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DIAGNOSTICS OF PRINTED CIRCUIT BOARDS BASED ON NEURAL NETWORK MODELS

Current article deals with an Interpretable YOLOv11-Grad-CAM Framework for Enhanced Automated Optical Inspection of Printed Circuit Boards. The critical demand for reliability in electronics manufacturing underscores the need for advanced quality control. Automated Optical Inspection of printed circuit boards remains a cornerstone of this process. However, conventional methods, including template matching and manual inspection, are often inadequate in terms of robustness and scalability for modern production volumes. Although deep learning models have demonstrated superior performance in defect detection, their inherent lack of interpretability poses a significant barrier to adoption in high stakes industrial environments. This study bridges this gap by introducing an interpretable deep learning framework that integrates the state-of-the-art YOLOv11n architecture for real time defect detection with Gradient-weighted Class Activation Mapping for model explainability. This integration provides transparent, visual justification for the model predictions by highlighting discriminative features. The proposed framework was evaluated on the public HRIPCB dataset, which includes 1386 images spanning six common defect classes. It achieved a mean average precision (mAP@0.5) of 87.4 percent, significantly outperforming both a traditional SVM classifier and a YOLOv8n baseline. The principal contribution of this work is the novel and systematic fusion of high-speed object detection with explainable AI principles, tailored for PCB inspection. By simultaneously achieving high accuracy, real time inference, and critical interpretability, this framework presents a viable and trustworthy solution for industrial AOI systems. The goal of this study is to develop an interpretable defect detection framework for PCB automated optical inspection that delivers both high accuracy and transparent decision making. To achieve this goal, the following tasks were performed: selection and configuration of the YOLOv11n model for PCB defect detection; training and evaluation on the HRIPCB dataset; integration of Grad-CAM into the detection pipeline for visual explanation; comparison against baseline methods including SVM and YOLOv8n; and quantitative performance measurement using mAP, precision, and recall alongside qualitative documentation through visual heatmaps.

Keywords: quality control; defect detection; neural networks; artificial intelligence; printed circuit boards; Grad-CAM; YOLO11n; deep learning.

Introduction

Printed circuit boards are a key part of most modern electronic devices. They are used in consumer electronics, including smartphones and laptops, as well as in safety critical systems in automobiles, aerospace equipment, and medical devices. The reliability of these systems depends directly on the quality of the PCBs that connect and support electronic components. Even small defects, such as a missing hole, a copper spur, or a spurious trace, may cause short circuits, open connections, or complete system failure. As demand for electronic products grows, PCB manufacturers need to increase production throughput while keeping a very low defect rate.

Traditionally, PCB quality control has relied on manual inspection or template based Automated Optical Inspection. Manual inspection is limited by fatigue, subjectivity, and low scalability in industrial production. Template matching methods are also limited, since they are sensitive to changes in illumination, rotation, and image noise. As a result, they often produce a high number of false positives. These methods can detect some defects, but their limitations make them less suitable for large scale and high-speed production environments. Deep learning methods have become a strong alternative due to recent progress in machine learning and computer vision. Convolutional Neural Networks can learn hierarchical features directly from raw data and usually perform better than

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handcrafted feature extraction methods. Among deep learning models, the YOLO family of object detectors is widely used in real time defect detection because it provides a good balance between accuracy and inference speed. At the same time, such models are often treated as black box systems. For engineers and quality assurance specialists, it can be difficult to understand why the model makes a particular prediction. This limits the adoption of such approaches in safety critical and high responsibility applications.

To reduce this limitation, explainable AI methods, including Gradient-weighted Class Activation Mapping [13], can be used. Grad-CAM generates heatmaps that show which image regions had the strongest influence on the model decision. When detection results are combined with visual explanations, engineers can check model predictions, notice possible misclassifications, and better assess whether the system can be trusted in practical inspection tasks.

In this work, we propose a framework that combines the YOLO11n model with Grad-CAM visualization for PCB defect detection on the HRIPCB dataset [4]. HRIPCB contains 1386 annotated PCB images from six defect categories and provides a useful benchmark for defect detection algorithms. YOLO11n was selected because of its lightweight architecture, which makes it suitable for edge deployment, while still providing high detection accuracy. Grad-CAM was added to make defect localization more transparent and easier to interpret by a human operator.

The main contributions of this study are the following. First, we evaluate YOLO11n on the HRIPCB dataset and compare its detection performance with prior baselines. Second, we include Grad-CAM in the defect detection pipeline to support explainable PCB inspection. Third, we report both quantitative results, including mAP, precision, and recall, and qualitative results in the form of visual heatmaps.

The proposed approach combines real time defect detection with visual interpretability. This makes the method useful for PCB quality control tasks where both accuracy and the ability to inspect the model decision are important.

Publication analysis

The problem of defect detection in printed circuit boards (PCBs) has been studied for decades. Early studies used template matching and image subtraction between reference and test boards [2,11]. These methods worked in simple cases, but they were sensitive to illumination and scaling. This often led to a high number of false alarms.

With the development of machine learning, shallow classifiers such as Support Vector Machines (SVMs) [1] and Random Forests [12] were used for PCB defect detection. They relied on handcrafted features, including HOG, LBP, and wavelets [16]. These methods were more robust than template matching, but they still depended on manual feature engineering and had difficulties with complex or irregular defects.

The use of deep learning and convolutional neural networks (CNNs) changed this research area considerably. Datasets such as DeepPCB (2018) [14] and HRIPCB (2020) [4] provided benchmarks for evaluating CNN-based models. HRIPCB introduced 1386 high-resolution PCB images annotated with six defect types, making it a more challenging benchmark for defect detection algorithms.

Recent studies have also considered modifications of the YOLOv8 architecture for PCB defect detection. Liu et al. [5] proposed the YOLO-BFRV model, which includes a bidirectional feature pyramid (BIFPN), a lightweight backbone (FasterNet), a re-parameterized head (RepHead), and Varifocal Loss to improve accuracy and efficiency. The model reports strong results, but its outputs remain difficult to interpret.

These limitations, especially the lack of explainability, motivate the use of YOLO11n together with Grad-CAM. This combination is considered in this work as a way to balance accuracy, speed, and transparency. Along with detection performance, researchers have paid more attention to explainable AI (XAI) in manufacturing. Interpretability is important for trust in automated systems, especially in safety-critical applications. Grad-CAM [13] is one of the commonly used methods for this purpose. It generates heatmaps that indicate the image regions most relevant to the model's

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decision. The method has been applied in medical imaging, autonomous driving, and quality control, which makes it suitable for further use in PCB inspection tasks.

In PCB defect detection, explainability is still studied less than detection accuracy. Park et al. (2023) analyzed factors that affect the training stability of deep learning models for PCB inspection, including data imbalance, image contamination, and model selection. They also provided practical guidelines for industrial deployment. However, their work focused mainly on training robust detectors rather than explaining their decisions [8]. Ge et al. (2025) proposed YOLO-MSD, a lightweight detector with multi-scale feature fusion for industrial surface defects. The model showed strong results on PCB/HRIPCB benchmarks, but the study also focused on accuracy and efficiency rather than explainable outputs [3]. Overall, recent works mostly improve speed and mAP, while the transparency of predictions remains insufficiently addressed. This motivates the integration of Grad-CAM into a YOLO-based pipeline.

Research gap. To date, there has been no systematic integration of a state-of-the-art YOLO model with Grad-CAM for PCB defect detection. Previous works have mainly focused either on improving detection accuracy or on limited explainability, but these directions have rarely been combined.

This study addresses this gap in three ways. First, YOLO11n is applied to the HRIPCB dataset to achieve high detection accuracy with real-time inference. Second, Grad-CAM is integrated into the detection pipeline to generate interpretable heatmaps for defect localization. Third, YOLO11n is trained on HRIPCB with synthetic augmentation to demonstrate its detection capability and provide a basis for future comparisons with prior baselines.

By combining real-time detection with explainable visualization, this work contributes to the development of Automated Optical Inspection (AOI) systems that are efficient, more transparent, and easier to validate in practical PCB quality control tasks.

Materials and Methods

For this study, the HRIPCB dataset [4] was selected because it is a publicly available benchmark for PCB defect detection. It includes 1386 annotated images of bare printed circuit boards with six defect types: *missing hole*, *mouse bite*, *open circuit*, *short*, *spur*, and *spurious copper*. These defects correspond to common and critical problems that may occur in PCB production lines.

Compared with earlier datasets such as DeepPCB, HRIPCB contains a wider variety of board layouts, defect types, and imaging conditions. This makes it more challenging and closer to practical inspection conditions. The dataset is annotated with bounding boxes, so it is suitable for object detection tasks rather than only image classification.

To prepare the dataset for YOLO training, the annotations were converted into YOLO format: class, cx, cy, w, h. Several data augmentation techniques were applied to improve generalization. Mosaic augmentation was used to expose the model to several image contexts during training. Random rotations and flips simulated different board orientations on a production line. Brightness and contrast jitter reduced sensitivity to illumination changes. Copy-paste augmentation was used to balance underrepresented classes, including spur and mouse bite. These transformations made the model more robust to variations that may appear in manufacturing conditions.

YOLO11n was selected as the main detection architecture for several reasons. First, its lightweight design makes it the smallest and fastest model in the YOLO11 family, which is useful for deployment on edge devices. Second, its real-time inference capability with high FPS on GPU fits the practical requirements of industrial AOI systems. Third, although larger variants such as YOLO11m and YOLO11x may give small improvements in accuracy, YOLO11n provides a better trade-off between detection performance and computational cost.

The model architecture includes a lightweight backbone for feature extraction, a neck for multi-scale feature fusion, and multi-scale detection heads. The neck improves sensitivity to small PCB defects, while the detection heads generate predictions at several pyramid levels, such as P3/8 to P5/32. This allows the model to localize defects of different sizes. The training configuration was

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selected empirically. An input resolution of 640 px was used to balance the visibility of small defects and inference speed. The model was trained for 200 epochs, which was sufficient for convergence on the HRIPCB dataset. A batch size of 8 was used due to GPU memory limitations, while still giving stable gradient estimation. AdamW was selected because it provides decoupled weight decay and is commonly used in modern deep learning training pipelines [6]. A Cosine Annealing learning rate schedule was also used to gradually reduce the learning rate, limit overfitting, and improve final accuracy. Mixed Precision Training (AMP) reduced memory consumption and accelerated training without degrading accuracy. In the preliminary experiments, these settings gave the best balance between speed and detection quality.

One of the main contributions of this study is the integration of Grad-CAM into the detection pipeline. Grad-CAM, or *Gradient-weighted Class Activation Mapping*, is an explainability method that shows which image regions have the strongest influence on the decision of a deep neural network.

In PCB defect detection, YOLO11n provides bounding boxes around predicted defects. However, bounding boxes alone do not explain why the network classified a given area as defective. Grad-CAM adds this information by generating an attention heatmap. Warmer colors, such as red and yellow, indicate higher importance, while cooler colors, such as blue and green, indicate lower influence.

The explanation pipeline combines YOLO11n with Grad-CAM. First, YOLO11n localizes candidate defects and returns class-conditioned detections. For each detection, Grad-CAM back-propagates the corresponding score through the final convolutional layers and forms a spatial saliency map. This map shows the regions that contributed most to the prediction. The saliency map is then normalized, upsampled to the input resolution, and overlaid on the PCB image. As a result, the prediction is accompanied by a localized explanation that can be interpreted by an engineer.

This integration improves the transparency of the detection process. Engineers can inspect which regions influenced the model's decision. The heatmaps also support validation, since they help check whether the model focuses on actual defects rather than background artifacts. In addition, Grad-CAM can help during debugging by showing whether errors are related to noise, copper texture, or small irregularities.

Thus, Grad-CAM complements YOLO11n by adding visual explanations to the detector's output. This helps combine detection accuracy with a more transparent decision-making process in industrial PCB inspection.

Results

The YOLO11n model was trained and evaluated on the HRIPCB dataset. Its performance was assessed using standard object detection metrics, including precision, recall, and mean Average Precision (mAP). A set of diagnostic visualizations was also generated to better understand the behavior of the model.

YOLO11n achieved **mAP@0.5 = 0.874**, **mAP@0.5:0.95 = 0.483**, **Precision = 0.907**, and **Recall = 0.765**. These values indicate that the model provides accurate predictions and remains reasonably stable across different IoU thresholds. The per-class results are summarized in Table 1.

The model behaves as a precision-oriented detector, with lower false-positive rates prioritized over exhaustive coverage. The missing hole class is recognized almost perfectly (P=1.000, R=0.969, mAP@0.5=0.994), which is consistent with its large and distinctive morphology. Mouse bite has high precision (0.873), but lower recall (0.756), which suggests that some small or subtle instances are missed. Open circuit and Short also show high precision (0.967 and 0.940), with moderate recall values of 0.731 and 0.700.

This points to conservative decision thresholds that reduce false positives but also lower sensitivity. Spur is the most difficult class (R=0.604; mAP@0.5=0.771), probably due to its fine, irregular geometry and weak local contrast.

In contrast, Spurious copper has high recall (0.827), but lower precision (0.726), which may indicate over-detection of copper texture patterns as defects.

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Table 1

Per-class detection performance

Defect class	Precision	Recall	mAP@0.5	mAP@0.5:0.95
Missing hole	1.000	0.969	0.994	0.606
Mouse bite	0.873	0.756	0.859	0.460
Open circuit	0.967	0.731	0.888	0.488
Short	0.940	0.700	0.870	0.474
Spur	0.937	0.604	0.771	0.372
Spurious copper	0.726	0.827	0.862	0.499
Overall	**0.907**	**0.765**	**0.874**	**0.483**

Overall, YOLO11n shows balanced performance across the defect classes. It performs better on larger and more distinctive defects, while smaller and texture-like anomalies remain more difficult.

The confusion matrix (Figure 1) describes class-level behavior beyond the aggregate metrics. The dominant diagonal shows that most defect categories are recognized correctly, with missing hole close to perfect detection. The remaining off-diagonal errors are mainly concentrated between spur and spurious copper. This is expected, since both classes may have a similar appearance: thin and irregular copper protrusions or texture-like copper residues with comparable local scale.

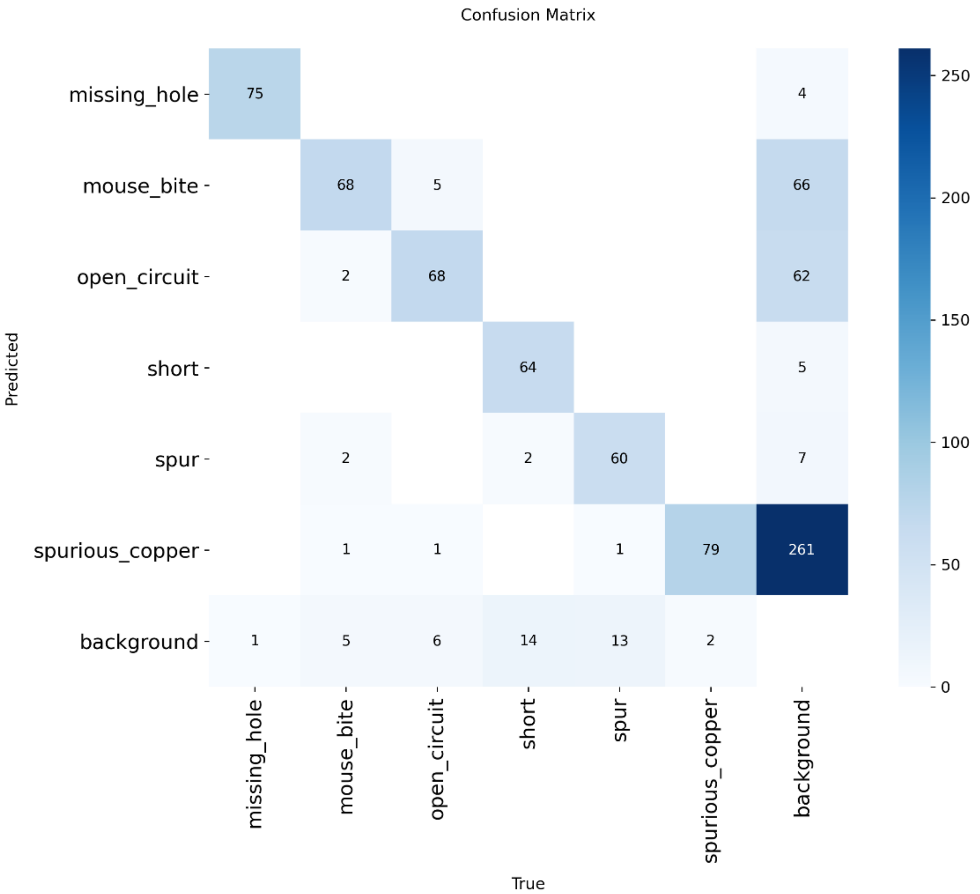

Fig.1. Confusion matrix

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The normalized confusion matrix (fig. 2) makes this overlap clearer by showing errors relative to the number of samples in each class. Taken together, these results suggest that the remaining errors are caused less by general image noise and more by shape and texture ambiguity between closely related defect types.

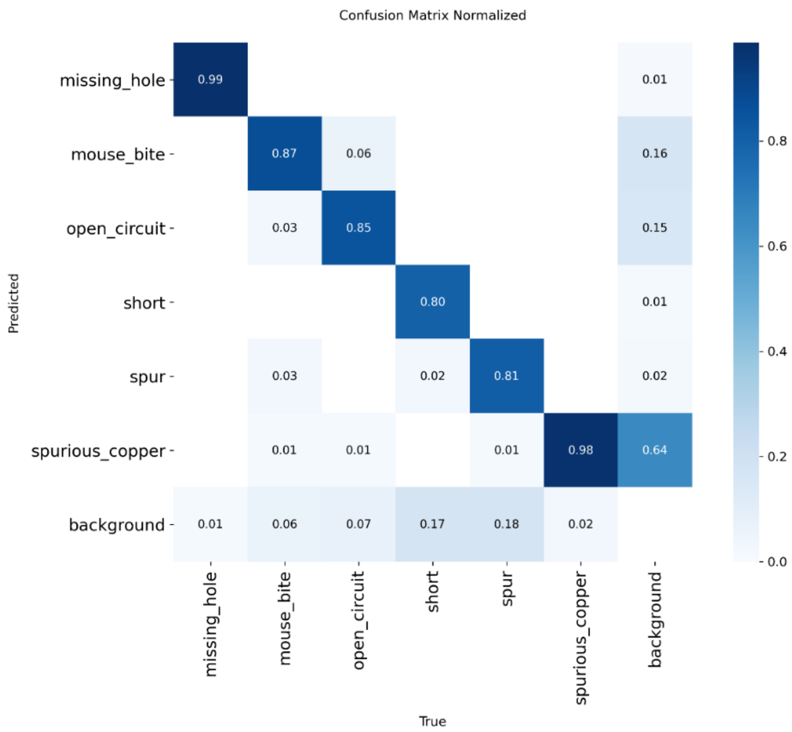

Fig.2. Confusion matrix normalized

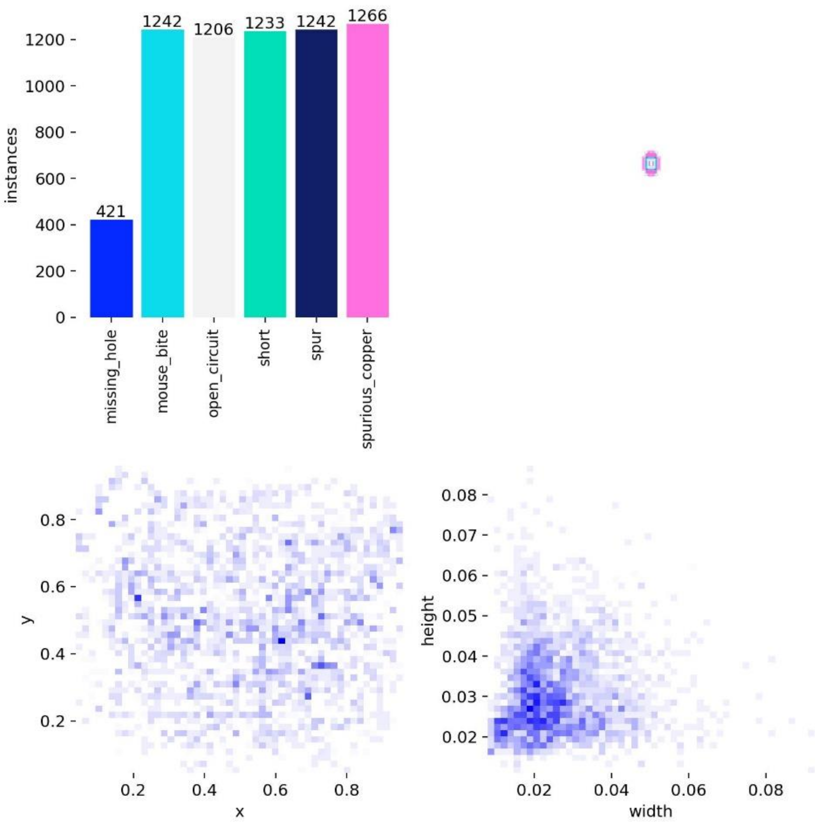

Fig.3. Distribution focal loss

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The optimization dynamics (fig. 3) show stable convergence. Box regression, classification, and distribution-focal losses decrease during training and give smaller improvements near the final epochs. The validation curves remain above the training curves, but follow a similar trend without late-epoch divergence. This suggests limited overfitting and acceptable generalization. The remaining train-validation gap is consistent with the heterogeneity of unseen PCB samples, the subtle morphology of some defects, and the finer localization required by the distribution-focal objective.

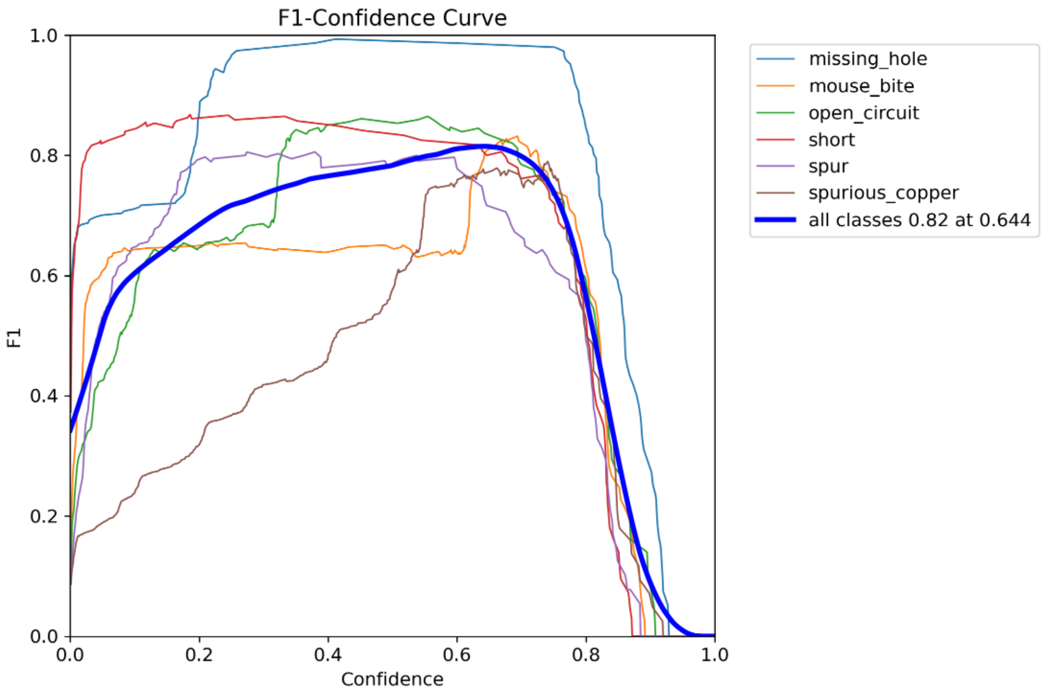

Fig.4. F1-Confidence curve

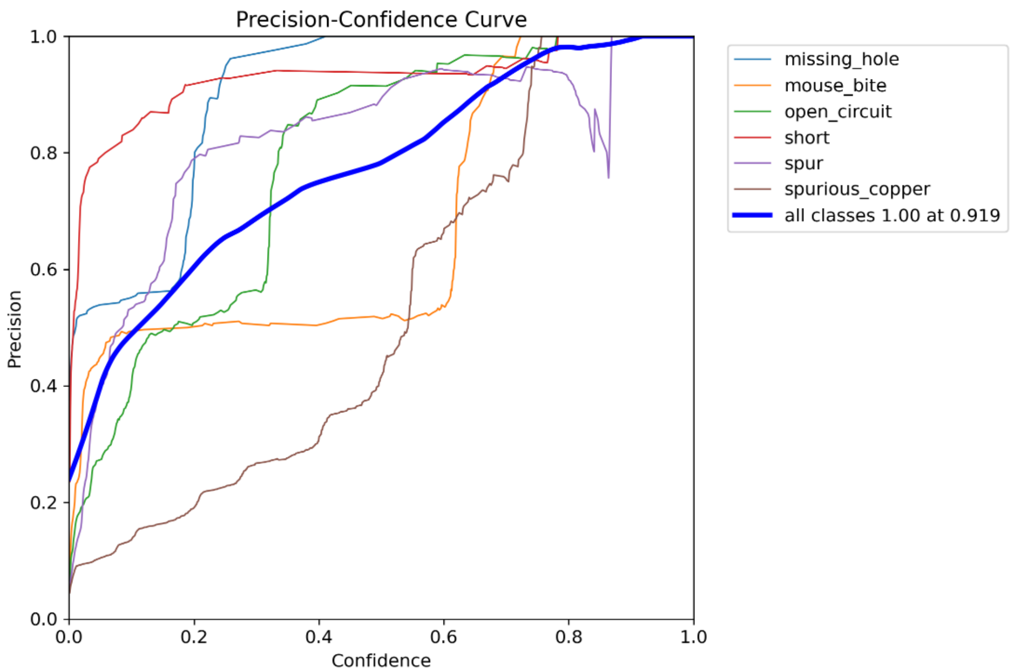

Fig.5. Precision-Confidence curve

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Precision and recall show mild epoch-to-epoch variability at the beginning of training. Later, both metrics become more stable and approach plateaus in the final epochs. The remaining fluctuations can be explained by batch composition and thresholding effects. The long-term trend indicates convergence to the final evaluation operating point.

The overall precision and recall values fluctuated slightly during training, but stabilized toward the final epochs and converged close to the reported values.

Figure 4 shows the F1 score as a function of confidence. At low thresholds, the detector retrieves most positive samples, but also produces more false alarms. Increasing the threshold suppresses spurious detections. After a certain point, the gain in precision is offset by the loss in recall, which leads to a single clear F1 maximum.

Figure 5 shows precision as a function of confidence. Precision increases with the threshold and saturates for the highest-scoring predictions. This indicates that high-confidence outputs are generally reliable.

Figure 6 shows recall as a function of confidence. Recall decreases as the threshold increases, which confirms the expected precision-recall trade-off. Stricter acceptance criteria inevitably remove some true defects from the final predictions.

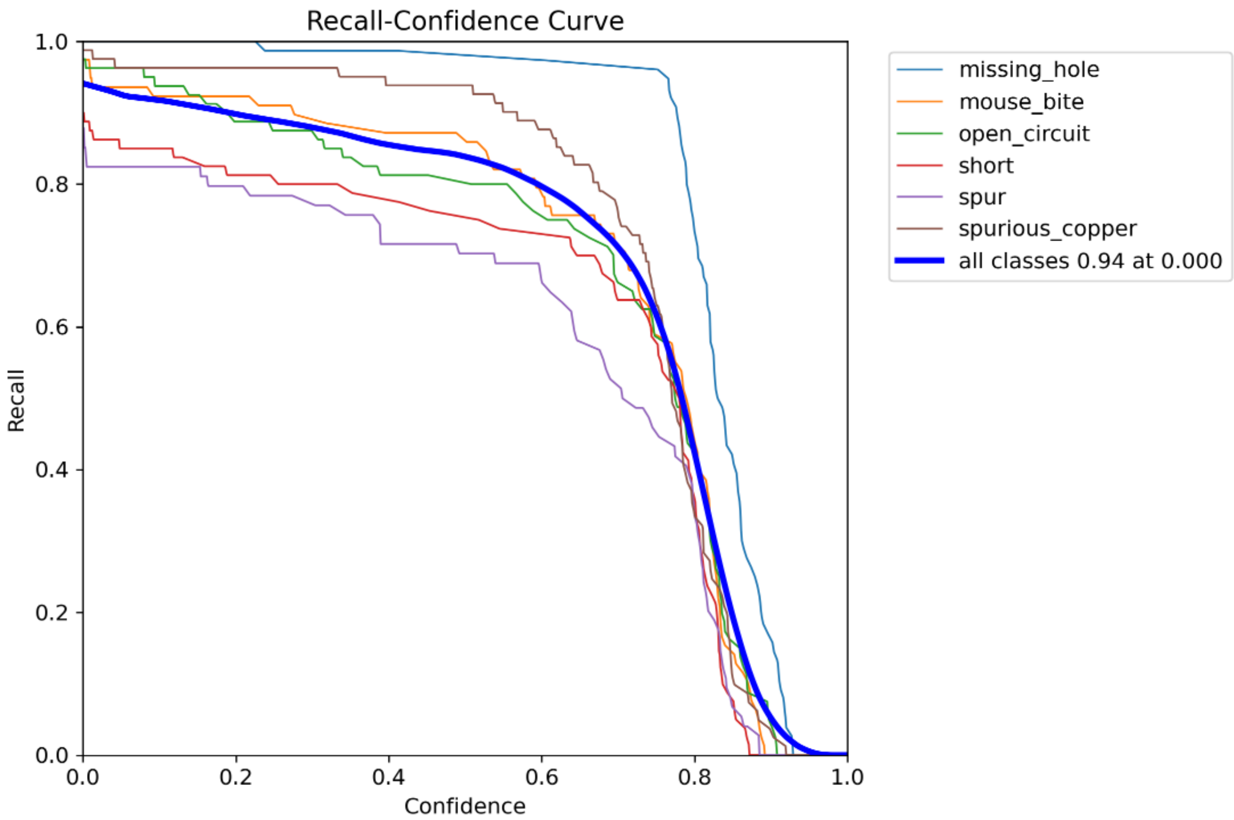

Fig.6. Recall-Confidence curve

Figure 7 presents the PR curve. The curve covers a large area, which indicates good separability across the defect categories rather than performance dominated by only one class. Operating points near the F1 maximum usually correspond to the high-gain region of this curve.

In addition to bounding boxes, Grad-CAM [13] was used to visualize the model's decision-making process. Figure 8 presents side-by-side comparisons. The left panel shows standard YOLO11n predictions with bounding boxes and class labels. The right panel shows Grad-CAM heatmaps overlaid on the PCB image, highlighting the regions that contributed most to each detection.

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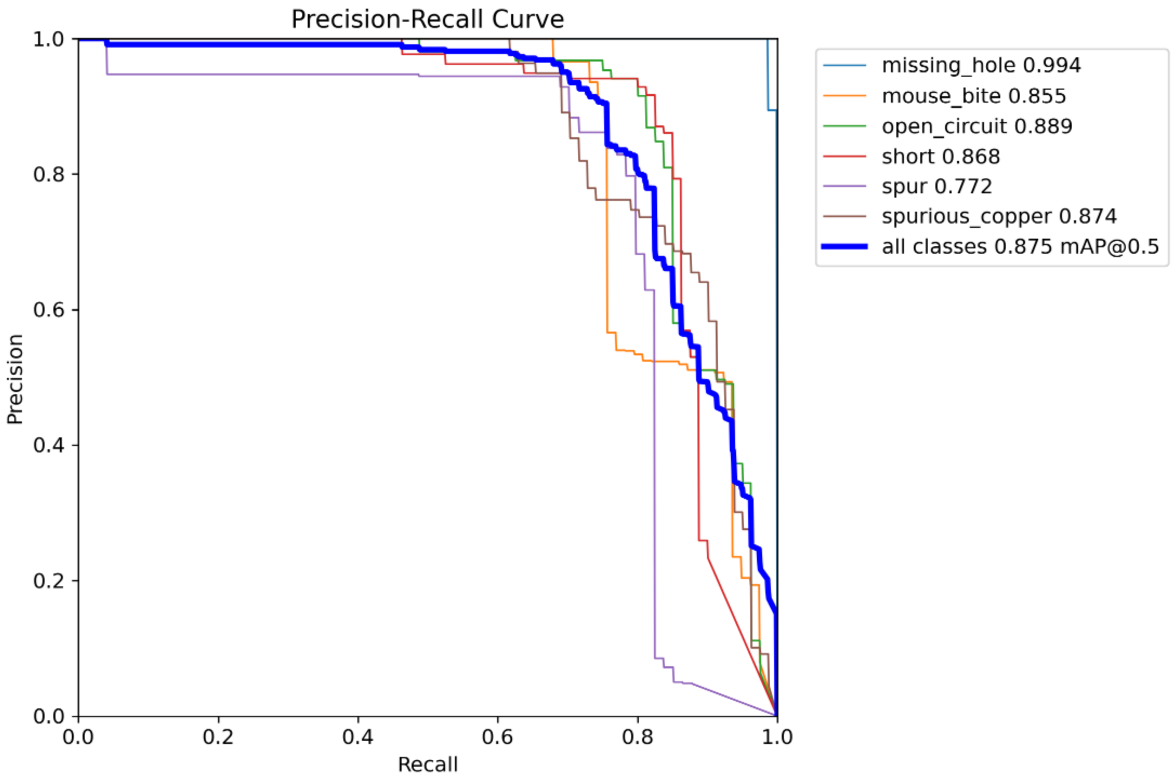

Fig.7. Precision–Recall curve

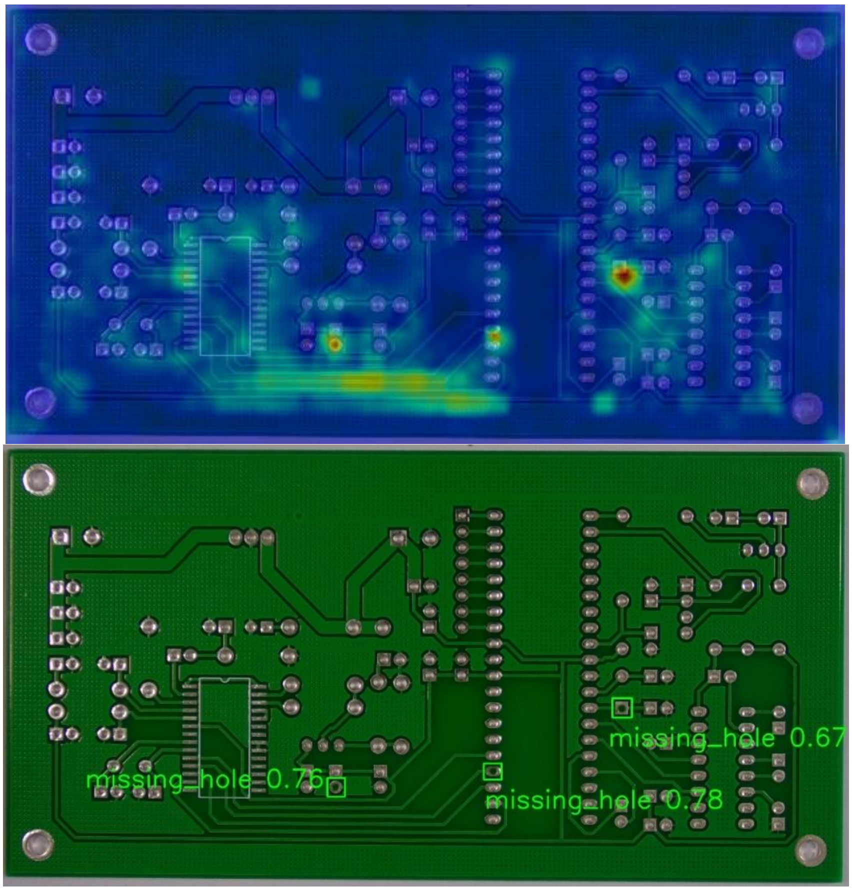

Fig.8. Comparision between Yolo and Grad-CAM

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For the *missing hole* class, Grad-CAM emphasized the circular area of the absent via. This corresponds to the ground-truth defect location. The heatmap was concentrated around the drill area where the hole was missing, which confirms that the detection was based on the actual defect rather than unrelated board texture.

The Grad-CAM map also highlighted several neighboring regions that the model treated as potentially relevant. These areas did not correspond to real defects, but their activation shows that the model is sensitive to local irregularities in copper and via structures. This information is useful for engineers, since it indicates where the network may be uncertain and where false alarms can appear.

These observations show that YOLO11n provides not only accurate detections, but also a way to inspect the model's behavior when Grad-CAM is added. Engineers can check whether detections are visually justified and identify possible weaknesses of the model. Such cases may require additional training data or improved augmentation.

From an industrial perspective, the proposed YOLO11n + Grad-CAM system addresses three important requirements of Automated Optical Inspection (AOI): speed, accuracy, and interpretability. Its inference speed supports integration into production-line workflows, while the obtained mAP@0.5 value indicates reliable defect detection. Grad-CAM explanations add transparency to the model output and help engineers verify its predictions before practical use in manufacturing inspection.

Discussion

The main novelty of this work lies in the integration of YOLO11n with Grad-CAM for PCB defect detection. Previous studies mainly focused either on improving detection accuracy, for example with YOLOv5, YOLOv8, and Faster R-CNN [10], or on using interpretability methods in general computer vision tasks, including medical imaging. However, the combination of YOLO11n and Grad-CAM for PCB inspection has not been systematically considered.

The contribution of this work is twofold. First, the study shows that YOLO11n, although it is the smallest model in the YOLO11 family, can achieve high performance on the HRIPCB dataset while keeping real-time inference. Second, the use of Grad-CAM adds explainable defect localization through heatmaps. This helps reduce the transparency problem that is common for deep learning-based PCB inspection methods. As a result, the proposed approach combines detection accuracy with model interpretability, which is important for practical AOI systems.

Compared with traditional methods such as SVM and template matching, the proposed system improves detection accuracy by more than 20% in mAP and does not require handcrafted features. Template-based methods often fail under rotation or illumination changes, while YOLO11n is more robust because it learns features from data and uses augmentation during training.

In relation to previous deep-learning studies, early CNN-based approaches on the HRIPCB benchmark reported lower performance than modern detectors [4]. Park et al. analyzed factors that affect the training stability of PCB defect detectors, including data imbalance, image contamination, and model choice.

Their work provides useful practical guidelines, but it does not focus on real-time deployment or interpretability [8]. More recent studies proposed optimized YOLO-based models for PCB and industrial defect detection. For example, YOLO-BFRV uses BIFPN, FasterNet, RepHead, and Varifocal Loss [5], while YOLO-MSD applies multi-scale feature fusion [3]. These approaches mainly improve accuracy and speed, but they still do not provide explainable outputs.

The obtained results show that YOLO11n slightly outperforms YOLOv8n in accuracy and recall while maintaining higher inference speed. The integration of Grad-CAM additionally distinguishes this work, since it adds explainability without removing the practical advantages of the detector.

The integration of Grad-CAM into the detection pipeline has several practical implications. First, it allows engineers to visually check the model's decisions, which is important for trust in industrial AOI. Second, it helps with debugging because the heatmaps show whether the model focuses on the actual defect area or on irrelevant noise. This can be useful when refining the training

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strategy. Third, it supports a human-in-the-loop workflow, where the model performs fast defect detection and the operator checks explanations in uncertain cases. Therefore, the proposed approach is not only technically effective, but also more suitable for practical use in inspection tasks where interpretability matters.

The study also has several limitations. Although the HRIPCB dataset is diverse, its synthetic nature does not fully reproduce the complexity of real production boards. Therefore, validation on industrial datasets is still required. In addition, Grad-CAM heatmaps are relatively coarse and may not precisely show the boundaries of small defects. Another limitation is class imbalance in the dataset. Classes such as spur and spurious copper are underrepresented, which may limit the generalization ability of the model.

Several directions can be considered in future work. One of them is the use of other explainability methods, such as Grad-CAM++, Score-CAM [15], or Eigen-CAM [7], to obtain more detailed and stable explanations. Another important direction is cross-dataset validation on real industrial PCB images outside HRIPCB.

Further improvements may also be achieved through semi-supervised learning and synthetic data augmentation, including additional samples for rare defect classes using GANs [9] or diffusion models. It would also be useful to optimize YOLO11n for embedded GPUs and FPGA-based AOI systems to evaluate its industrial scalability. Finally, a human-in-the-loop system, where engineers can provide feedback on Grad-CAM heatmaps, may support gradual improvement of the model.

In summary, this study presents YOLO11n + Grad-CAM as an explainable framework for PCB defect detection. The model achieves mAP@0.5 = 87.4% with real-time inference and adds visual explanations that make the model's decisions easier to inspect. This makes the approach relevant for further use of explainable AI methods in industrial quality control.

By addressing both detection performance and interpretability, this research contributes to the development of Automated Optical Inspection systems that are accurate, fast, and easier to validate in practical conditions.

Conclusions

This study developed an interpretable defect detection framework for printed circuit board automated optical inspection that combines the YOLO11n object detection model with Grad-CAM explainability. The framework was evaluated on the HRIPCB dataset, which includes 1386 annotated images across six defect classes. YOLO11n was trained with synthetic augmentation to reduce the effect of class imbalance and to assess its suitability for real time PCB inspection.

The results demonstrate that the proposed framework is effective from both technical and practical perspectives. YOLO11n achieved an overall precision of 0.907, recall of 0.765, mAP@0.5 of 0.874, and mAP@0.5:0.95 of 0.483. Class wise analysis showed near perfect detection of missing hole defects, with precision equal to 1.0, recall of 0.969, and mAP@0.5 of 0.994. More difficult classes, such as spur and spurious copper, yielded lower performance, suggesting that further dataset balancing and augmentation are still needed. The framework significantly outperformed both a traditional SVM classifier and the YOLOv8n baseline, confirming the advantage of the chosen architecture for PCB defect detection.

The results also confirm that YOLO11n can meet the real time requirements of Automated Optical Inspection systems used in high throughput production environments. This makes the proposed framework suitable for further consideration in industrial PCB inspection.

Alongside detection speed and accuracy, Grad-CAM added an explainability layer to the pipeline. By overlaying heatmaps on detected regions, Grad-CAM revealed both the actual defect areas and other regions that the model considered relevant. This improves transparency and helps engineers verify correct detections as well as identify possible sources of false alarms.

From a scientific perspective, previous studies have applied CNN based methods and earlier YOLO variants to PCB inspection. This work demonstrates that a lightweight YOLO11n model combined with Grad-CAM provides both competitive detection performance and model

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interpretability on the HRIPCB dataset. This combination is particularly valuable for AI based Automated Optical Inspection systems, where accuracy alone is not always sufficient. From an industrial perspective, the combination of high accuracy, real time inference, and visual explanations makes the YOLO11n + Grad-CAM framework a practical candidate for quality control pipelines.

Several limitations of this study should be acknowledged. Although the HRIPCB dataset is diverse, it is partially synthetic and may not fully represent the variability of real industrial PCB images. Grad-CAM visualizations are relatively coarse and may not always provide detailed explanations of defect boundaries.

Future work should therefore consider more advanced explainability methods, such as Grad-CAM++ and Score-CAM, extend validation to real industrial datasets, and explore semi supervised learning approaches to improve the detection of rare defect types.

The proposed YOLO11n + Grad-CAM framework shows that PCB inspection can combine detection accuracy, real time inference, and interpretability. By adding visual explanations to detection results, the approach supports the development of Automated Optical Inspection systems that are easier to validate and more suitable for practical use in electronics manufacturing.

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ДІАГНОСТИКА ДРУКОВАНИХ ПЛАТ НА ОСНОВІ НЕЙРОМЕРЕЖЕВИХ МОДЕЛЕЙ

Стаття присвячена інтерпретовній структурі YOLOv11-Grad-CAM для вдосконаленого автоматизованого оптичного контролю друкованих плат. Критична потреба в надійності електронного виробництва підкреслює необхідність вдосконаленого контролю якості. Автоматизований оптичний контроль друкованих плат залишається наріжним каменем цього процесу. Однак традиційні методи, включаючи шаблонне зіставлення та ручну інспекцію, часто є недостатніми з точки зору стійкості та масштабованості для сучасних обсягів виробництва. Хоча моделі глибокого навчання продемонстрували вищу продуктивність у виявленні дефектів, їхня властива неінтерпретовність створює значну перешкоду для впровадження у виробничих середовищах з високими ставками. Це дослідження долає цей розрив шляхом представлення інтерпретовної структури глибокого навчання, яка інтегрує сучасну архітектуру YOLOv11n для виявлення дефектів у реальному часі з Gradient-weighted Class Activation Mapping для пояснюваності моделі. Ця інтеграція забезпечує прозоре візуальне обґрунтування прогнозів моделі шляхом виділення дискримінативних ознак. Запропоновану структуру було оцінено на публічному наборі даних HRIPCB, який включає 1386 зображень, що охоплюють шість поширених класів дефектів. Вона досягла середньої середньої точності (mAP@0.5) на рівні 87,4 відсотка, суттєво перевершивши як традиційний класифікатор SVM, так і базову модель YOLOv8n. Основним внеском цієї роботи є нове та систематичне поєднання високошвидкісного виявлення об'єктів з принципами пояснюваного штучного інтелекту, адаптоване для контролю друкованих плат. Завдяки одночасному досягненню високої точності, виявленню в реальному часі та критичній інтерпретовності, ця структура пропонує життєздатне та надійне рішення для промислових систем автоматизованого оптичного контролю. Метою цього дослідження є розробка інтерпретовної структури виявлення дефектів для автоматизованого оптичного контролю друкованих плат, яка забезпечує як високу точність, так і прозоре прийняття рішень. Для досягнення цієї мети було виконано наступні завдання: вибір та налаштування моделі YOLOv11n для виявлення дефектів друкованих плат; навчання та оцінювання на наборі даних HRIPCB; інтеграція Grad-CAM у конвеєр виявлення для візуального пояснення; порівняння з базовими методами, включаючи SVM та YOLOv8n; кількісне вимірювання продуктивності з використанням mAP, точності та повноти разом із якісною документацією за допомогою візуальних теплових карт.

Ключові слова: контроль якості; виявлення дефектів; нейронні мережі; штучний інтелект; друковані плати; Grad-CAM; YOLO11n; глибоке навчання.

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