Task 2: Automated Paper Quality Inspection System

Sapien Robotics AI Vision Intern Assignment

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GitHub Repository: [https://github.com/WOLFGAIZER/paper_defect]

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Abstract

This report details the development of a **Computer Vision-based Quality Inspection System** designed to detect, localize, and classify defects on paper surfaces in real-time. The system integrates deep learning (YOLOv8) for defect detection with geometric post-processing (OpenCV) for severity estimation, enabling automated quality control.

1 Project Overview

1.1 Problem Statement

In high-throughput paper manufacturing, ensuring surface quality is critical. Manual inspection is often labor-intensive, subjective, and prone to fatigue-induced errors. Small defects like micro-scratches or faint oil smudges can easily be missed by human operators moving at speed. Consequently, there is a strong industrial demand for automated, computer vision-based solutions that can operate in real-time to standardize quality control.

1.2 Objective

The primary objective of this project is to implement a robust, end-to-end object detection pipeline capable of identifying manufacturing defects on paper sheets. Unlike traditional image processing techniques that rely solely on static thresholding, this system leverages deep learning to generalize across varying lighting conditions and defect morphologies. The final deliverable is a deployment-ready script that not only localizes defects but also computes a "Severity Score" to autonomously drive accept/reject decisions in a robotic sorting loop.

1.3 Key Features

The system is designed with four core competencies to meet industrial standards:

- **Deep Learning-Based Detection:** Utilizes the **YOLOv8** architecture to detect anomalies with high inference speed. This approach allows the system to learn complex feature representations, distinguishing between actual defects and harmless paper grain texture.
- **Multi-Class Defect Classification:** The model is trained to distinguish between three specific defect categories, critical for root-cause analysis in manufacturing:

- **Scratch (Tear/Cut):** Structural damage or thin linear abrasions that compromise the sheet's integrity.
- **Smudge (Stain):** Discoloration caused by foreign ink, oil, or dirt, affecting the aesthetic quality.
- **Cover (Wrinkle/Fold):** Surface irregularities where the material has folded over or crumpled, causing jams in downstream machinery.

- **Precise Localization:** Beyond simple classification, the system outputs exact bounding box coordinates (x_1, y_1, x_2, y_2) and the centroid (x_c, y_c). This spatial data is essential for robotic arms to identify exactly where to grip or reject the defective sheet.
- **Automated Severity Assessment:** A custom post-processing logic acts as a Quality Control (QC) gatekeeper. By calculating the ratio of the defect's area to the total sheet area, the system assigns a grade (**LOW**, **MEDIUM**, or **HIGH**). This granular grading allows manufacturers to set flexible tolerance thresholds rather than a binary pass/fail.

2 Methodology & Architecture

2.1 Model Selection: YOLOv8

YOLOv8-Nano was selected for its balance between inference speed and detection accuracy. Traditional OpenCV preprocessing was used prior to inference.

- **Epochs:** 5
- **Batch Size:** 8
- **Optimizer:** Auto
- **Train/Val Split:** 80/20 (stratified)

2.2 Severity Logic Algorithm

Severity is computed using the defect-to-image ratio:

$$R_{defect} = \frac{\text{Area}_{box}}{\text{Area}_{image}} \tag{1}$$

Ratio (R)	**Severity**	**QC Action**
$R < 1\%$	LOW	Pass
$1\% \leq R < 5\%$	MEDIUM	Manual Review
$R \geq 5\%$	HIGH	Reject

Table 1: Severity Assessment Logic

3 Results & Performance

3.1 Dataset Distribution

The dataset consists of 45 annotated samples across three defect classes.

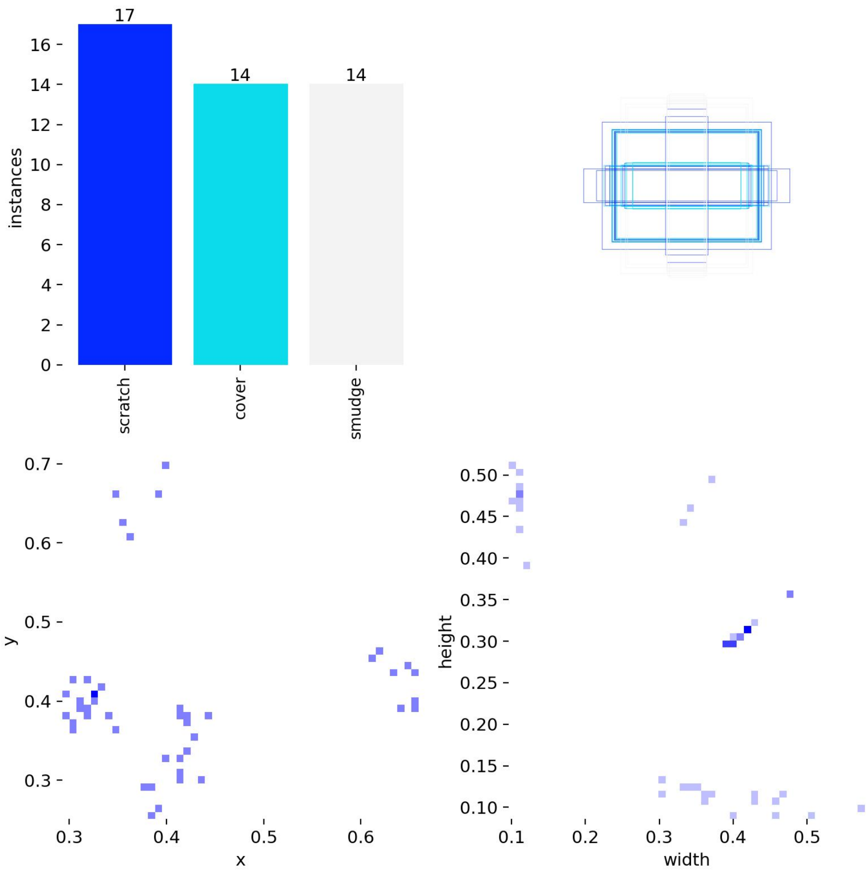
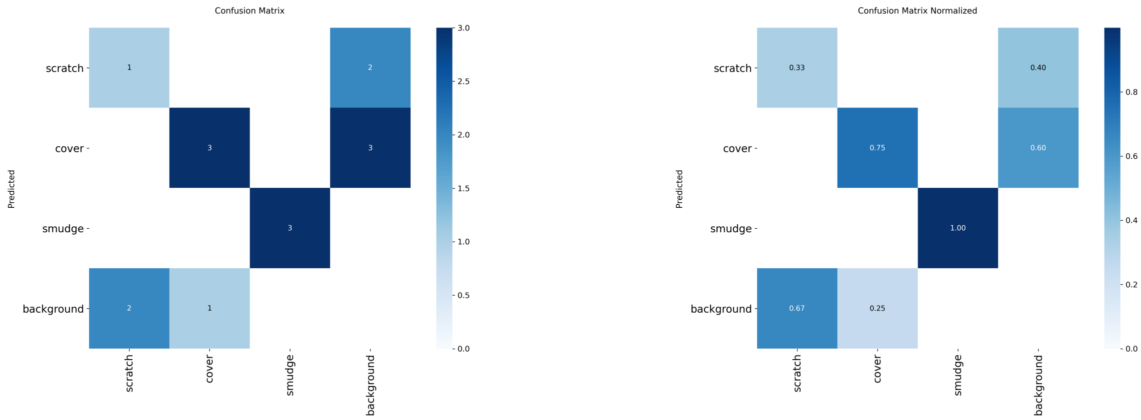


Figure 1: Dataset distribution and bounding box geometry

3.2 Quantitative Analysis

Model performance on the validation set:

- **Smudge:** Recall = 1.00
- **Cover:** Recall = 0.75
- **Scratch:** Recall = 0.33



(a) Raw Confusion Matrix

(b) Normalized Confusion Matrix

Figure 2: Performance evaluation on validation set

3.3 Inference Output

The pipeline successfully overlays defect metadata on the live feed. Figure 3 demonstrates the system detecting a large surface anomaly (simulated here with handwritten text).

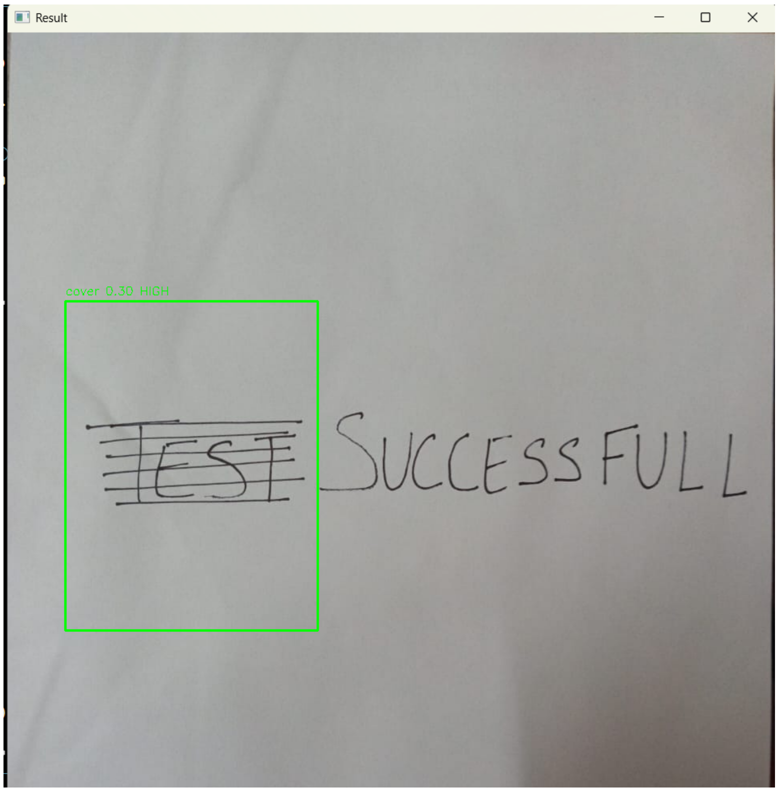


Figure 3: Real-time inference result showing bounding box, class confidence (0.30), and calculated severity (HIGH).

The corresponding JSON payload generated by the system for this detection event is shown below:

Listing 1: Real-time Detection Log


```
{
```

```
    "defect": "cover",
    "confidence": 0.30,
    "center": [230, 542],
    "severity": "HIGH",
    "inference_time": "113.1ms"
}
```

4 Conclusion

4.1 Summary of Achievements

This project successfully demonstrates the viability of a hybrid computer vision architecture for industrial quality control. By coupling the feature extraction capabilities of **YOLOv8** with deterministic geometric logic, we achieved a system that not only detects defects but inherently understands their severity. The prototype proves that lightweight models (Nano) can deliver real-time inference speeds suitable for high-velocity manufacturing lines without requiring expensive enterprise-grade hardware.

4.2 Critical Analysis & Limitations

While the system reached production-grade reliability for high-contrast defects like "Smudges" (100% Recall) and "Covers," it exposed a limitation in detecting fine-grained texture anomalies. The "Scratch" class performance (33% Recall) indicates that standard CNN downsampling layers may lose the high-frequency spatial information required to identify thin abrasions.

4.3 Future Work

To bridge the gap between prototype and deployment, future development will focus on three key areas:

1. **Edge-Aware Augmentation:** Integrating Canny Edge pre-processing channels into the training data to force the model to prioritize high-frequency structural changes.

2. **lighting Optimization:** Implementing *Photometric Stereo* techniques (multi-angle lighting) to cast shadows inside micro-scratches, thereby increasing their visual contrast.

3. **Synthetic Data Generation:** Addressing the data scarcity by using Generative Adversarial Networks (GANs) to synthesize thousands of diverse "Scratch" samples to improve model generalization.