Deep Learning Approaches in Fabric Defect Detection: A Comprehensive Review

Your Name *Department of Computer Science*
Your University
City, Country
email@domain.com

***Abstract*—Automated fabric defect detection is crucial for quality control in textile manufacturing. This review synthesizes recent advances (2023-2025) in deep learning-based approaches, analyzing key studies covering YOLO variants, Mask R-CNN, transfer learning, and real-time systems. We identify consistent challenges in small-defect detection, real-time performance, and lighting variability. Innovations include RG-C2f modules, DySample upsampling, and industrial post-processing integration. While YOLO variants achieve high FPS, segmentation models reach 97.8% accuracy. Critical gaps remain in standardized benchmarking, multi-defect handling, and edge deployment optimization. Future research should prioritize lightweight hybrid architectures and cross-material generalization.**

***Index Terms*—Fabric defect detection, computer vision, deep learning, YOLO, Mask R-CNN, quality control, industrial automation.**

I. Introduction

Automated visual inspection has transformed textile manufacturing, replacing error-prone manual methods. Traditional approaches to fabric defect detection have evolved from manual inspection to computer vision techniques including statistical methods [2], spectral analysis [6], and texture-based algorithms [14]. Deep learning approaches have demonstrated remarkable success in defect detection, with recent models achieving over 97% accuracy in controlled settings [1]. This review analyzes methodological innovations, performance benchmarks, and implementation challenges across seminal papers published between 2023-2025. We systematically compare architectures (YOLO, Faster R-CNN, Mask R-CNN), preprocessing techniques (CLAHE, Sobel edge detection), and deployment strategies (edge computing, real-time systems) to identify effective solutions and persistent research gaps.

II. Methodological Approaches

A. YOLO-Based Architectures

Modified YOLO variants dominate real-time applications. Kim & Lee [3] enhanced YOLO with attention modules and focal loss function, improving classification performance without additional computational requirements. The study demonstrated effective fault detection capability on publicly available Kaggle datasets. Key innovations include attention mechanisms and optimized loss functions for textile images. Jin et al. [4] implemented an improved YOLOv8 model with RG-C2f module for faster processing of high-resolution images, DySample upsampling operator for better edge preservation, and adaptive inner-WIoU loss function for enhanced generalization. The model achieved mAP improvements of 6.4% and 1.5% on TILDA and Tianchi datasets respectively compared to baseline YOLOv8.

TABLE I
Performance comparison across architectures

Model	Accuracy/mAP	Defect Types	Year
Improved Mask R-CNN [1]	97.8%	6 classes	2023
YOLO with attention [3]	High (not specified)	Multiple	2023
Improved YOLOv8 [4]	6.4% mAP improvement	Multiple	2025
YOLOv8 (Chenab Textiles) [7]	84.8% mAP	7 classes	2024

B. Transfer Learning & Classification

For defect classification, transfer learning with pretrained CNNs shows strong performance. Malik et al. [2] evaluated several machine learning models including Convolutional Neural Networks (CNNs) and Transfer Learning architectures such as ResNet and VGG for their performance in defect detection. Their results indicate that CNN-based models, particularly those leveraging Transfer Learning, achieve high accuracy in detecting and classifying fabric defects, significantly outperforming traditional approaches [16]. The study used a labeled dataset of fabric images with various defect types with data augmentation techniques applied to enhance robustness.

C. Real-Time Hybrid Systems

Industrial deployment requires end-to-end solutions. Researchers [7] trained YOLOv8 on an indigenous dataset from Chenab Textiles containing printed and plain fabric images captured in various manufacturing conditions. YOLOv8n achieved the highest performance with a mAP of 84.8%, precision of 0.818, and recall of 0.839 across seven different defect classes, outperforming YOLOv5 and MobileNetV2-SSD FPN-Lite models trained on the same dataset. The study addressed challenges of real-world manufacturing scenarios where images are not high-quality and precisely positioned, with variations in backlight intensity, noise, and blurriness.

D. Segmentation & Advanced CNNs

For pixel-level accuracy, Mask R-CNN variants excel. Revathy & Kalaivani [1] presented a deep learning-based IM-RCNN for sequentially identifying image defects in patterned fabrics. Their approach involved gathering images from the HKBU database, denoising using CLAHE filter, utilizing Sobel edge detection algorithm to extract pertinent attention features, and finally using improved Mask R-CNN (IM-RCNN) for classifying defected fabric into six classes. The dataset evaluation using true-positive rate and false-positive rate parameters yielded a higher accuracy of 0.978 for the proposed improved Mask R-CNN, improving overall accuracy by 6.45%, 1.66%, 4.70%, and 3.86% better than MobileNet-2, U-Net, LeNet-5, and DenseNet, respectively.

III. Datasets & Evaluation

TABLE II
KEY DATASETS IN FABRIC DEFECT DETECTION

Dataset	Images	Defects	Adoption
HKBU Patterned	-	6	Paper 1
TILDA	300-5000	6	Multiple papers
Tianchi	-	-	Paper 4
Chenab Textiles	-	7	Paper 7
Kaggle Fabric Defect	Public	Multiple	Paper 3

Evaluation metrics reveal trade-offs between different approaches. The most commonly used metrics include:

- **Accuracy/mAP**: Preferred for detection tasks (Improved Mask R-CNN: 97.8%, YOLOv8: 84.8% mAP)
- **Precision/Recall**: Critical for classification tasks (YOLOv8: Precision 0.818, Recall 0.839)
- **FPS**: Important for real-time deployment (not consistently reported across studies)

Standardization remains problematic as studies use diverse custom datasets [18], making direct comparisons challenging.

IV. Performance Challenges

A. Accuracy Limitations

Key detection challenges include:

- **Small defects**: Most methods show reduced performance on small defects
- **Texture interference**: Complex backgrounds reduce detection accuracy [13]
- **Class imbalance**: Some defect types are underrepresented in datasets
- **Lighting variations**: Real-world conditions affect detection performance [12]

B. Real-World Deployment

Industrial implementation faces several critical challenges:

- **Lighting sensitivity**: Accuracy drops under variable illumination conditions
- **Speed constraints**: Real-time performance requirements for high-speed production lines
- **Edge compromises**: Accuracy loss when deploying on resource-constrained devices [15]
- **Dataset limitations**: Lack of high-quality, precisely positioned images in real manufacturing scenarios

V. Critical Innovations

Several key technical advances have emerged from the reviewed literature:

1) **Preprocessing Enhancement**: CLAHE (Contrast Limited Adaptive Histogram Equalization) and Sobel edge detection consistently boosted performance across multiple studies [1].
2) **Attention Mechanisms**: Attention modules improved classification and detection performance without additional computation [3].
3) **Architecture Optimization**: Efficient modules like RG-C2f improved processing speed for high-resolution images while maintaining accuracy [4].
4) **Loss Function Innovations**: Adaptive loss functions like inner-WIoU dynamically adjust focus on low-quality samples to enhance generalization capability [4].
5) **Real-world Validation**: Studies using indigenous datasets from manufacturing environments [7] provide better understanding of practical challenges.

VI. Research Gaps & Future Directions

TABLE III
RESEARCH GAPS AND PROPOSED SOLUTIONS

Gap	Potential Solutions
Standardized benchmarks	Create open-source datasets with manufacturing variations
Multi-defect handling	Hierarchical detection frameworks
Cross-material generalization	Domain adaptation techniques
Edge optimization	Neural architecture search for lightweight models
Real-time segmentation	Hybrid YOLO-Mask R-CNN architectures
Limited defect categories	Expanded classification schemes

The identified research gaps present significant opportunities for future development. The lack of standardized benchmarks particularly hampers progress, as it prevents meaningful comparisons between different approaches [7]. Multi-defect handling remains challenging, with most systems designed for limited defect types. Cross-material generalization is another critical area, as models trained on one fabric type often fail on others [17].

VII. Conclusion

Deep learning has revolutionized fabric defect detection, with YOLO variants dominating real-time applications and Mask R-CNN excelling in segmentation accuracy. Key innovations include attention mechanisms, architecture optimizations, and industrial post-processing integration. Persistent challenges include small-defect detection, lighting sensitivity, and edge deployment efficiency.

Future research should prioritize three main areas: (1) standardized open datasets that include diverse lighting conditions and fabric types, (2) multi-defect recognition systems capable of handling complex scenarios, and (3) hardware-aware neural architecture search for optimized edge deployment. Bridging these gaps will accelerate adoption in high-speed manufacturing environments and improve overall quality control in textile production.

The field shows tremendous promise, with accuracy rates exceeding 97% in controlled settings. However, translating these laboratory successes to robust industrial deployment remains the primary challenge. Addressing the identified research gaps will be crucial for the next generation of fabric defect detection systems.

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