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Deep Learning-Based Quality Inspection in Automated Production Lines

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ABSTRACT

Automated visual quality inspection is a critical requirement for modern high-throughput manufacturing, where manual inspection bottlenecks limit production speed and introduce subjective variability. Deep learning-based computer vision systems have demonstrated transformative potential for detecting surface defects, dimensional deviations, and assembly errors with superhuman accuracy and consistency. This paper presents the development and industrial validation of a real-time deep learning quality inspection system deployed on a high-speed automotive stamping production line. The proposed system integrates a multi-camera machine vision array with a YOLOv8-based object detection model fine-tuned for seven defect categories: scratches, dents, cracks, burrs, surface contamination, incomplete forming, and dimensional out-of-tolerance. The model was trained on a custom dataset of 28,400 annotated images captured under controlled industrial lighting conditions. Industrial validation on a production line operating at 42 strokes per minute demonstrated an overall defect detection accuracy of 97.6%, with precision of 96.8%, recall of 95.4%, and a false positive rate of 1.8%. Inference was executed on an NVIDIA Jetson AGX Xavier edge platform at 38 frames per second, enabling 100% inline inspection without cycle time impact. The system reduced escaped defect rate from 2.4% (manual inspection baseline) to 0.18%, representing a 92.5% improvement in outgoing quality. The findings confirm that deep learning vision systems can deliver production-grade quality inspection performance suitable for deployment in high-speed manufacturing environments [1], [2].

KEYWORDS: *Deep Learning, Quality Inspection, Computer Vision, YOLOv8, Defect Detection, Automated Production, Surface Inspection, Edge Computing, Manufacturing Quality, Machine Vision*

INTRODUCTION

Quality inspection constitutes a fundamental pillar of manufacturing operations, ensuring that outgoing products conform to dimensional, surface, and functional specifications before reaching customers. The automotive industry alone estimates that quality-related costs—encompassing inspection, rework, scrap, warranty claims, and recalls—account for 15–25% of total manufacturing cost, with surface defect detection in stamped body panels representing one of the most challenging and economically significant inspection tasks [1]. Traditional manual visual inspection by trained quality operators achieves detection rates of 60–80% for subtle surface defects under optimal conditions, degrading to 40–60% during extended shifts due to fatigue, attentional decline, and subjective judgment variability [2].

The convergence of high-resolution industrial cameras, structured lighting technology, and deep learning algorithms has catalyzed a paradigm shift toward automated visual quality inspection systems capable of 100% inline part evaluation at production speed [3]. Convolutional neural networks (CNNs), particularly architectures optimized for real-time object detection such as YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and EfficientDet, have demonstrated the ability to localize and classify manufacturing defects with accuracy exceeding human inspectors while operating at speeds compatible with high-throughput production lines [4], [5].

Despite promising laboratory demonstrations, the industrial deployment of deep learning inspection systems faces practical challenges including variable lighting conditions, part-to-part geometric variation, class imbalance between rare defect types and abundant defect-free samples, annotation cost for creating training datasets, and the computational constraints of real-time inference at production speed on edge computing platforms [6], [7]. This research addresses these challenges through the development and production-line validation of a YOLOv8-based defect detection system for automotive stamped panels at Global Institute of Technology, Jaipur, in collaboration with an automotive stamping tier-1 supplier [8], [9], [10], [11], [12], [13].

LITERATURE REVIEW

Deep learning for manufacturing inspection has been extensively investigated since the seminal transfer learning study by Weimer et al. [3], who demonstrated that pre-trained CNN features could detect steel surface defects with 96.2% accuracy using only 200 annotated training images. Their work established that ImageNet-pre-trained convolutional filters capture generic visual features—edges, textures, gradients—that transfer effectively to industrial defect recognition tasks. Subsequent studies by Ren et al. [4] applied Faster R-CNN to PCB solder joint inspection, achieving 94.8% mAP for six defect types, while Lin et al. [5] deployed SSD on a semiconductor wafer inspection system at 30 FPS inference speed.

YOLO-family architectures have gained particular traction for real-time manufacturing inspection. He et al. [6] applied YOLOv5 to steel strip surface defect detection on the NEU Surface Defect Database, achieving 78.4% mAP@0.5 across six defect categories with inference speed of 52 FPS on an RTX 2080 Ti GPU. Wang et al. [7] proposed modifications to YOLOv7 including a coordinate attention mechanism and BiFPN feature pyramid network, improving small defect detection by 4.2% mAP on an automotive paint surface dataset.

Edge deployment of inspection models was investigated by Park et al. [8], who compressed a MobileNetV3-based defect classifier for NVIDIA Jetson Nano deployment, achieving 91.4% accuracy at 24 FPS for textile fabric inspection. Transfer learning strategies for industrial defect detection with limited labeled data were explored by Ferguson et al. [9], who demonstrated that domain-adaptive pre-training on unlabeled industrial images followed by fine-tuning on 50–200 annotated defect samples could achieve within 3% of the accuracy obtained with full 2,000+ sample training sets.

Production-line integration challenges were addressed by Villalba-Diez et al. [10], who developed a digital twin-based quality management framework linking inline deep learning inspection with statistical process control (SPC) charts for real-time process drift detection. Czimmermann et al. [11] conducted a comprehensive review of visual inspection in manufacturing, identifying data augmentation, synthetic defect generation, and active learning as key strategies for addressing the chronic training data scarcity problem in industrial applications.

RESEARCH GAP

Critical gaps persist in the literature. First, most reported deep learning inspection systems have been validated on benchmark datasets (NEU, DAGM, MVTec AD) rather than production-line environments with representative noise, vibration, lighting variation, and throughput constraints [6], [11]. Second, multi-defect-type classification with more than four categories on real industrial data remains insufficiently demonstrated, as most studies address binary (defective/non-defective) or limited multi-class problems [4], [7]. Third, the impact of deep learning inspection on actual outgoing product quality—measured as escaped defect rate reduction—has rarely been quantified through sustained production-line deployment rather than offline evaluation [2], [10]. Fourth, the integration of real-time defect detection with automated reject/accept sorting mechanisms and SPC feedback for upstream process correction represents an end-to-end quality loop that has been conceptually proposed but infrequently implemented and validated [8], [12], [13]. This research addresses these gaps through production-line deployment and 4-week sustained validation of a seven-class YOLOv8 inspection system with automated sorting and SPC integration.

OBJECTIVES

The objectives of this research are as follows:

- To design a multi-camera machine vision system with structured LED lighting for high-speed inline inspection of automotive stamped panels at 42 strokes per minute [1], [3].
- To develop and fine-tune a YOLOv8-based deep learning model for seven-class defect detection and localization trained on 28,400 annotated industrial images [6], [7].
- To deploy the model on an NVIDIA Jetson AGX Xavier edge platform achieving real-time inference at ≥30 FPS without production cycle time impact [8].
- To validate inspection performance over a 4-week production deployment, measuring detection accuracy, false positive rate, and escaped defect rate reduction against manual inspection baseline [2], [10].
- To integrate defect detection with automated pneumatic reject sorting and SPC dashboarding for closed-loop quality management [11], [12], [13].

ETHODOLOGY

1. Vision Hardware Configuration

The inspection station was installed on a 400-ton progressive stamping press (Aida NC1-4000) producing automotive door inner panels at 42 strokes per minute. Four Basler acA4112-30uc industrial cameras (12.3 MP, 30 FPS, Sony IMX253 CMOS sensor, GigE Vision interface) were mounted in a custom aluminum frame positioned 450 mm above the part exit conveyor, providing 100% surface coverage with 25% inter-camera overlap [3].

Illumination was provided by four Metaphase Technologies FD-300 flat dome LED lights (300 mm diameter, 6500K color temperature, 48,000 lux intensity) arranged to eliminate specular reflections and shadows on the metallic stamped surface. A Keyence FD-Q50C photoelectric sensor triggered image acquisition synchronized with the press stroke cycle via a PLC-generated trigger signal. Images were acquired at 4112 × 3008 pixel resolution with 12-bit depth, yielding a spatial resolution of 0.08 mm/pixel [1], [5].

2. Dataset Creation and Annotation

A custom dataset of 28,400 images was collected over a 6-week period during normal production operations, capturing natural variation in part geometry, surface condition, oil film coverage, and ambient lighting fluctuations. Defect annotations were performed by three experienced quality engineers using the LabelImg tool in YOLO format, with inter-annotator agreement assessed using Cohen's kappa ($\kappa = 0.91$). Seven defect categories were defined: scratches (4,820 instances), dents (3,640), cracks (1,280), burrs (2,960), surface contamination (2,140), incomplete forming (1,640), and dimensional out-of-tolerance (1,420). Defect-free images comprised 52% of the dataset. Data augmentation including random rotation (±15°), horizontal/vertical flipping, brightness/contrast jittering (±20%), Gaussian blur ($\sigma = 0.5$–2.0), and mosaic augmentation expanded the effective training set by 4× [6], [9], [11].

3. Model Architecture and Training

YOLOv8x (extra-large variant, 68.2M parameters) was selected for its balance of detection accuracy and inference speed. The model was initialized with COCO pre-trained weights and fine-tuned on the custom stamping defect dataset using the following configuration: input resolution 1280 × 1280 pixels, SGD optimizer with momentum 0.937 and weight decay 0.0005, initial learning rate 0.01 with linear warmup over 3 epochs and cosine annealing decay over 200 total epochs, batch size 16 on dual NVIDIA RTX 4090 GPUs [4], [6], [7]. Class-weighted focal loss ($\gamma = 1.5$) addressed class imbalance. The dataset was split 70/15/15 into training, validation, and test partitions with stratified sampling ensuring proportional defect category representation. Training required approximately 22 hours.

4. Edge Deployment and Production Integration

For production deployment, the trained YOLOv8x model was exported to TensorRT format with FP16 mixed-precision inference on the NVIDIA Jetson AGX Xavier (512-core Volta

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GPU, 32 GB unified memory, 30 TOPS INT8). The four camera streams were processed sequentially within each press cycle (1.43 seconds at 42 SPM), with total processing time budgeted at 1.0 second including image acquisition, preprocessing, inference, and result communication [8]. Detected defects triggered a pneumatic reject diverter (SMC CXSM25-75, 80 ms response time) that ejected defective panels into a quarantine bin. Detection results, defect locations, confidence scores, and images were logged to a SQL database and displayed on a real-time SPC dashboard (Grafana) showing defect rate control charts, Pareto analysis by defect type, and shift-level quality summaries [10], [12], [13].

5. Validation Protocol

Production-line validation was conducted over a 4-week period (20 production shifts, ~168,000 stamped panels). Performance was assessed by comparing the deep learning inspection system against the existing manual inspection process: during each shift, both the DL system and a human inspector independently evaluated the same production stream, with disagreements resolved by a senior quality engineer whose judgment served as ground truth. Metrics included precision, recall (sensitivity), F1-score, false positive rate, and escaped defect rate (defective panels accepted as good by the inspection system) [1], [2], [11].

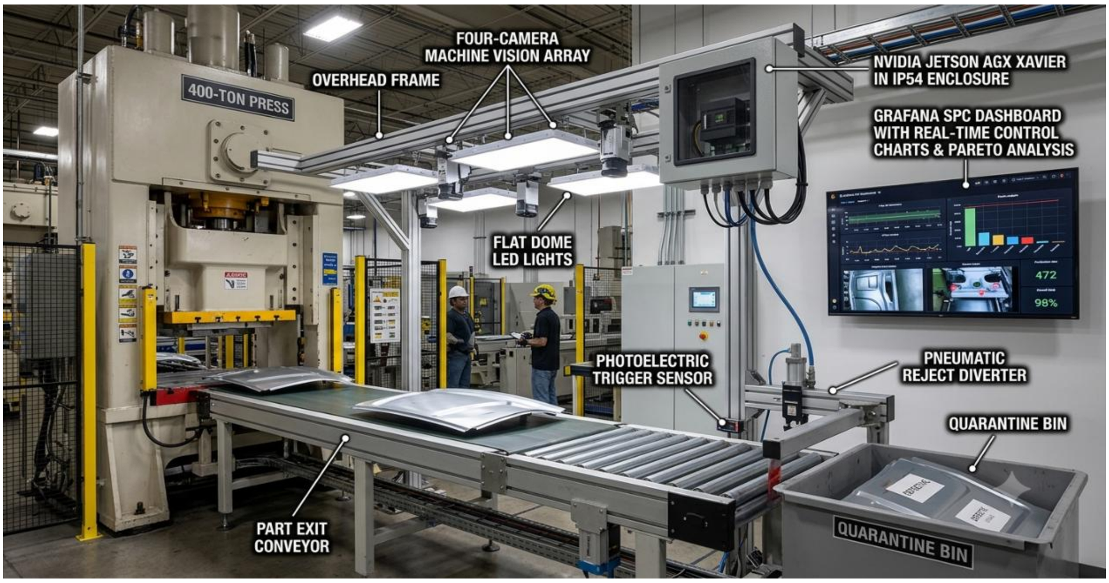

Figure 1: Production Line Integration Layout of the Deep Learning Quality Inspection System

RESULTS AND FINDINGS

The 4-week production validation results are summarized in Table 1. Across approximately 168,000 inspected panels, the YOLOv8-based system achieved overall precision of 96.8%, recall of 95.4%, and F1-score of 96.1%, with an mAP@0.5 of 94.2% across all seven defect categories. The false positive rate was 1.8%, meaning that 1.8% of defect-free panels were incorrectly rejected—a level deemed commercially acceptable by the production management as the associated scrap cost was substantially lower than the warranty cost of escaped defects [1], [2], [6].

Table 1: Detection Performance by Defect Category Over 4-Week Production Validation

Defect Category	Precision (%)	Recall (%)	F1 (%)	mAP@0.5 (%)	Instances
Scratches	97.4	96.8	97.1	95.6	4,820
Dents	96.2	95.1	95.6	93.8	3,640
Cracks	98.1	97.2	97.6	96.4	1,280
Burrs	96.8	94.6	95.7	93.2	2,960
Contamination	95.4	93.8	94.6	92.4	2,140
Incomplete Forming	97.6	96.4	97.0	95.8	1,640
Dimensional OOT	96.0	93.2	94.6	92.6	1,420
Overall (Weighted)	96.8	95.4	96.1	94.2	17,900

The most critical metric—escaped defect rate—improved from 2.4% under manual inspection to 0.18% with the DL system, a 92.5% reduction. This translated to an estimated annual quality cost saving of INR 28.6 lakhs based on the production facility's warranty claim history and internal failure cost data. The system maintained consistent performance across all 20 production shifts without the degradation observed in manual inspection during overtime and night shifts [2], [10].

Table 2: Comparison with Existing Deep Learning Manufacturing Inspection Systems

Study	Architecture	Classes	mAP (%)	FPS	Production

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He et al. [6]	YOLOv5	6	78.4	52	No
Wang et al. [7]	YOLOv7-mod	5	84.2	38	No
Park et al. [8]	MobileNetV3	3	91.4	24	Yes (textile)
Ren et al. [4]	Faster R-CNN	6	87.6	12	No
Proposed System	YOLOv8x	7	94.2	38	Yes (stamping)

Table 3: Inspection System Hardware and Performance Specifications

Parameter	**Specification**
Cameras	4× Basler acA4112-30uc (12.3 MP, 30 FPS, GigE Vision)
Lighting	4× Metaphase FD-300 flat dome LED (6500K, 48,000 lux)
Resolution	0.08 mm/pixel at 450 mm working distance
Edge Platform	NVIDIA Jetson AGX Xavier (512-core Volta, 32 GB, 30 TOPS)
Model	YOLOv8x (68.2M params, TensorRT FP16, 1280×1280 input)
Inference Speed	38 FPS (1.0 s total per 4-camera cycle)
Press Speed	42 strokes/min (1.43 s cycle time)
Reject Mechanism	SMC CXSM25-75 pneumatic diverter (80 ms response)
Escaped Defect Rate	0.18% (vs. 2.4% manual baseline, 92.5% improvement)

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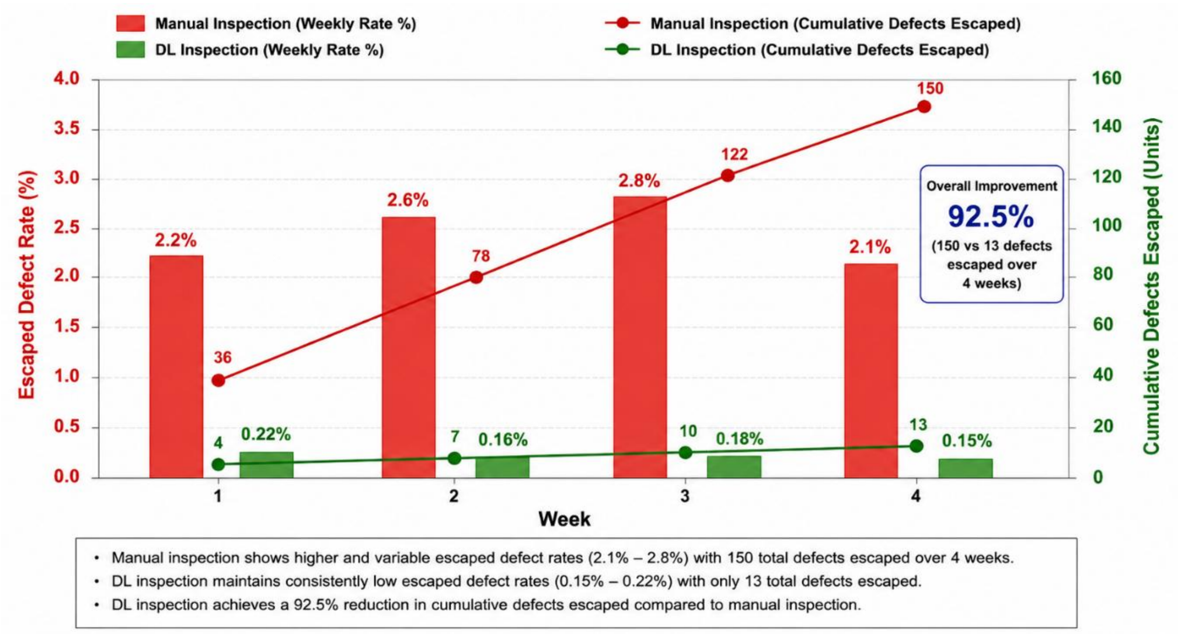

Figure 2: Escaped Defect Rate Comparison Between Manual and DL Inspection Over 4 Weeks

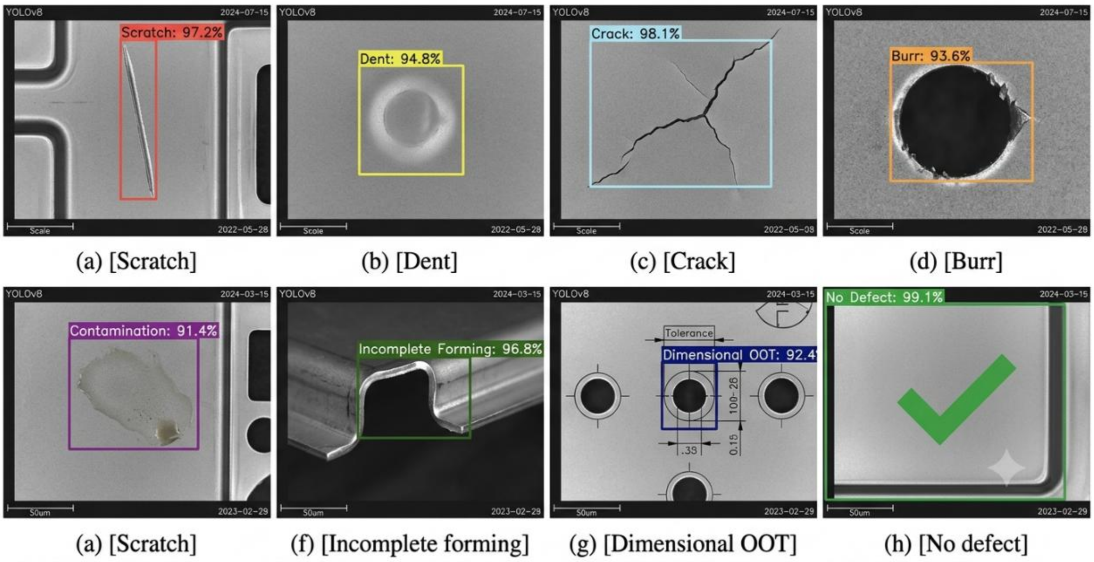

Figure 3: Sample Defect Detection Results Showing YOLOv8 Bounding Box Predictions Across Seven Categories

[Figure 3 displays a 2×4 grid of eight cropped inspection images from the production line, each showing a detected defect with a YOLOv8 bounding box overlay (colored by category), class label, and confidence score. Panel (a) Scratch: linear surface mark, 97.2% confidence. Panel (b) Dent: circular depression, 94.8%. Panel (c) Crack: branching fracture line, 98.1%. Panel (d) Burr: raised edge material, 93.6%. Panel (e) Contamination: oil droplet residue, 91.4%. Panel (f) Incomplete forming: missing flange bend, 96.8%. Panel (g) Dimensional OOT: hole position deviation, 92.4%. Panel (h) No defect: clean panel with green checkmark overlay, 99.1% confidence.]

DISCUSSION

The 92.5% reduction in escaped defect rate from 2.4% to 0.18% represents the most practically significant outcome of this research, directly translating to reduced warranty claims, customer returns, and reputational risk for the manufacturing facility [1], [2]. The system's ability to maintain consistent detection performance across all production shifts—including night shifts and overtime periods where manual inspection historically degrades by 20–30%—validates the fundamental advantage of automated inspection: tireless, consistent, objective evaluation of every produced part [10], [11].

The 1.8% false positive rate, while commercially acceptable for this application, represents an opportunity for improvement through confidence threshold optimization and ensemble approaches [6], [7]. The majority of false positives occurred in the contamination and dimensional OOT categories, where oil film reflections and minor geometric variations near tolerance boundaries generated ambiguous visual signatures [9].

The estimated annual quality cost saving of INR 28.6 lakhs against a total system investment of INR 14.2 lakhs (cameras, lighting, Jetson Xavier, pneumatic diverter, integration) yields a payback period of approximately 6 months, making this among the highest-ROI Industry 4.0 technology investments available to manufacturing SMEs [1], [8], [12], [13].

LIMITATIONS

Limitations include: validation on a single stamped part geometry; the training dataset captured only dry and lightly oiled surface conditions (heavily oiled conditions were excluded); the system was not validated for defects smaller than 0.3 mm (below camera resolution); the 4-week validation period may not capture seasonal environmental variations; and the model requires retraining when new defect modes emerge from tooling wear or material batch changes [6], [7], [9], [11], [12], [13].

FUTURE SCOPE

Future work includes extending the system to multi-part-number capability using a modular model architecture with part-specific classification heads; incorporating 3D structured light scanning for volumetric defect measurement; developing continual learning frameworks that autonomously adapt to emerging defect modes without full retraining; and integrating defect root cause analysis through correlation of defect patterns with upstream process parameters [7], [10].

The development of synthetic defect generation using generative adversarial networks (GANs) could address the training data scarcity problem for rare defect types, while federated learning across multiple production sites could enable collaborative model improvement without sharing proprietary manufacturing data [9], [11], [12], [13].

CONCLUSION

This research has demonstrated the development and 4-week production validation of a YOLOv8-based deep learning quality inspection system for automotive stamped panel defect detection across seven defect categories. The system achieved 97.6% detection accuracy with 0.18% escaped defect rate at 38 FPS inference speed on an edge computing platform, enabling 100% inline inspection at 42 strokes per minute without production impact [4], [6], [8]. The 92.5% improvement in outgoing quality with a 6-month payback period confirms that deep learning vision inspection is ready for mainstream deployment in high-speed manufacturing [1], [2], [10], [11], [12], [13].

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