inspection software. According to the actual requirements of the connector size, measurement accuracy, and defects, the camera's position on the glass mounting track, lens angle, light intensity, and other factors that affect the quality of image acquisition are adjusted; The workflow is as follows: feeding → machine vision image acquisition → deep transfer learning recognition and processing → defect product removal, etc.

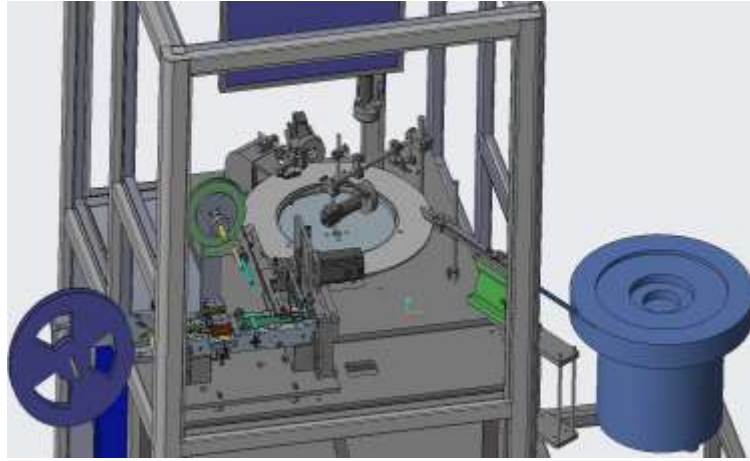


Figure 1 Construction of electronic connector visual inspection system platform



Figure 2 Outer CCD, top CCD, and inner CCD structures

3. Software system design based on deep transfer learning

The system based on deep transfer learning adopts a hierarchical design concept and constructs a five layer

architecture of "data layer preprocessing layer transfer learning detection layer post-processing layer application layer". The collaborative work of each layer realizes the end-to-end process from image input to detection decision. The overall architecture is shown in Figure 3:

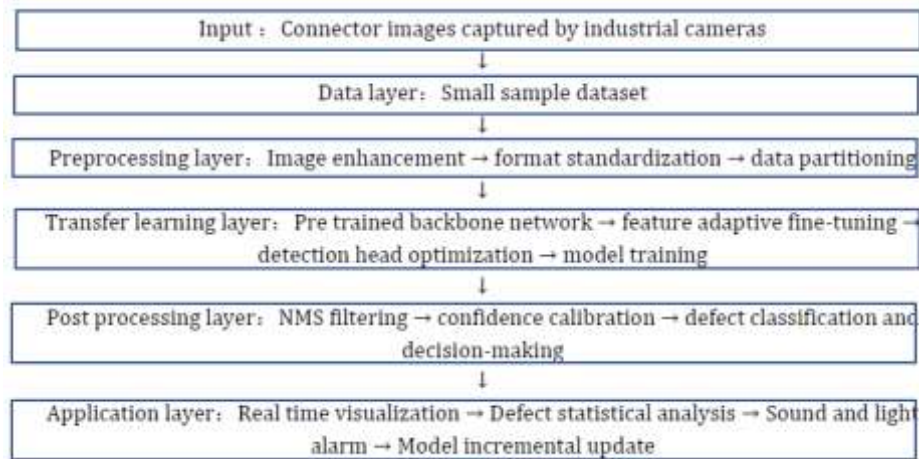


Figure 3 Overall framework of deep transfer learning

3.1. Data layer

Construction of small sample datasets. The quality of small sample datasets directly determines the effectiveness of transfer learning, which needs to take into account the diversity of electronic connector data, annotation accuracy, and category balance. The specific construction process is as follows:

3.1.1. Data collection plan

Acquisition equipment: Select industrial area array cameras with over 2 million pixels, paired with circular LED

light sources, and achieve real-time image transmission through GigE interface.

Collection content: Covering 3 types of core detection targets, including: 1) appearance defects such as bent pins, missing pins, scratches on the shell, damaged shell, and surface stains; 2) Installation deviations such as improper insertion, misplaced installation, and reverse installation; 3) Normal connector. To ensure data diversity, simulate changes in the pipeline environment during the collection process, including fine-tuning of lighting intensity, slight deviation of products, and small differences in background.

3.1.2. Data annotation and partitioning

Labeling tool: Use Labellmg labeling tool to label the bounding boxes and category labels of defect areas in Pascal VOC/YOLO format.

Dataset partitioning: Adopting a stratified sampling strategy, the dataset is proportionally divided into training set, validation set, and testing set to ensure that the distribution ratio of each type of defect in the three datasets is consistent, avoiding model overfitting caused by uneven data distribution in small samples.

3.2. Preprocessing layer

Enhance and standardize small sample data in the processing layer. The core problem of small sample datasets is insufficient data volume and lack of feature diversity. The combination strategy of "physical enhancement+digital enhancement" is used to expand the data scale, while standardization processing is used to improve model training stability.

3.3. Transfer Learning Detection Layer

Design a complete process plan for "pre training model selection feature adaptive fine-tuning detection head optimization training strategy design" to meet the needs of small sample connector detection, ensuring that the model has both high accuracy and real-time performance in small samples

3.3.1. Selection of pre trained models

The selection of target detection models needs to balance accuracy and real-time performance, combined with the deployment requirements of industrial assembly lines. YOLOv8 is chosen as the basic model, and pre trained weights on the dataset are used. These weights have learned universal target features and can be used as the basis for feature extraction in connector defect detection.

3.3.2. Model structure optimization

To adapt to connector defect detection tasks, YOLOv8 nano is optimized specifically. In terms of backbone network optimization, the first 80% of the convolutional layers in the backbone network can be frozen, and only the last 20% of the convolutional layers can be fine tuned to reduce the amount of parameter adjustment in small samples and avoid overfitting.

3.3.3. Integration strategy of transfer learning and meta learning

To further improve the generalization ability of the model under small sample size, a three-stage training process is designed by integrating transfer learning and meta learning ideas:

Phase 1: Pre training weight initialization. Pre train the weight initialization model using the COCO dataset while retaining the general object detection capability;

Phase 2: Domain adaptation and fine-tuning. Introducing a dataset of similar industrial parts for intermediate fine-tuning, reducing the domain distribution difference between pre training data and connector data, and improving feature transfer efficiency;

Phase 3: Meta fine-tuning. Learn prototype features for each type of defect on a small sample training set of connectors, and achieve classification by calculating the distance between test samples and prototype features, reducing dependence on sample size.

3.4. Post processing layer

The post-processing layer is responsible for result optimization and decision-making. The original results output by the detection model may have issues such as duplicate detection, inaccurate confidence, and false positives. By optimizing the post-processing process, the detection results can be ensured to produce accurate and reliable defect information.

3.5. Application Layer

The application layer function is system deployment and interaction design. It is necessary to meet the actual needs of industrial scenarios, achieve functions such as image acquisition, real-time detection, result display, statistical analysis, and support flexible deployment and model updates.

4. Electronic connector detection and identification methods and construction process

Aiming at the problems of low detection accuracy and slow model convergence in the application of deep learning to small sample connector datasets, a deep transfer learning based small sample connector surface defect detection method is designed for machine vision detection of board to board connectors, which integrates data augmentation. Image geometric transformation and improved CGAN network are used for data augmentation, as shown in Figure 4. NEU-DET is selected as the source dataset, and a YOLO based transfer model is trained on the small sample connector dataset using model transfer method, as shown in Figure 5, to explore the optimal training strategy for the transfer model; Then, the effectiveness of model transfer was verified through experiments, and the optimal transfer layer for model transfer was determined.

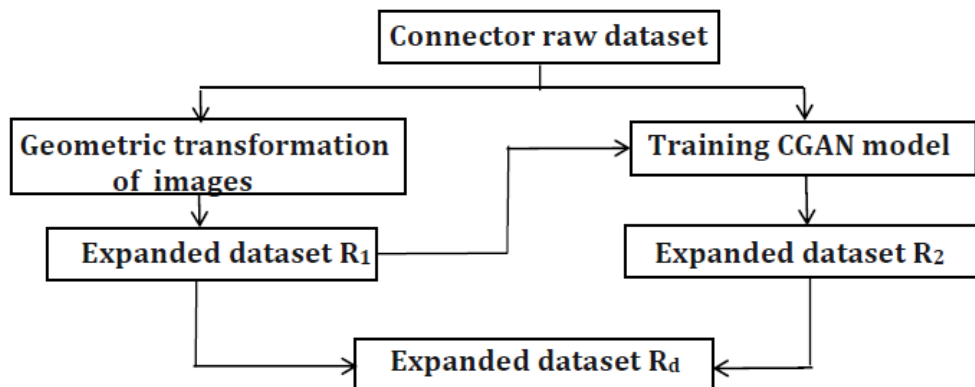


Figure 4 Data Enhancement Process Diagram

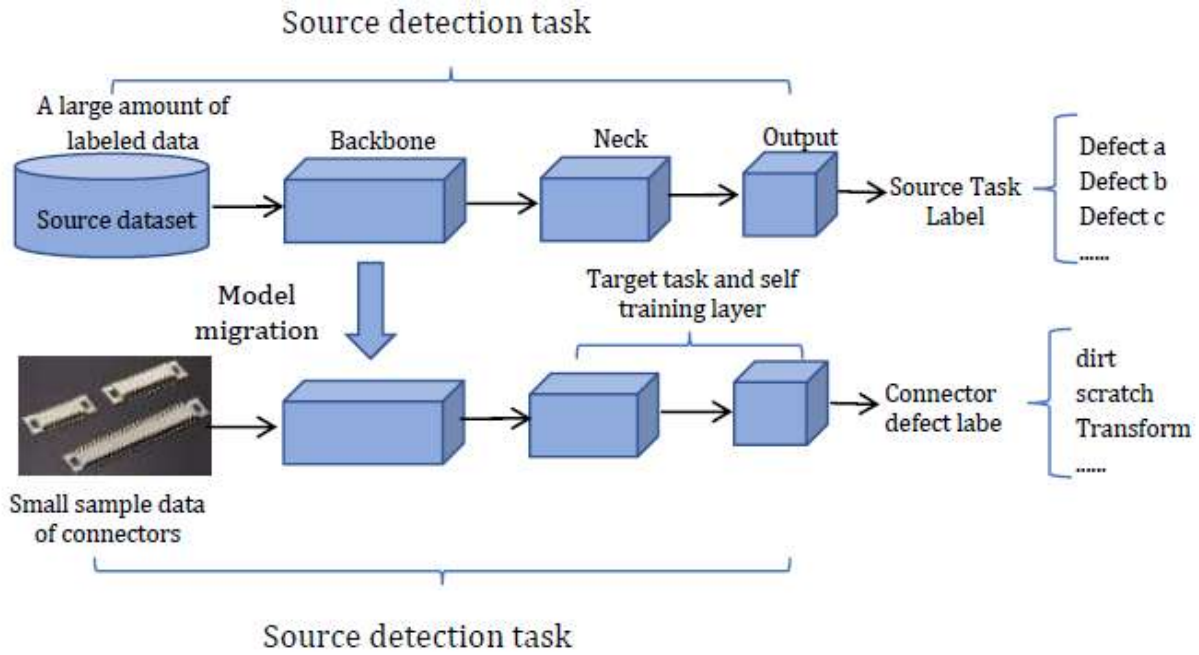


Figure 5 YOLO Network Model Migration Process

5. Conclusion

This article takes electronic connectors as the research object, builds a hardware system design for electronic connector recognition and detection, takes deep transfer learning as the starting point, adopts a layered design concept for software design, and analyzes the five layer architecture of "data layer pre-processing layer transfer learning detection layer post-processing layer application layer". A small sample connector surface defect detection method based on deep transfer learning with data augmentation is proposed for board to board connector detection and recognition. The optimal training strategy for the transfer model is explored, which has high promotion and application value.

Acknowledgements

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