Automated Quality Inspection System for Manufacturing

1. Introduction

This report presents an automated quality inspection system designed for manufacturing environments using computer vision and deep learning. The system focuses on Printed Circuit Board (PCB) inspection to automatically identify and localize manufacturing defects. A YOLOv8 object detection model is employed to learn visual defect patterns from annotated images. The approach reduces reliance on manual inspection, improves consistency, and supports faster quality control decisions in production pipelines.

2. Dataset and Annotation Verification

A Pascal VOC formatted PCB defect dataset was used in this work. The dataset contains 693 annotated images with a total of 2,953 defect instances across six defect classes. Annotations are provided as XML files with bounding box information. Prior to training, the dataset and annotations were verified to ensure correct parsing and class coverage. This verification step confirms data readiness for model training.

3. Model Training and Performance

The YOLOv8 model was trained on the verified dataset using Google Colab with GPU acceleration. Training was conducted for multiple epochs, during which loss values decreased steadily, indicating effective learning. Model performance was evaluated using precision, recall, and mAP metrics. The training performance graphs summarize loss trends and mAP improvements over epochs, demonstrating the model's ability to generalize across PCB defect classes.

```
      20/20      1.57G      1.732      1.334     0.9548         22        640: 100% ━━━━━━━━━━━━ 87/87 2.0it/s 43.4s
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% ━━━━━━━━━━━━ 44/44 1.4it/s 31.4s
...                all        693       2953      0.899      0.781      0.847      0.433

20 epochs completed in 0.421 hours.
Optimizer stripped from /content/runs/detect/pcb_defect_detector2/weights/last.pt, 6.2MB
Optimizer stripped from /content/runs/detect/pcb_defect_detector2/weights/best.pt, 6.2MB

Validating /content/runs/detect/pcb_defect_detector2/weights/best.pt...
Ultralytics 8.3.249 🚀 Python-3.12.12 torch-2.9.0+cu126 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 72 layers, 3,006,818 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% ━━━━━━━━━━━━ 44/44 1.3it/s 33.5s
                   all        693       2953      0.899      0.781      0.847      0.432
          missing_hole        115        497       0.99      0.984      0.991      0.607
             mouse_bite        115        492      0.827      0.675      0.769       0.36
          open_circuit        116        482      0.861      0.714      0.785      0.355
                 short        116        491      0.888      0.839      0.908       0.45
                  spur        115        488      0.935      0.703      0.789      0.387
       spurious_copper        116        503      0.895      0.773      0.843      0.433
Speed: 0.2ms preprocess, 2.7ms inference, 0.0ms loss, 2.5ms postprocess per image
Results saved to /content/runs/detect/pcb_defect_detector2
 Training completed successfully!
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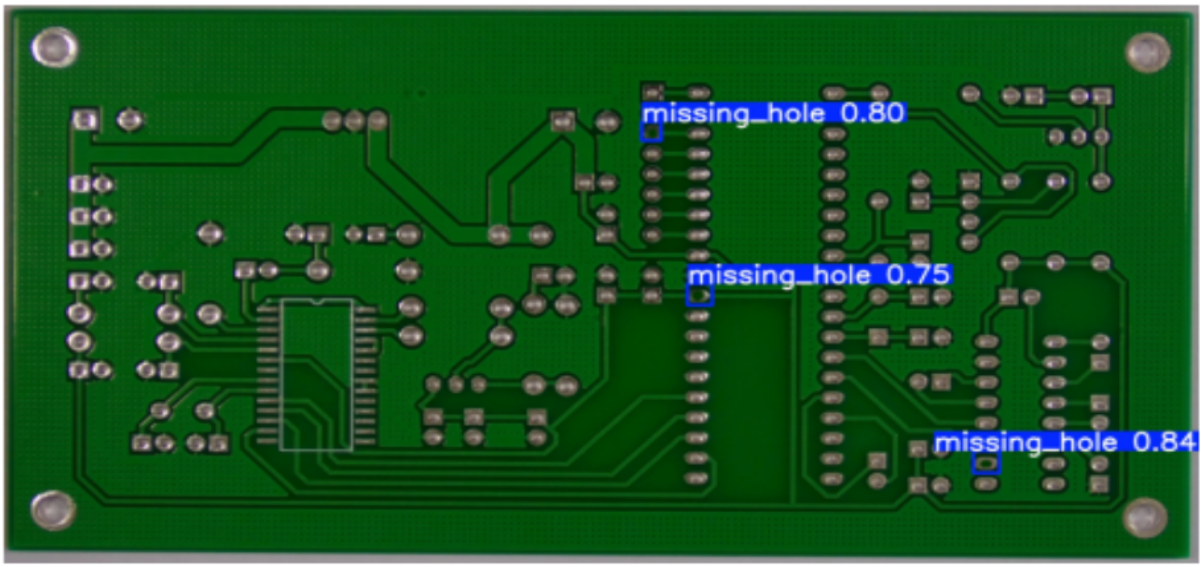
4. Detection and Inference Results

After training, the model was used to perform inference on PCB images. The system successfully detected defects such as missing holes and highlighted them using bounding boxes along with confidence scores. Inference results visually demonstrate accurate localization of defects on PCB surfaces. Additionally, inference logs show processing time per image, indicating near real-time performance. These results validate the applicability of the system for automated inspection tasks.




```
image 1/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_01.jpg: 352x640 3 missing_holes, 78.4ms
image 2/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_02.jpg: 352x640 3 missing_holes, 5.9ms
image 3/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_03.jpg: 352x640 3 missing_holes, 5.9ms
image 4/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_04.jpg: 352x640 3 missing_holes, 10.7ms
image 5/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_05.jpg: 352x640 3 missing_holes, 6.0ms
image 6/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_06.jpg: 352x640 3 missing_holes, 6.0ms
image 7/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_07.jpg: 352x640 3 missing_holes, 6.0ms
image 8/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_08.jpg: 352x640 3 missing_holes, 5.9ms
image 9/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_09.jpg: 352x640 3 missing_holes, 6.3ms
image 10/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_10.jpg: 352x640 3 missing_holes, 7.7ms
image 11/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_11.jpg: 352x640 3 missing_holes, 6.1ms
image 12/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_12.jpg: 352x640 3 missing_holes, 6.2ms
image 13/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_13.jpg: 352x640 3 missing_holes, 5.9ms
image 14/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_14.jpg: 352x640 3 missing_holes, 5.9ms
image 15/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_15.jpg: 352x640 3 missing_holes, 10.6ms
image 16/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_16.jpg: 352x640 3 missing_holes, 5.9ms
image 17/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_17.jpg: 352x640 3 missing_holes, 6.1ms
image 18/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_18.jpg: 352x640 3 missing_holes, 6.2ms
image 19/693 /content/pcb_yolo_dataset/images/train/01_missing_hole_19.jpg: 352x640 3 missing_holes, 9.9ms
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5. Conclusion

This project demonstrates an end-to-end automated quality inspection system for manufacturing using YOLOv8. From dataset verification to model training and inference, each stage was systematically executed. The trained model achieved strong detection performance across multiple defect categories. Such systems can significantly enhance manufacturing quality control by reducing manual effort and errors. Future work may include deployment on real-time production lines and further optimization.