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Defect Inspection of Voltage Control IC in Electric Vehicle Chargers Using Surface-Mount Technology †

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Abstract

Ensuring the reliability of solder joints is essential for stable operation in electric vehicle chargers, particularly for components assembled using surface-mount technology. Therefore, we developed a defect inspection system for welding joint defects using a Faster Region-based Convolutional Neural Network model to classify results as insufficient defect, shifting defect, and normal (pin-qualified) on voltage control IC pins. The model was trained on 72,000 pin samples and achieved a training accuracy of 99.93%. Evaluation of 65,700 pin samples resulted in an accuracy of 98.89%. The experimental results demonstrate that the system provides stable recognition of reflective solder joints, reliably identifies critical pin-level defects, and is suitable for deployment in practical inspection environments.

Keywords: Faster R-CNN; defect inspection; voltage control IC; welding joint defect

1. Introduction

The rapid proliferation of electric vehicles (EVs) necessitates increasingly stringent reliability standards for energy conversion systems. In this context, the stability of the EV charger heavily relies on the quality of solder joints produced via surface-mount technology (SMT) assembly. Even minor soldering flaws can negatively impact power transfer efficiency and long-term durability under harsh operating conditions. As noted by Eisentraut et al. [1], the existing industrial visual quality inspection is challenging due to highly reflective surfaces and the shrinking size of the solder regions. This mandates the development of more-precise automated methods for the recognition of these microstructures in advanced manufacturing.

Voltage control IC (VCIC) serves as the controller for the secondary-side synchronous rectifier in the EV charger system. The exposed terminals of the SMT-packaged VCIC significantly heighten the sensitivity of solder quality to positional misalignment and solder volume variation. As Mendizabal-Arrieta et al. [2] indicated, the identification of these micro-flaws is highly challenging; these defects often possess non-obvious boundaries and are prone to confusion under industrial lighting conditions.

Deep learning-based quality inspection has emerged as a robust solution for capturing subtle changes in solder joint geometry. Ren et al. [3] introduced the Faster Region-Convolutional Neural Network (Faster R-CNN) model, which utilizes a Region Proposal Network, enabling accurate object localization while preserving geometric fidelity. Shen [4] and Fan et al. [5] found the superior performance of this architecture in inspecting defects

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on electronic components and connectors. The two-stage mechanism of Faster R-CNN helps maintain high accuracy even with low-contrast, fine-grained objects.

In contrast, single-stage models, such as those in the You Only Look Once (YOLO) family, are favored for their speed. Recent variants, including YOLOX by Kong et al. [6], YOLO-AFK by Wang et al. [7], and the improved YOLOv8 by Zhang et al. [8], enhanced their identification capabilities. However, these models show limitations in defining precise solder boundaries on highly reflective surfaces compared with the R-CNN family. Therefore, to maximize the accuracy of critical components such as VCIC, we used Faster R-CNN for the automated identification of insufficient defects and shifting defects, ultimately ensuring reliable quality control in EV charger SMT production.

2. Classification of Automatic Component Classification (ACC) Defect

The ACC module is responsible for identifying the soldering condition of each VCIC pin before determining the overall device quality. In this study, defect inspection is performed at the pin level to ensure reliable assessment of solder joint quality in EV charger power modules. As illustrated in Figure 1, each pin of the VCIC is individually annotated using a bounding box, enabling fine-grained localization and classification of solder joint conditions. The dataset was collected from an industrial SMT production line using a high-resolution optical inspection system with diffused lighting to reduce surface reflections.

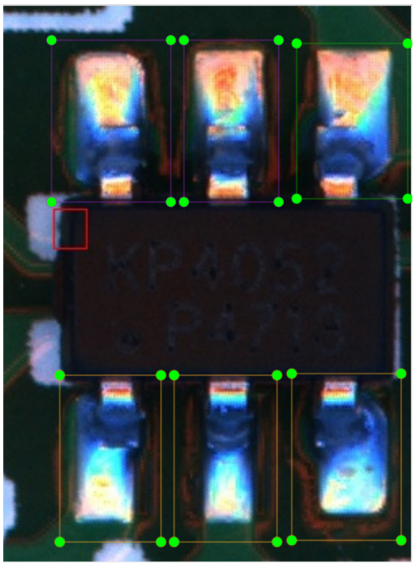
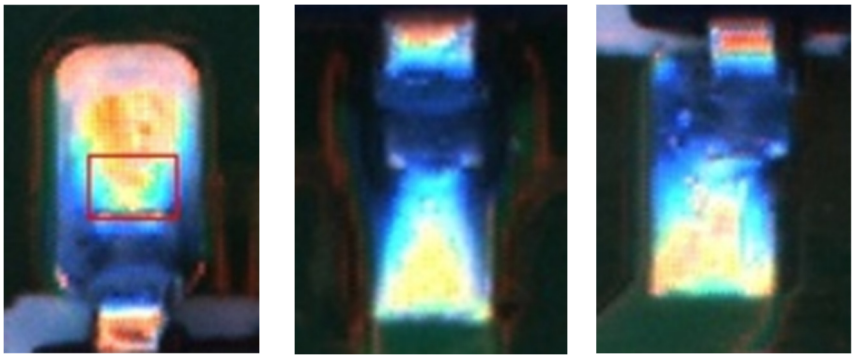


Figure 1. Bounding box image of VCIC pins on a printed circuit board.

Figure 2 illustrates the three classes of types used: pin-qualified, insufficient defect, and shifting defect. The pin-qualified (a) class represents standard welds with an evenly coated tin surface, and the pins are correctly aligned with the pad. The insufficient defect (b) layer describes cases of tin deficiency, usually with coverage of less than 75% of the pad area or with a pronounced gap. The shifting defect (c) layer occurs when pin leads are displaced from the pad center by a significant distance, usually exceeding 1/3 of the pad width.

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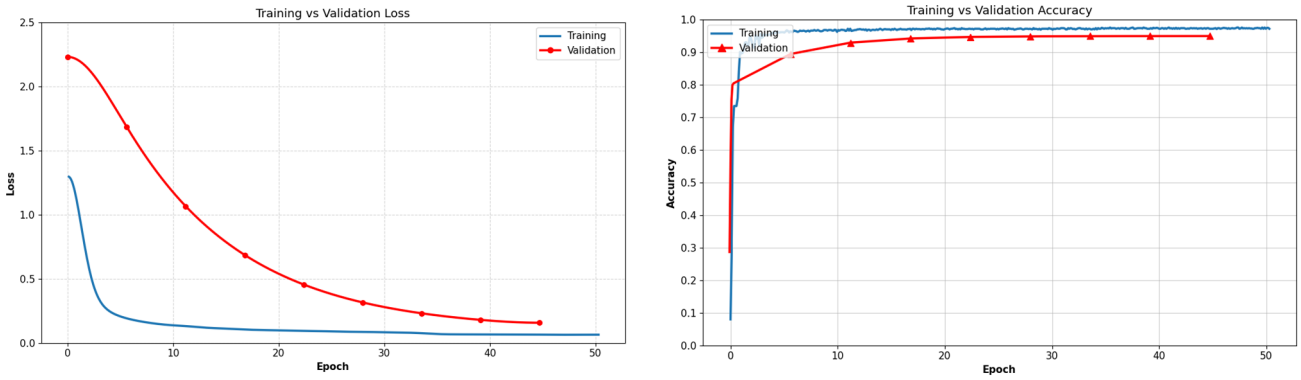


(**a**) (**b**) (**c**)

Figure 2. Types of solder joints: (**a**) Pin-qualified; (**b**) insufficient defect; (**c**) shifting defect.

3. System Training and Validation

The Faster R-CNN model was trained with a batch size of 4, corresponding to approximately 50 epochs over the dataset of 72,000 pin samples for 12,000 VCIC. With three labels, pin-qualified, insufficient defect, and shifting defect, the model exhibits stable learning behavior throughout the training stage, as shown in Figure 3.



(**a**) (**b**)

Figure 3. Faster R-CNN model training and validation process. Training vs. validation loss: (**a**) Training accuracy; (**b**) validation accuracy.

The loss chart (Figure 3a) shows that the training loss decreases rapidly and converges to a low value. Furthermore, the validation loss closely tracks the training trend, indicating that the model generalizes well and avoids significant overfitting. Regarding the accuracy chart (Figure 3b), the training accuracy improves steadily, reaching 97%. Correspondingly, the validation accuracy, measured by mAP, achieves a high, robust level of 90.4%. These experimental results confirm the stability and reliability of the proposed system in classifying solder joint conditions on VCIC components.

4. Testing Defect Inspection

The performance of the trained Faster R-CNN model was evaluated on a comprehensive test dataset. The dataset consists of 10,950 VCIC units, corresponding to a total of 65,700 individual pins. The evaluation aims to determine the model's ability to identify specific defect types and assess the final quality status of each component. Based on the outcomes of testing numerous single-pin samples, a confusion matrix at the VCIC pin level was created, reflecting trustworthy assessment data (Table 1). It demonstrates that the model runs steadily and accurately up to 99.96%. Because of their identical geometry

and reflective surface properties, pin-qualified (PQ) samples exhibit higher classification reliability than insufficient defect (ID) and shifting defect (SD) samples.

Table 1. Confusion matrix of the pins.

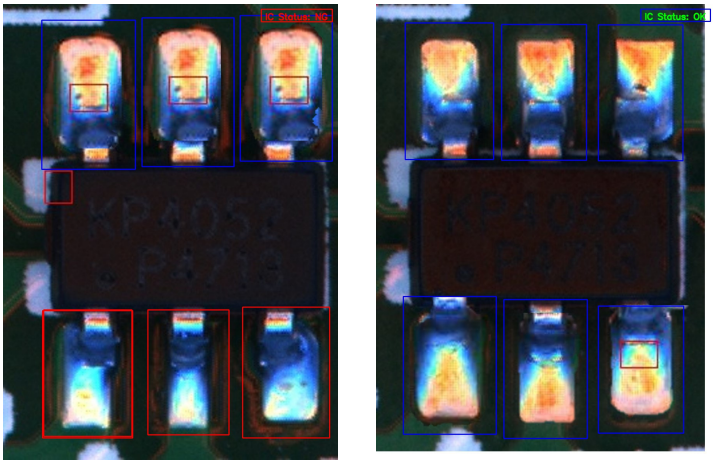
Prediction	PQ	ID	SD	Recall
PQ	65,425	5	2	99.98%
ID	5	135	6	92.46%
SD	2	2	118	96.72%
Precision	99.98%	95.07%	93.65%	Accuracy = 99.96%

With an overall accuracy of 99.89% at the IC level, Table 2 displays the confusion matrix at the VCIC level. This demonstrates that the model is sensitive to situations in which both ID and SD mistakes occur, reliably identifies Normal ICs, and effectively differentiates between both (ID + SD) errors. The model's great reliability for quality control is demonstrated by the extremely low number of instances of defective ICs being misclassified.

Table 2. Confusion matrix of the chips.

Prediction	Qualified	ID	SD	ID + SD	Recall
Qualified	10,838	0	0	2	99.96%
ID	0	28	1	2	90.32%
SD	0	2	29	0	93.54%
Both	1	2	0	45	93.75%
Precision	99.99%	87.50%	96.67%	91.83%	Accuracy = 99.89%

Visual results of the model on the test set are shown in Figure 4, demonstrating that the model accurately localizes and classifies pin-qualified, insufficient defect, and shifting defects.



(**a**) (**b**)

Figure 4. Inspection results of the VCIC: (**a**) No-good sample; (**b**) OK sample.

Beyond defect classification, the system's capability to make final decisions for good samples of VCICs was evaluated. A device is considered OK only when all six pins are classified as pin-qualified (PQ). Conversely, if any pin is identified as defective, the device is labeled as NG. Table 3 presents the final classification results at the VCIC level. Among

10,950 tested VCICs, the model correctly classified 10,838 OK samples and 109 no-good samples, resulting in an overall device-level accuracy of 99.97%. Only three VCICs were misclassified, including one defective chip incorrectly predicted as an OK sample and two qualified chips rejected as no-good samples, indicating a very low false-acceptance rate suitable for industrial inspection. Overall, the experimental results demonstrate that the proposed system provides stable recognition of reflective solder joints, reliably identifies critical defects, and is suitable for deployment in practical SMT inspection environments.

Table 3. VCIC classification results (OK/NG).

Prediction	OK Sample	No Good Sample	Recall (%)
OK	10,838	2	99.98%
NG	1	109	99.09%
Precision (%)	99.99%	98.19%	Accu = 99.97%

5. Conclusions

We developed a robust automated inspection system. The Faster R-CNN model of the system achieved a training accuracy of 99.93% and a testing accuracy of 99.89% at the VCIC level. Based on the final OK/NG decision rule, the production yield reached 98.97%, confirming the practical applicability of the proposed method in SMT inspection for EV charger production.

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Informed Consent Statement: Since this study did not involve individual human participants or identifiable personal data, obtaining informed consent was not required.

Data Availability Statement: Researchers who are interested in the data or code used in this study may contact the corresponding author.

Conflicts of Interest: The authors confirm that there are no conflicts of interest that could have influenced the results of this study.

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