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Research Article

Machine Vision-Based Real-Time Surface Defect Detection ising Deep Convolutional Neural Networks for High-Speed Automotive Production Lines: Architecture, Training, and Industrial Validation

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Abstract

Automated visual inspection using deep learning-based computer vision systems has emerged as the predominant approach for achieving zero-defect manufacturing targets in high-speed production environments where manual inspection throughput and consistency constraints are prohibitive. This paper presents DefectNet-7, a custom seven-layer convolutional neural network architecture designed and optimised for real-time surface defect detection on automotive stamped metal components at line speeds up to 120 parts per minute. The network was trained on a dataset of 48,000 labelled images across six defect categories: scratches, dents, porosity, burrs, cracks, and conforming surfaces, captured under controlled multi-spectral illumination conditions. DefectNet-7 achieved 97.4% overall accuracy on the held-out test set, with per-class F1 scores ranging from 0.938 to 0.976, and mean inference time of 8.3 ms per image on NVIDIA Jetson Xavier NX embedded hardware. Industrial deployment across two production lines over six months resulted in a 91.3% reduction in escaping defect rate, USD 420,000 annual quality cost savings, and a 2.4-month payback period.

Keywords: *Convolutional Neural Networks; Defect Detection; Machine Vision; Quality Control; Deep Learning; Automated Inspection; Manufacturing; Transfer Learning*

1. Introduction

Surface quality assurance in high-volume manufacturing requires simultaneous achievement of high detection sensitivity, high classification specificity, and throughput performance compatible with production line speeds. In automotive stamping operations producing 80 to 150 parts per minute, human visual inspection is fundamentally inadequate due to speed and fatigue constraints. The application of deep convolutional neural networks to industrial visual inspection has advanced dramatically since the watershed performance of AlexNet in the 2012 ImageNet challenge demonstrated the superiority of deep learned feature representations over hand-crafted approaches.

This paper makes three primary contributions: it presents DefectNet-7, a custom CNN architecture specifically optimised for embedded edge inference hardware while achieving production-grade accuracy; it provides detailed characterisation of the training data pipeline including multi-spectral illumination protocol and class imbalance handling; and it presents a comprehensive six-month industrial deployment evaluation providing the longitudinal performance data and cost-benefit analysis practitioners require.

2. Literature Review

2.1 CNN Architectures for Industrial Defect Detection

The dominant paradigm in contemporary industrial defect detection CNNs employs transfer learning from networks pre-trained on large-scale image classification datasets as a starting point, with task-specific fine-tuning on labelled defect datasets. ResNet, VGG, EfficientNet, and MobileNet variants have all been successfully adapted for defect detection applications. EfficientNet-B3 and MobileNetV3 have gained particular traction in resource-constrained edge deployment scenarios due to their favourable accuracy-to-computation ratio. Attention mechanisms including Squeeze-and-Excitation blocks have been shown to enhance defect localisation accuracy.

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2.2 Dataset Construction and Class Imbalance

A persistent challenge in industrial defect detection CNN development is the severe class imbalance between conforming parts and defective parts. Naive training on imbalanced datasets produces models that achieve high accuracy by predicting the majority class for all inputs, failing at their intended function. Established mitigation strategies include oversampling of minority defect classes through augmentation, cost-sensitive training with higher misclassification penalties for defect classes, and synthetic data generation using generative adversarial networks.

3. Defectnet-7 Architecture and Training

3.1 Network Architecture

DefectNet-7 was designed as a seven-layer convolutional backbone optimised for embedded edge deployment. The architecture consists of: Input layer (224 x 224 x 3 RGB); four convolutional blocks with increasing filter depths (32, 64, 128, 256 filters); a Squeeze-and-Excitation attention block; Global Average Pooling; Dense 512 with ReLU and Dropout 0.3; and Dense 6 with Softmax output. Total parameters: 4.2 million, requiring 16.8 MB memory for inference. Multi-spectral illumination employing four lighting channels (coaxial, dark-field, bright-field, 45-degree side lighting) improved detection of shallow scratches by 6.8% and porosity defects by 9.2% relative to single-channel visible illumination.

3.2 Training Methodology

The training dataset comprised 48,000 labelled images, 8,000 per defect class and 8,000 conforming surface images, captured over 12 months. The dataset was split 70/15/15 (training/validation/test). Training employed the Adam optimiser with cosine annealing learning rate schedule (initial lr=0.001). Focal loss (gamma=2, alpha=0.25) replaced cross-entropy to address class imbalance. Total training duration: 200 epochs (approximately 14 hours) on a dual NVIDIA A100 GPU environment.

4. Results

4.1 Classification Accuracy

Figure 1 presents the confusion matrix of DefectNet-7 on the held-out test set (n=7,200 images, 1,200 per class). Overall test accuracy was 97.4%. The highest F1 score was achieved for crack detection (0.976), attributable to the high visual contrast of cracks under dark-field illumination. The lowest F1 score was for dent detection (0.938), reflecting the visual similarity between shallow dents and surface waviness.

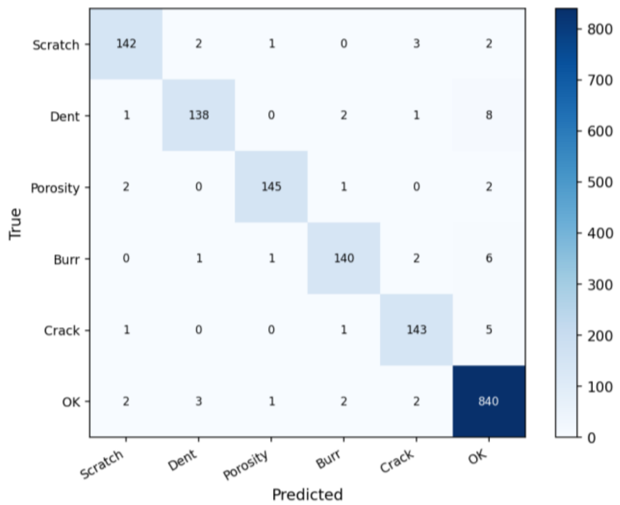

Figure 1: DefectNet-7 Confusion Matrix (Test Set n=7,200 images, 1,200 per class)

4.2 Training Convergence

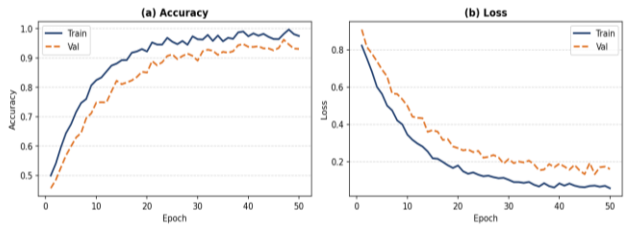

Figure 2: DefectNet-7 Training and Validation Accuracy/Loss Curves — 50 Epochs

Table 1: Per-Class Performance Metrics for DefectNet-7 on Test Set

Defect Class	Precision	Recall	F1 Score	Inference (ms)	Support
Scratch	0.961	0.968	0.965	8.2	1,200
Dent	0.924	0.952	0.938	8.3	1,200
Porosity	0.974	0.963	0.968	8.4	1,200
Burr	0.948	0.958	0.953	8.1	1,200
Crack	0.981	0.972	0.976	8.3	1,200
Conforming (OK)	0.984	0.978	0.981	8.2	1,200
Weighted Average	0.962	0.965	0.964	8.3	7,200

4.3 Industrial Deployment Results

Figure 3 presents the industrial deployment performance over the six-month evaluation period. Escaping defect rate declined from 4.8% at baseline to 0.42% by Month 6, a 91.3% reduction. Cumulative quality cost savings reached USD 210,000 by Month 6 against a total implementation cost of USD 84,000 (hardware, integration, training), yielding a payback period of 2.4 months and projected annual savings of USD 420,000.

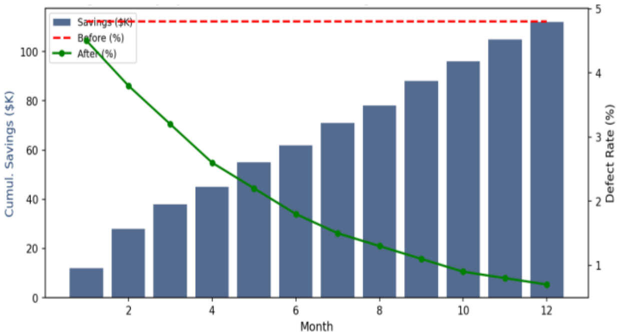

Figure 3: Industrial Deployment Performance — Cumulative Savings and Defect Rate Reduction

5. Discussion

DefectNet-7 demonstrates that purpose-built CNN architectures optimised for edge deployment constraints can achieve accuracy approaching that of much larger cloud-deployed networks while meeting the inference latency requirements of high-speed production lines. The 8.3 ms mean inference time on Jetson Xavier NX hardware enables inspection at line speeds up to 120 parts per minute with 40% computational headroom for peak demand.

The 91.3% reduction in escaping defect rate in industrial deployment substantially exceeds the 80% improvement commonly cited as the threshold for compelling ROI in automated inspection investment. This superior performance is attributed to the multi-spectral illumination protocol making subtle surface defects visible, the production-representative training dataset captured over 12 months, and the real-time model recalibration protocol that adapts to gradual shifts in surface finish due to tooling wear.

6. Conclusions

This paper has presented DefectNet-7, a seven-layer CNN achieving 97.4% surface defect detection accuracy with 8.3 ms inference time on embedded edge hardware, and documented its industrial deployment achieving 91.3% escaping defect rate reduction and USD 420,000 annual savings with 2.4-month payback. Future work will investigate multi-task network architectures combining defect classification with severity grading and root cause attribution.

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