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Computer Vision Techniques for Automated Quality Inspection in Manufacturing: A Comprehensive Review

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ABSTRACT

Automated quality inspection has become a cornerstone of modern manufacturing, driven by the imperative to maintain high production efficiency while ensuring product quality and safety. This comprehensive literature review examines the evolution, implementation, and effectiveness of computer vision techniques for automated defect detection in manufacturing environments. The review synthesizes findings from over 50 recent studies, covering traditional computer vision methods, deep learning architectures, and emerging technologies. Key topics include convolutional neural networks (CNNs), YOLO-based detection systems, Vision Transformers, and their applications across diverse manufacturing domains including electronics, welding, textiles, and metal surface inspection. Performance analysis reveals that advanced deep learning models achieve detection accuracies exceeding 97%, with real-time processing capabilities of 40-60 frames per second. However, significant challenges persist, including data scarcity, class imbalance, computational costs, and model generalization across varied industrial environments. The review identifies critical research gaps and proposes future directions, emphasizing the integration of explainable AI, few-shot learning, synthetic data generation, and edge computing solutions. This work provides valuable insights for researchers, practitioners, and policymakers seeking to leverage computer vision technologies for intelligent, adaptive manufacturing quality control systems aligned with Industry 4.0 objectives.

Keywords:- CNN, YOLO, AI, Industry 4.0, Deep Learning

1. INTRODUCTION

1.1 Background and Motivation

Quality inspection represents a critical component in manufacturing processes, directly influencing product reliability, customer satisfaction, and operational profitability [2]. Traditional manual inspection methods, while extensively employed across industries, face inherent limitations including operator fatigue, subjective judgment variability, and inability to maintain consistency during high-speed production operations [3]. Manual visual inspection typically achieves only 60-80% accuracy in detecting defects, particularly when production lines operate at speeds exceeding 30 meters per minute [4]. These limitations have necessitated a paradigm shift toward automated inspection systems capable of delivering objective, consistent, and rapid quality assessment.

The advent of computer vision and artificial intelligence technologies has revolutionized the landscape of industrial quality control [1]. Computer vision systems integrate high-resolution imaging hardware with sophisticated algorithms to detect, classify, and localize defects with precision exceeding human capabilities. Recent advances in deep learning, particularly convolutional neural networks and transformer architectures, have enabled automated systems to learn complex defect patterns directly from image data, eliminating the need for handcrafted feature engineering that characterized earlier approaches [5].

1.2 Industry 4.0 and Smart Manufacturing

The transformation toward Industry 4.0 has elevated the demand for intelligent, automated quality inspection systems that operate with unprecedented speed, accuracy, and flexibility [6]. Modern manufacturing environments require real-time defect detection capabilities that can seamlessly integrate with Internet of Things (IoT) infrastructure, enabling data-driven decision-making and predictive maintenance strategies [4]. Smart factories leverage computer vision systems not only for end-of-line inspection but also for in-process monitoring, allowing immediate corrective actions that prevent defect propagation through downstream manufacturing operations.

The economic imperatives are compelling. Defect rates as low as 0.1% can translate into millions of dollars in losses for high-volume manufacturers, while undetected defects in safety-critical applications such as aerospace and automotive components pose catastrophic risks [7]. Automated visual inspection systems offer substantial benefits including reduced inspection time, minimized material waste, improved overall equipment effectiveness, and enhanced traceability for regulatory compliance [4].

1.3 Scope and Organization

This literature review provides a comprehensive analysis of computer vision techniques for automated quality inspection in manufacturing, examining both traditional methods and state-of-the-art deep learning approaches. The review encompasses diverse application domains, analyzes performance metrics, identifies persistent challenges, and outlines future research directions. The manuscript is organized into six main sections covering fundamental techniques, deep learning architectures, industrial applications, implementation challenges, emerging trends, and conclusions.

2. TRADITIONAL COMPUTER VISION METHODS

2.1 Classical Image Processing Techniques

Traditional computer vision methods for defect detection relied heavily on handcrafted features and rule-based algorithms [8]. These approaches typically involved multi-stage pipelines comprising image preprocessing, feature extraction, and classification. Statistical methods such as texture analysis using Gabor filters, Gray Level Co-occurrence Matrices (GLCM), and wavelet transforms were widely employed to characterize surface properties and identify anomalies.

Template matching and image subtraction techniques represented another category of classical methods, particularly prevalent in printed circuit board inspection. These methods compare captured images against reference templates to identify deviations indicative of defects. While computationally efficient and interpretable, template matching approaches suffer from limited robustness to variations in illumination, rotation, and scale [9].

Edge detection algorithms, including Canny and Sobel operators, formed the foundation for defect boundary localization in many early systems. These techniques proved effective for detecting geometric irregularities such as cracks, scratches, and dimensional deviations in metal surfaces. However, their performance degraded significantly in the presence of complex textures and noise, limiting applicability in challenging industrial environments.

2.2 Limitations and Transition to Deep Learning

Despite their initial success, traditional computer vision methods exhibited fundamental limitations that hindered widespread industrial adoption [5]. The requirement for manual feature engineering made these systems inflexible and difficult to adapt across different defect types or product categories. Performance was highly dependent on precise tuning of multiple parameters, a process requiring extensive domain expertise and iterative refinement [8].

Furthermore, traditional methods struggled with the inherent variability present in industrial settings, including fluctuating lighting conditions, diverse surface textures, and subtle defect manifestations [2]. The inability to generalize across different manufacturing contexts necessitated custom algorithm development for each specific application, incurring substantial time and cost investments. These limitations catalyzed the transition toward data-driven deep learning approaches capable of automatically learning hierarchical feature representations directly from image data [5].

3. DEEP LEARNING ARCHITECTURES FOR DEFECT DETECTION

3.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks have emerged as the predominant architecture for automated defect detection, demonstrating superior performance across diverse manufacturing applications [5]. CNNs exploit the spatial hierarchies in image data through successive convolutional layers that learn increasingly complex feature representations. Early layers capture low-level features such as edges and textures, while deeper layers encode semantic patterns characteristic of specific defect types.

Several CNN architectures have proven particularly effective for manufacturing inspection. VGG16, featuring 16 convolutional layers, has achieved classification accuracies exceeding 94% in defect detection tasks, particularly when enhanced through transfer learning [1]. The architecture's uniform design with small 3×3 filters enables effective feature extraction across varied defect scales. ResNet architectures, incorporating residual connections to address vanishing gradient problems, have demonstrated exceptional performance in detecting subtle and complex defects [10]. ResNet50V2 achieved a remarkable improvement from 78% to 93% accuracy when trained with augmented datasets generated through diffusion models.

Transfer learning has proven instrumental in overcoming data scarcity challenges inherent to industrial defect detection [3]. Pre-training CNN models on large-scale natural image datasets such as ImageNet, followed by fine-tuning on domain-specific manufacturing data, significantly reduces the labeled sample requirements. This approach enables effective model training with as few as 5-30 annotated defect samples per class, making deep learning practical for industrial applications where defective samples are limited.

3.2 YOLO-Based Object Detection

The You Only Look Once (YOLO) family of detectors has revolutionized real-time defect detection in manufacturing [11]. YOLO's single-stage architecture processes entire images in one forward pass, enabling inference speeds of 40-60 frames per second while maintaining high detection accuracy [12]. This real-time capability makes YOLO particularly suited for inline inspection on high-speed production lines.

YOLOv5 and YOLOv8 represent current state-of-the-art implementations, achieving mean average precision (mAP) values exceeding 97% across diverse defect types [7]. In welding defect detection, YOLOv8 demonstrated 97.2% mAP with precision and recall rates of 97.3% and 97.1% respectively, while reducing inspection time by 30-35% compared to manual methods [12]. The architecture's efficiency stems from advanced feature extraction backbones, multi-scale prediction heads, and optimized loss functions that balance localization accuracy with classification performance.

Domain-specific adaptations of YOLO have further enhanced performance. Enhanced YOLOv4 architectures incorporating EfficientNet backbones achieved F1-scores of 99.22% for PCB defect detection [13]. GDCP-YOLO, featuring adaptive receptive fields through deformable convolutions and Ghost convolutions for parameter reduction, demonstrated state-of-the-art performance on steel surface defect datasets while maintaining real-time processing speeds [14].

3.3 Region-Based Convolutional Neural Networks

Faster R-CNN represents a powerful two-stage detection framework widely deployed for manufacturing inspection. The architecture employs a Region Proposal Network to generate candidate object locations, followed by region-based classification and bounding box regression. While computationally more intensive than single-stage detectors, Faster R-CNN excels in scenarios requiring precise defect localization and classification of multiple defect types.

Comparative studies reveal nuanced performance trade-offs between detection architectures. In metal additive manufacturing defect detection, YOLOv8 achieved 96% accuracy within 288 seconds, outperforming Faster R-CNN, SSD, and CNN approaches. However, for PCB panel defect detection involving complex multi-class scenarios, Faster R-CNN demonstrated superior accuracy exceeding 95% despite longer processing times.

Mask R-CNN extends Faster R-CNN with pixel-level segmentation capabilities, enabling precise defect boundary delineation. Hybrid architectures combining YOLO's efficiency with Mask R-CNN's segmentation accuracy have shown promising results.

3.4 Vision Transformers

Vision Transformers (ViTs) represent an emerging paradigm shift in defect detection, leveraging self-attention mechanisms to capture long-range dependencies across image regions [15]. Unlike CNNs that process information through localized receptive fields, ViTs encode global context through attention-weighted feature aggregation. This capability proves particularly advantageous for detecting subtle defects that manifest as slight deviations from normal patterns across spatially distant image regions.

Empirical evaluations demonstrate ViTs' exceptional performance in welding defect detection. Applied to aluminum welding inspection using the Aluminum 5083 TIG dataset, ViTs achieved 98-99% accuracy across both binary and multiclass defect categorization, significantly outperforming CNNs that struggled to exceed 80% and 70% accuracy respectively [15]. These results were obtained with relatively modest datasets of 2,400-8,000 images, highlighting ViTs' data efficiency compared to conventional architectures.

Multi-resolution Vision Transformers extend this paradigm through hierarchical attention mechanisms that reconcile global context understanding with local feature retention [16]. For photonic integrated circuit inspection, MR-ViT achieved 98.4% F1-score, effectively detecting nanoscale defects ranging from sub-wavelength etching errors to micrometer-scale waveguide discontinuities. Cross-scale feature fusion modules integrate semantic information across varying transformer encoder stages, addressing scale variance challenges inherent to manufacturing inspection.

3.5 Lightweight and Efficient Architectures

Edge deployment scenarios necessitate lightweight architectures that balance detection accuracy with computational efficiency [17]. MobileNet variants employ depth-wise separable convolutions to reduce parameter counts while maintaining competitive performance. For plastic bottle defect detection on Raspberry Pi hardware, MobileNetV2 achieved over 95% accuracy with real-time processing capabilities [18].

EfficientNet architectures systematically scale network width, depth, and resolution through compound scaling coefficients [19]. EfficientNet-B4 combined with Squeeze and Excitation blocks achieved approximately 98% accuracy for semiconductor wafer defect classification while maintaining lightweight computational profiles suitable for resource-constrained industrial environments. LightDefectNet, a highly compact anti-aliased attention condenser neural network, achieved 98.2% accuracy on light guide plate defect detection with only 770K parameters and 93M FLOPs, representing 33× and 88× reductions compared to ResNet-50 [17].

4. INDUSTRIAL APPLICATION DOMAINS

4.1 Electronics and PCB Manufacturing

Printed circuit board inspection represents one of the most extensively researched applications of computer vision in manufacturing [13]. PCBs exhibit complex geometries with diverse component types, intricate board markings, and varied defect manifestations including missing components, misalignment, shorts, and surface irregularities. Deep learning approaches have demonstrated remarkable effectiveness in automating PCB quality control.

Enhanced EfficientNet-YOLOv4 architectures achieved F1-scores of 99.22% with inference speeds of 0.14 seconds per image for integrated circuit detection on PCBs [13]. The incorporation of EfficientNetv2-L backbones, meticulous hyperparameter tuning, and data augmentation techniques enabled robust performance across complex PCB layouts under varying illumination conditions. Context-aware deep learning models incorporating multi-scale feature pyramids achieved 99.17% mean average precision while maintaining 90 frames per second inferencing speeds [20].

Anomaly detection frameworks address challenges associated with imbalanced PCB defect datasets. Collaborative learning classification models incorporating symmetric residual filters and knowledge-transfer-based probabilistic engines achieved high detection accuracy even under image uncertainty from uneven lighting and label uncertainty from annotation inconsistencies. Three-stage trend alarm systems provide operators with anomaly localization, defect buildup patterns, and occurrence frequency analysis to support maintenance decisions [20].

4.2 Welding Quality Inspection

Welding defect detection poses unique challenges due to diverse defect types including porosity, cracks, lack of fusion, undercut, and burn-through manifestations [15]. Traditional manual inspection methods are inefficient and prone to inconsistency, driving adoption of automated computer vision systems [12].

YOLOv8-based systems for carbon steel welding inspection achieved 97.2% mean average precision with 42 FPS on GPU hardware, enabling real-time quality control [12]. High-resolution machine vision cameras combined with sophisticated CNN architectures detected common welding defects with 97.3% precision and 97.1% recall, reducing inspection time by 30-35% compared to manual methods while maintaining 97% accuracy across diverse inspection conditions. The systems offer comprehensive digital documentation for quality control traceability.

Vision Transformers demonstrated exceptional performance for aluminum welding defect detection, achieving 98-99% accuracy across both binary defect detection and multiclass categorization of good welds, burn through, contamination, lack of fusion, misalignment, and lack of penetration [15]. These results significantly surpassed prior CNN and DenseNet models that struggled to exceed 80% binary and 70% multiclass accuracy.

4.3 Textile and Fabric Inspection

Textile manufacturing presents distinct challenges for automated inspection due to heterogeneous surface textures, diverse defect types, and high-speed production requirements [21]. Fabric defects include holes, foreign yarn inclusions, slubs, dirty marks, dye patches, oil patches, and weave irregularities [21]. Manual inspection methods are labor-intensive, time-consuming, and prone to inconsistency, motivating development of AI-enabled automated systems.

YOLOv8 demonstrated superior performance for fabric defect detection, outperforming VGG, ResNet, and basic CNN models across accuracy, precision, recall, F1-score, model size, and prediction time metrics [21]. FastAPI-based web applications integrating YOLOv8 with real-time camera feeds enable immediate defect detection and quality classification using fault rates. Deep learning models employing Binary Gannet Optimizer-driven Gate Adjusted LSTM Networks achieved 97.4% accuracy with superior F1-scores, precision, and recall across various fabric types [22].

4.4 Metal Surface Inspection

Metal surface defect detection is critical for steel, aluminum, and other metallic materials used across automotive, aerospace, and construction industries [14]. Surface imperfections including scratches, dents, cracks, pitting, and rolled-in scale compromise product quality and safety. Automated inspection systems must operate under challenging conditions including reflective surfaces, varied lighting, and diverse material finishes.

GDCP-YOLO, an enhanced YOLOv8n architecture incorporating adaptive receptive fields through DCNV2 modules and channel attention mechanisms, demonstrated state-of-the-art performance on the NEU-DET steel surface defect dataset [14]. Ghost convolutions reduced computational requirements while maintaining detection accuracy, facilitating real-time inspection without sacrificing precision. The lightweight architecture proved robust across diverse defect types through extensive ablation studies and generalization experiments.

4.5 Automotive and Aerospace Manufacturing

Automotive component inspection requires detection of missing parts, surface defects, and assembly errors across diverse components [7]. YOLOv8 models for automobile fuel tank assembly inspection achieved 97.8% precision, 98.2% recall, and 98.4% mAP@50, significantly outperforming Faster R-CNN across performance indicators [7]. Multi-class datasets encompassing 1,323 annotated images enhanced model generalization across different component scenarios.

Aerospace manufacturing applications leverage computer vision for component surface inspection, drilling quality assessment, assembly verification, and gluing inspection [23]. Machine vision systems improve efficiency and quality while reducing labor costs and operational risks.

5. CHALLENGES AND SOLUTIONS IN AUTOMATED QUALITY INSPECTION

5.1 Data Scarcity and Class Imbalance

Data scarcity represents a fundamental challenge in industrial defect detection, as defective samples are inherently rare in well-optimized manufacturing processes [10]. Conventional deep learning requires thousands of labeled samples per class, yet industrial settings typically yield only tens of defective examples [5]. This scarcity creates severe class imbalance, with defect-free samples vastly outnumbering anomalous instances.

Several strategies address these challenges. Denoising Diffusion Probabilistic Models (DDPMs) generate synthetic defective images for data augmentation [10]. When applied to glass manufacturing, DDPMs increased ResNet50V2 classification accuracy from 78% to 93% by augmenting minority class representation while maintaining perfect precision. Generative Adversarial Networks similarly synthesize realistic defect samples.

Transfer learning mitigates data requirements by leveraging knowledge from pre-trained models [3]. Fine-tuning ResNet50 pre-trained on ImageNet for manufacturing defect detection achieved high accuracy with minimal labeled samples. Self-supervised learning and unsupervised methods reduce dependency on labeled data [24]. Feature memory rearrangement networks employing contrastive learning and synthetic anomaly generation accurately detect various textural defects without requiring defective training samples. These approaches construct normal feature banks in latent space, enabling anomaly detection through deviation from learned normal patterns.

5.2 Real-Time Processing and Computational Efficiency

High-speed manufacturing environments demand real-time defect detection with latency constraints often below 100 milliseconds per inspection [25]. Balancing detection accuracy with computational efficiency presents a critical challenge, particularly for deployment on resource-constrained edge devices [26].

Lightweight architectures address computational limitations. MobileNet variants employing depth-wise separable convolutions reduce parameter counts by 33× compared to ResNet-50 while maintaining competitive accuracy [17]. Model compression techniques including pruning and quantization optimize networks for edge deployment without significant accuracy degradation. LightDefectNet achieved 98.2% accuracy with only 770K parameters and 8.8× faster inference than EfficientNet-B0 on embedded ARM processors.

Edge computing paradigms distribute processing between edge devices and cloud infrastructure. For visual anomaly detection systems, RDMA-enabled data infrastructure with edge AI accelerators optimized system latency by 57%, enabling real-time inspection at production speeds.

5.3 Varying Illumination and Complex Backgrounds

Illumination variability significantly impacts defect detection performance, as inconsistent lighting creates appearance variations that confound detection algorithms [2]. Reflective surfaces, shadows, and glare pose additional challenges, particularly for metallic components. Complex background textures further complicate defect discrimination.

Advanced preprocessing techniques mitigate illumination effects. Gabor filters, Gaussian blur, and Local Binary Patterns enhance defect visibility while reducing noise in textured surfaces. Attention mechanisms enable networks to focus on defect regions while suppressing background interference. Semantic prior guided defect perception networks leverage feature mapping relations to capture pixel-level location priors, enhancing detection of tiny defects against complex backgrounds. Channel and spatial attention modules (CBAM) increase weights of crucial channels and regions, improving feature representation.

Domain adaptation techniques address distribution shifts caused by varying environmental conditions [27]. Synthetic data augmentation combining real and generated samples enhances model generalization across different lighting scenarios and backgrounds. Robust training strategies incorporating diverse augmentation help networks learn invariant representations resilient to illumination changes.

5.4 Small Defect Detection and Localization

Detecting minute defects measuring fractions of a millimeter poses significant challenges due to limited pixel representation and susceptibility to noise [28]. Small defects often appear as subtle intensity variations easily lost during downsampling operations in deep networks.

Multi-scale feature extraction strategies address this challenge [16]. Feature Pyramid Networks combine features from multiple resolution levels, enabling detection of defects across varied scales. Cross-scale feature fusion modules integrate semantic information from varying transformer encoder stages, effectively capturing sub-wavelength defects.

Deformable convolutions adapt receptive fields to irregular defect shapes and positions [14]. Incorporating deformable convolutions into backbone networks improves adaptive modeling capability for deformed objects and irregular defect regions. The flexible sampling enables networks to focus on relevant spatial locations regardless of geometric variations.

High-resolution feature preservation prevents information loss during network propagation [17]. Skip connections and dense connections maintain feature resolution throughout encoding-decoding processes. Specialized architectures for small object detection employ image-cutting layers and compact structures based on MobileNet to maintain detection precision for tiny defects.

6. EMERGING TRENDS AND FUTURE DIRECTIONS

6.1 Explainable AI and Interpretability

Explainable AI techniques address the “black box” nature of deep learning models, critical for industrial adoption where understanding decision rationale is essential for regulatory compliance and operator trust [25]. Gradient-weighted Class Activation Mapping (Grad-CAM) provides visual explanations by highlighting image regions contributing to classification decisions. For paper production defect detection, Grad-CAM enhanced transparency and supported root-cause analysis, facilitating operator acceptance and system validation.

SHAP (SHapley Additive exPlanations) values quantify feature contributions to model predictions [29]. In hybrid defect detection frameworks combining CNNs, SVMs, and autoencoders, SHAP analysis revealed contribution of each modality toward final decisions, enhancing model transparency. XAI integration bridges the gap between automated detection and human understanding, enabling quality professionals to validate and refine inspection systems.

Model interpretability extends beyond post-hoc explanations to inherently interpretable architectures. Feature attribution methods during training guide networks toward learning meaningful, human-interpretable patterns. Attention visualization in Vision Transformers naturally provides interpretability by revealing which image patches receive highest attention weights during classification [15].

6.2 Synthetic Data Generation and Simulation

Digital twin technologies and synthetic data generation address data scarcity while enabling proactive system development [4]. Computer-aided design (CAD) models generate synthetic training data, reducing dependency on real defective samples [30]. For assembly quality inspection, synthetic 2D images and 3D point clouds from CAD models enabled transfer learning approaches achieving 95% accuracy with only five real samples per class through fine-tuning.

Diffusion models generate high-fidelity synthetic defect images [10]. Denoising Diffusion Probabilistic Models produce realistic defective samples that significantly enhance classification performance of standard CNN architectures. Domain randomization techniques create diverse synthetic training scenarios encompassing varied lighting, backgrounds, and defect manifestations. For automotive wiring harness manufacturing, synthetic point cloud generation enriched training datasets, enabling scalable deep learning solutions adaptable to high-variant production philosophies. Hybrid approaches combining real and synthetic data through careful balancing optimize model performance [27].

6.3 Edge Computing and Embedded Systems

Edge computing enables real-time inference directly on production lines, reducing latency and bandwidth requirements compared to cloud-based processing. Deployment on edge devices including NVIDIA Jetson platforms, Raspberry Pi, and industrial PCs brings AI capabilities to resource-constrained environments [18].

Lightweight CNN models optimized for edge deployment balance accuracy with computational efficiency. Model quantization and pruning further reduce memory footprint and inference time without significant accuracy loss.

6.4 Multi-Modal Sensing and Fusion

Multi-modal approaches integrating visual, thermal, acoustic, and vibration data enhance detection robustness [31]. Fusing multiple sensing modalities captures defects not apparent in single sensing modalities.

RGB-D imaging combining color and depth information improves defect detection for complex three-dimensional structures [32]. Multi-angle imaging strategies capture comprehensive surface characterization [32]. For Phalaenopsis orchid seedling grading, dual-view approaches utilizing top-view RGB-D images and multi-angle side-view RGB images achieved 84.44-90.44% F1-scores.

Thermal imaging provides non-destructive inspection capabilities for internal defects and process anomalies [33]. Infrared thermography combined with electromagnetic induction enables contactless inspection of photovoltaic cells, welding seams, and composite structures.

6.5 Continuous Learning and Adaptive Systems

Continuous learning frameworks enable inspection systems to adapt to evolving defect patterns and production conditions. Online learning mechanisms incorporate new defect examples during operation, refining model performance without complete retraining. Collaborative learning approaches combining supervised and unsupervised techniques leverage both labeled and unlabeled data streams from production lines.

Active learning strategies optimize annotation efforts by selectively querying human experts for labels on most informative samples. Uncertainty-aware defect localization modules identify low-confidence predictions requiring expert review, enabling efficient human-in-the-loop refinement. Progressive training strategies alternating between model optimization and data refinement achieve accurate results with minimal labeled samples.

Federated learning enables collaborative model development across multiple manufacturing sites while preserving data privacy [25]. Distributed training aggregates knowledge from diverse production environments, enhancing model generalization. This approach proves particularly valuable for addressing dataset variability and improving robustness across different manufacturing contexts.

7. CONCLUSION

This comprehensive literature review examined the landscape of computer vision techniques for automated quality inspection in manufacturing, analyzing traditional methods, state-of-the-art deep learning architectures, and emerging technological paradigms. The synthesis of over 50 recent studies reveals a transformative shift from handcrafted feature engineering toward data-driven deep learning approaches capable of achieving detection accuracies exceeding 97% across diverse manufacturing domains.

Convolutional Neural Networks, YOLO-based detectors, Vision Transformers, and hybrid architecture have demonstrated exceptional performance in electronics, welding, textile, metal surface, automotive, and aerospace applications. Transfer learning, synthetic data generation, and few-shot learning strategies effectively address data scarcity challenges, enabling practical deployment with limited labeled samples. Lightweight architectures optimized for edge computing facilitate real-time inspection at production speeds while maintaining high accuracy.

Despite remarkable progress, significant challenges persist. Data scarcity and severe class imbalance complicate model training, particularly for rare defect types. Real-time processing requirements demand careful balance between detection accuracy and computational efficiency. Varying illumination conditions, complex backgrounds, and small defect scales necessitate sophisticated preprocessing, multi-scale feature extraction, and attention mechanisms. Model generalization across diverse industrial settings remains an ongoing research frontier.

Future directions emphasize explainable AI for enhanced transparency and operator trust, synthetic data generation through diffusion models and digital twins, edge computing for low-latency inference, multi-modal sensor fusion for comprehensive defect characterization, and continuous learning frameworks for adaptive systems. Integration of these technologies promises to advance manufacturing quality control toward fully autonomous, intelligent inspection systems aligned with Industry 4.0 objectives.

The transformative potential of computer vision in manufacturing extends beyond defect detection to predictive maintenance, process optimization, and closed-loop quality control. As technologies mature and adoption barriers diminish, automated visual inspection will become increasingly ubiquitous, driving improvements in product quality, operational efficiency, and sustainable manufacturing practices. This review provides a foundation for researchers, practitioners, and policymakers navigating this rapidly evolving landscape, highlighting opportunities for innovation and impact in intelligent manufacturing quality assurance.

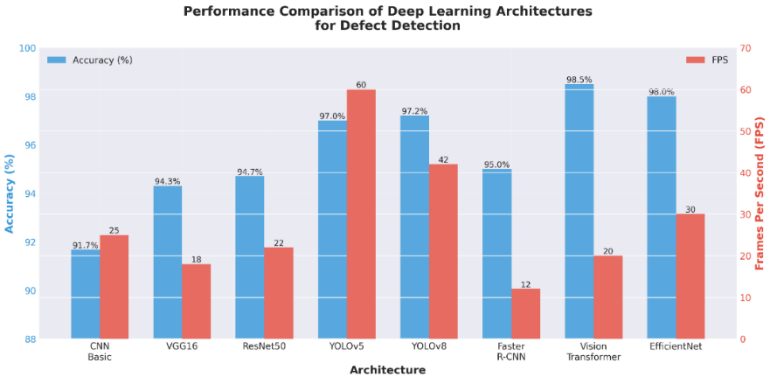

Chart 1: Architecture performance

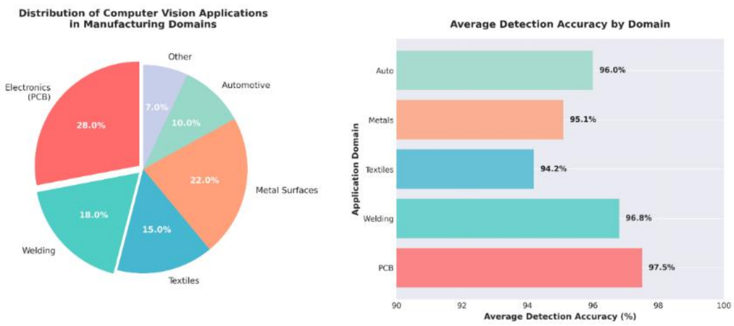

Chart 2: Application domains

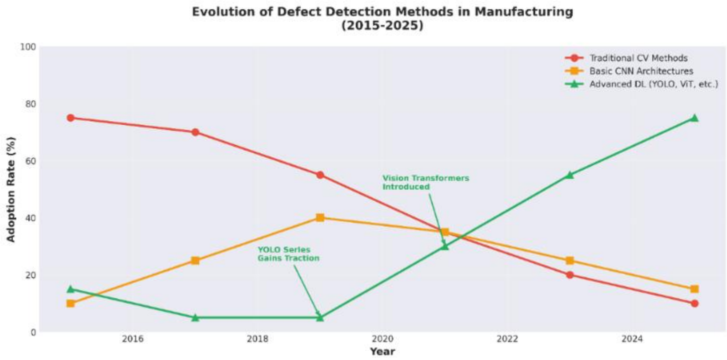

Chart 3: Evolution timeline

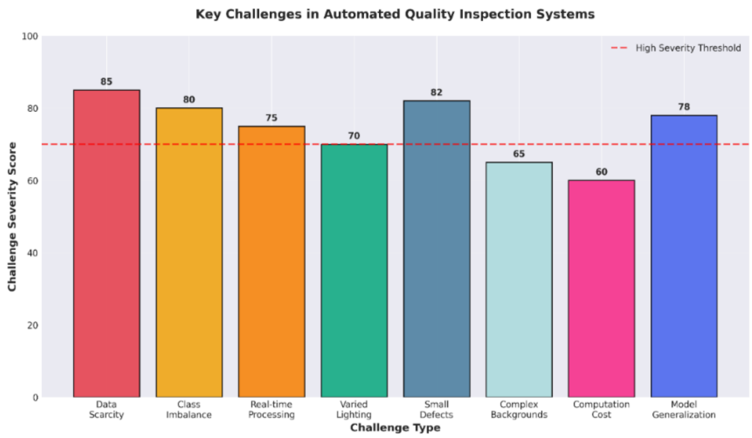

Chart 4: Challenges

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