

CBAM–ECA–YOLO: An Automated Fabric Defect Detection Framework for Textile Engineering Applications

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Abstract: Fabric defect inspection is a critical quality assurance task in textile engineering, as surface defects such as holes, spots, and irregular textures can significantly reduce product quality and manufacturing efficiency. Conventional manual inspection is time-consuming and subjective, while existing automated vision systems based on convolutional neural networks and YOLO architectures often face limitations in detecting small-scale defects, handling complex fabric textures, and maintaining robustness under uneven illumination conditions. To address these challenges, this study proposes CBAM-ECA-YOLO, an automated fabric defect inspection framework tailored for textile engineering applications. The proposed framework builds upon the YOLOv8 baseline and integrates two complementary attention mechanisms: the Convolutional Block Attention Module (CBAM) to enhance spatial and channel-wise feature representation, and Efficient Channel Attention (ECA) to improve inter-channel dependency modeling with minimal computational overhead. These enhancements enable the model to effectively emphasize defect-relevant regions while suppressing background noise caused by fabric patterns and lighting variations. Extensive experiments conducted on a publicly available fabric defect dataset demonstrate that the proposed framework achieves superior detection performance compared to the baseline YOLOv8 model, with notable improvements in mean Average Precision while preserving real-time inference speed. The results indicate that CBAM-ECA-YOLO provides a robust and efficient solution for automated fabric defect inspection, making it well suited for deployment in modern textile manufacturing and quality control systems.

Keywords: Fabric Defect Detection; YOLOv8; CBAM; Efficient Channel Attention; Computer Vision; Textile Inspection

INTRODUCTION

1.1 Background and Importance

Fabric defect detection is a critical quality control task in textile engineering, as surface defects such as holes, stains, slubs, and knots directly affect fabric performance, customer satisfaction, and production costs. With the increasing scale and speed of modern textile manufacturing, automated inspection systems have become essential to reduce material waste and ensure consistent quality across production

lines [1]. Conventional manual inspection suffers from human fatigue, subjectivity, and inconsistency, particularly for complex textures and subtle defects, resulting in low efficiency and unreliable performance in continuous industrial environments [2].

Advances in machine learning have enabled convolutional neural networks (CNNs) to learn discriminative texture features for accurate defect classification, while object detection frameworks such as YOLO support

real-time defect localization and identification [3,4]. However, many existing approaches rely on complex architectures, extensive parameter tuning, or large annotated datasets, limiting scalability and practical deployment in textile factories [5]. Within the Industry 4.0 paradigm, textile inspection systems are increasingly expected to balance accuracy, efficiency, and transparency, motivating research into lightweight models, configuration-efficient optimization, semi-supervised learning, and explainable artificial intelligence [1,6].

Recent progress in object detection further strengthens automated fabric inspection through lightweight architectures and attention-driven feature enhancement. FD-YOLO, based on the YOLOv11n framework, demonstrates that integrating multi-scale attention and cross-scale feature fusion can improve sensitivity to small and subtle defects while maintaining real-time performance [7]. More broadly, textile inspection research has evolved from rule-based vision systems toward data-driven machine vision frameworks applicable across diverse materials and production stages [8,9]. Comprehensive reviews emphasize that modern textile quality control increasingly adopts intelligent vision systems aligned with Industry 4.0, integrating real-time analytics, automation, and scalable learning across the textile production chain [10–12]. Extensions of YOLO-based inspection to related domains, such as leather surface defect detection, further confirm the robustness and adaptability of real-time detectors under complex textures and illumination conditions [13].

1.2 Challenges in Fabric Defect Detection

One major challenge in fabric defect detection is identifying subtle and low-contrast defects, which often manifest as minor texture irregularities rather than clear structural anomalies. Such defects are scarce in datasets and visually similar to normal fabric patterns, making discriminative learning difficult. Recent studies show that even attention-enhanced deep

networks struggle to capture fine-grained texture variations when training samples are limited [14], particularly when defect cues are easily masked by normal texture fluctuations [15].

Dense and repetitive fabric textures further complicate defect localization by introducing strong background interference. High-frequency structural patterns lead to feature redundancy and confusion between texture variation and actual defects. Reviews of fabric inspection systems indicate that insufficient modeling of normal texture distributions is a primary cause of false detections [16]. Texture-aware one-stage detectors demonstrate that incorporating texture perception and adaptive feature fusion is essential for distinguishing defects embedded in dense backgrounds [17].

In real manufacturing environments, illumination variation and small defect scale present additional challenges. Nonuniform lighting caused by surface reflectivity and material diversity significantly alters fabric appearance, reducing inspection robustness [18]. Meanwhile, many defects occupy only a small image region with fuzzy boundaries, resulting in poor feature representation and missed detections [19]. Although illuminance-invariant modeling, multiscale fusion, and lightweight biologically inspired frameworks have been proposed to address these issues [20–22], achieving robust detection under combined texture, illumination, and scale variations remains an open research problem.

1.3 Deep Learning for Fabric Inspection

Deep learning plays a central role in automated fabric inspection, with convolutional neural networks (CNNs) widely adopted for learning discriminative texture features under complex fabric backgrounds. However, CNN architectures originally designed for natural images often contain redundant parameters for defect detection, motivating pruning and optimization strategies to improve inference

efficiency for industrial deployment [23]. Real-time CNN-based inspection systems further demonstrate that task-specific preprocessing and hard negative mining can enhance defect visibility and classification performance in loom environments [24]. More recent models incorporate global context modeling and bidirectional feature fusion to improve sensitivity to weak and low-contrast defects [25].

Attention mechanisms inspired by transformer architectures have increasingly influenced fabric inspection by enhancing global context awareness and feature discrimination. Hybrid CNN–attention designs effectively amplify subtle defect cues while suppressing background interference in complex textured scenarios [25]. In parallel, YOLO-based object detectors have gained prominence due to their unified architecture and real-time performance. Feature-augmented YOLO variants integrate attention modules, additional detection heads, and advanced feature fusion to improve small defect localization without sacrificing speed [26]. Practical YOLOv4-based systems validate the feasibility of online textile inspection with industrial frame rates [27], while recent reviews highlight the shift toward lightweight and attention-enhanced YOLO architectures for modern textile quality control [28].

1.4 Research Gap and Contributions

Despite substantial progress in deep learning–based fabric defect inspection, several limitations persist in real industrial settings. CNN-based methods often struggle to distinguish subtle defects embedded in dense and repetitive textures, while transformer-inspired models typically incur high computational overhead that restricts real-time deployment. Although YOLO-based detectors provide a favorable trade-off between accuracy and speed, existing variants are not sufficiently tailored to fabric-specific challenges such as small defect scale, low contrast, and strong

background interference. In addition, most approaches rely on single-attention mechanisms and standard RGB inputs, limiting their ability to enhance defect-relevant features under complex texture and illumination conditions.

To address these gaps, this work proposes a CBAM–ECA–YOLOv8 framework that integrates complementary attention mechanisms with a multi-channel input representation for robust and efficient fabric defect detection. The main contributions are summarized as follows:

1. A CBAM–ECA–YOLOv8 architecture specifically designed for fabric defect inspection, achieving enhanced feature refinement while preserving real-time inference capability.
2. A four-channel RGB–grayscale input strategy that improves texture contrast and enhances the visibility of subtle defect patterns.
3. Dual attention integration, employing CBAM in the backbone and ECA in the detection head to jointly strengthen spatial and channel-wise feature representations with minimal computational overhead.
4. A hybrid WIoU–NWD localization loss that improves the detection and localization accuracy of small and low-contrast fabric defects.
5. Comprehensive experimental validation demonstrating superior detection accuracy and real-time performance compared with the baseline YOLOv8 model.

The remainder of this article is organized as follows. Section 2 reviews related work, Section 3 presents the proposed methodology, Section 4 describes the experimental setup, and Section 5 discusses the results.

2. RELATED WORK

2.1 Traditional Fabric Defect Detection

Traditional fabric defect detection methods rely on handcrafted features and classical image processing techniques due to their low computational cost and interpretability. These methods are commonly categorized into statistical, spectral, structural, and model-based approaches and form the foundation of early textile inspection systems [29]. Texture analysis is widely used to model repetitive fabric patterns, as texture features are strongly correlated with fabric structure and quality parameters [30]. Model-based approaches using geometric and structural descriptors have also been explored to detect surface irregularities with robustness to noise and scale variations [31].

Among spectral methods, Gabor filters are extensively employed for fabric defect detection because of their ability to capture orientation- and scale-sensitive texture information. Optimized Gabor filter banks combined with adaptive thresholding effectively suppress background textures and enhance defect regions, while multi-scale filtering improves detection of defects with varying sizes and orientations [32,33]. More recently, Gabor features have been integrated with deep learning architectures, including U-Net–ViT hybrids and region-based detectors, to improve robustness and defect localization accuracy [34,35].

Thresholding-based techniques aim to separate defect and background regions using intensity or feature distributions. Adaptive and multi-level thresholding, as well as dynamic local sensitivity adjustment, improve performance under nonuniform illumination and noise [32,36]. However, these methods generally struggle with subtle or low-contrast defects and lack adaptability across diverse fabric materials and inspection scenarios [37,38].

Overall, while traditional methods provide valuable insights into texture modeling and defect characterization, their dependence on handcrafted features and sensitivity to imaging conditions limit scalability, motivating the transition toward learning-based inspection frameworks.

2.2 CNN-Based Approaches

Convolutional Neural Networks (CNNs) are widely adopted for fabric defect detection due to their strong texture feature learning capability. Early studies mainly employed classification networks such as VGG, Inception, and ResNet, where transfer and residual learning improved recognition accuracy but lacked pixel-level defect localization required for industrial inspection [39]. To address this limitation, U-Net–based encoder–decoder architectures were introduced for end-to-end segmentation. Lightweight variants such as Mobile-Unet improved efficiency through depthwise separable convolutions [40], while attention-enhanced models like AGUR-Net further improved segmentation performance on color-patterned fabrics using gated skip connections and multi-scale features [41]. However, U-Net-based methods often suffer from high computational cost and sensitivity to reconstruction noise.

Reconstruction-based CNN frameworks have also been explored for unsupervised defect detection, combining pixel- and feature-level reconstruction to improve anomaly localization in complex fabrics [42]. Despite improved robustness, these approaches typically rely on multi-branch architectures and post-processing, increasing model complexity. ResNet-based CNN classifiers remain popular due to stable optimization and strong feature extraction. Two-stage frameworks combining local patch classification and global decision strategies have shown effective defect detection under controlled conditions [43], while self-transfer learning methods reduce annotation dependency and improve generalization with limited

samples [44]. Nevertheless, such classifiers are generally limited to patch-level analysis and lack end-to-end localization.

Recent reviews indicate that CNN-based approaches, including U-Net and ResNet variants, provide strong texture modeling but struggle to balance localization accuracy, computational efficiency, and robustness under complex textures and illumination variations [45,46], motivating the development of unified and lightweight detection frameworks.

2.3 YOLO-Based Fabric Inspection

YOLO-based object detectors are widely used in fabric defect inspection due to their unified architecture and real-time performance. Early studies based on YOLOv3 optimized anchor generation and multi-scale feature fusion to improve defect localization in gray and patterned fabrics, demonstrating the feasibility of one-stage detectors for industrial textile inspection [47,48]. Subsequent works extended these approaches to deeper models such as YOLOv4 and YOLOv5. YOLOv4-based systems achieved reliable real-time inspection through data preprocessing and augmentation strategies [49], while attention-enhanced YOLOv5 variants integrated squeeze-and-excitation mechanisms to improve feature discrimination and robustness [50]. Lightweight models such as YOLOv7-tinier further reduced parameter size while maintaining high detection accuracy and real-time speed, supporting deployment in resource-constrained environments [51].

Despite these advances, detecting small and subtle fabric defects remains challenging due to limited pixel representation and interference from dense textures. To address this issue, several studies enhanced low-level feature reuse, added prediction layers, and incorporated attention mechanisms to improve sensitivity to small defects [52,53]. More recent YOLOv8-based approaches, such as DCFE-YOLO, indicate that feature fusion efficiency and

localization loss design still limit accurate detection of small and elongated defects [54]. Overall, existing YOLO-based methods typically rely on single attention or isolated feature enhancement strategies, which restrict their ability to simultaneously model spatial and channel-wise defect characteristics, motivating the development of multi-attention YOLO frameworks for accurate and real-time fabric defect inspection.

3. METHODOLOGY

3.1 YOLOv8 Baseline

The proposed fabric defect detection framework is built upon the YOLOv8 architecture, one of the most recent and efficient advancements in the YOLO family. YOLOv8 achieves an excellent balance between detection accuracy, inference speed, and computational efficiency through its anchor-free design and optimized training strategy. The architecture consists of three primary components: a backbone for feature extraction, a neck for multi-scale feature fusion, and a detection head for object classification and localization.

During preprocessing, fabric images are resized to 640×640 pixels and undergo normalization and data augmentation to improve robustness against variations in texture, color, and illumination commonly encountered in textile manufacturing environments. These processed images are then passed to the backbone network.

The backbone adopts a Cross Stage Partial (CSP) Darknet structure with C2f modules, which enhance gradient propagation while reducing feature redundancy. This design is particularly beneficial for fabric defect detection, where subtle anomalies such as broken yarns, holes, stains, or misweaves may appear across highly repetitive patterns. A Spatial Pyramid Pooling–Fast (SPPF) layer is employed at the end of the backbone to

aggregate multi-scale contextual information efficiently, enabling effective detection of defects of varying sizes and shapes.

The neck utilizes a Path Aggregation Network (PAN) to fuse features from shallow and deep layers, strengthening the representation of both fine-grained and large-scale defects. This is crucial for accurately identifying defects that vary in size, orientation, and contrast against complex fabric backgrounds.

The YOLOv8 detection head follows an anchor-free and decoupled design, where classification and localization tasks are optimized independently. A Task-Aligned Assigner improves the matching between predictions and ground truths, resulting in faster convergence and improved localization accuracy.

Overall, YOLOv8 serves as a robust baseline for fabric defect detection, offering fast inference, reliable feature extraction, and adaptability to complex textile textures and production-line environments.

3.2 Proposed WCE-YOLOv8 Architecture

The overall architecture of the proposed CBAM-ECA-YOLOv8 framework is illustrated in **Fig. 1**. The model extends the YOLOv8 baseline by integrating multi-channel input fusion, dual attention mechanisms, and a hybrid loss function to enhance defect detection performance under challenging textile conditions such as uneven lighting, dense weave patterns, and low-contrast defects.

To enhance texture discrimination, the model employs a four-channel input consisting of RGB channels and an additional grayscale channel. The grayscale channel strengthens texture contrast and emphasizes structural irregularities, which is especially effective for detecting subtle fabric defects such as fine

scratches, pinholes, or yarn inconsistencies that may not be clearly visible in color images alone.

In the backbone, a Convolutional Block Attention Module (CBAM) is integrated to enhance both channel-wise and spatial feature representation. CBAM guides the network to focus on defect-relevant regions while suppressing repetitive background patterns inherent in fabric surfaces. This attention-driven refinement significantly improves the detection of small, faint, or irregular defects.

Overall, the proposed CBAM-ECA-YOLOv8 framework achieves an optimal balance between accuracy, efficiency, and robustness, making it well-suited for real-world fabric defect detection applications.

3.3 Convolutional Block Attention Module (CBAM)

The CBAM module enhances the network's ability to focus on defect-relevant features while suppressing background noise from repetitive fabric textures. As illustrated in **Fig. 2**, CBAM refines feature maps through two sequential stages: channel attention followed by spatial attention.

In the channel attention stage, CBAM analyzes inter-channel relationships to determine which feature channels are most informative for fabric defect characteristics. By combining global average pooling and max pooling operations, the module generates channel-wise attention weights that emphasize defect-sensitive features while reducing redundant or irrelevant responses.

In the spatial attention stage, CBAM identifies critical spatial regions within the feature maps. This mechanism allows the network to highlight defect locations such as tears, stains, or weaving faults while minimizing the influence of background textures and lighting variations.

By sequentially applying channel and spatial attention, CBAM significantly enhances both global and local feature representation, enabling robust detection of subtle fabric defects under complex industrial conditions

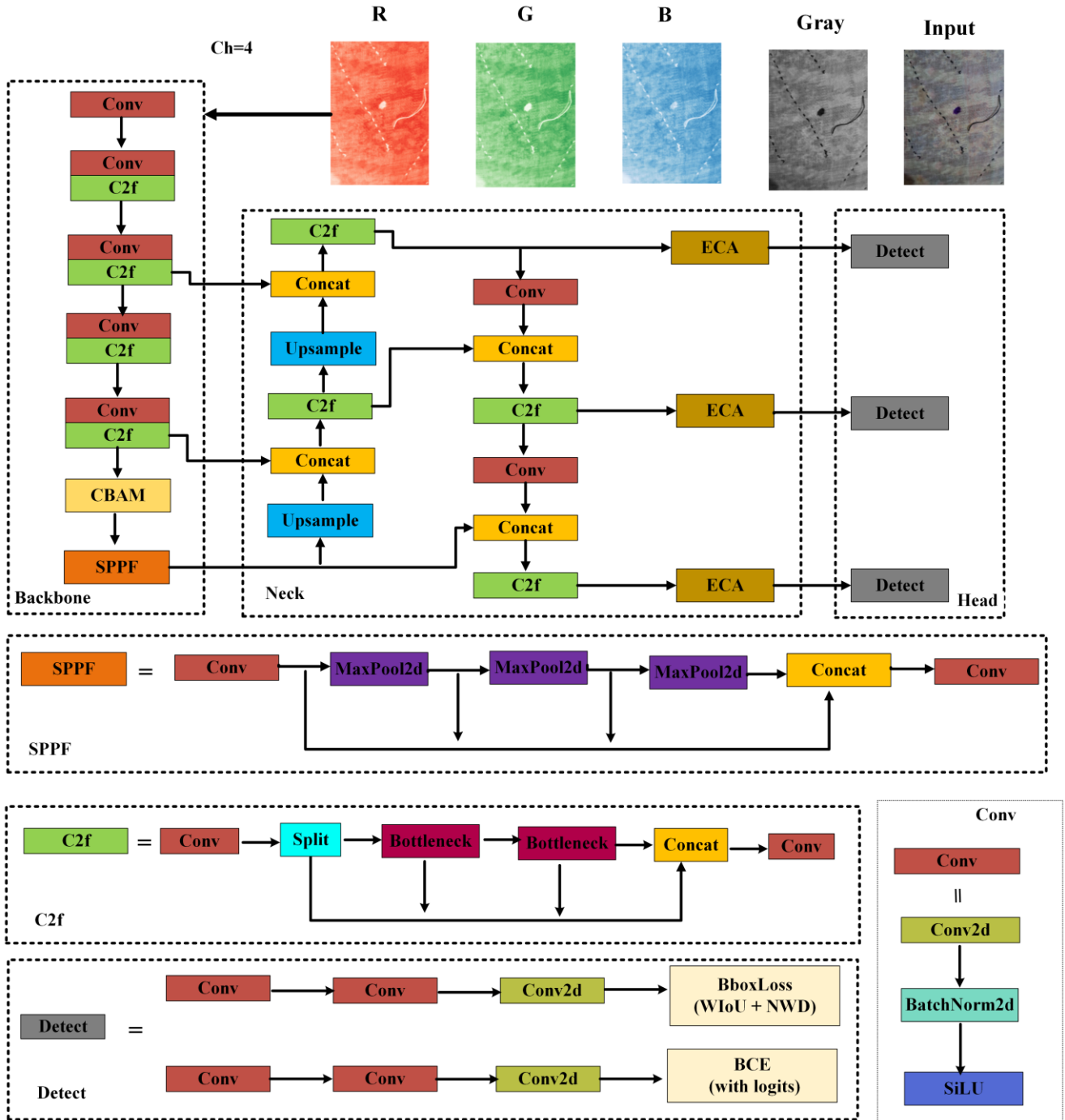


Fig.1. Overall architecture of the proposed WCE-YOLOv8 model integrating CBAM and ECA attention mechanisms for concrete crack detection.

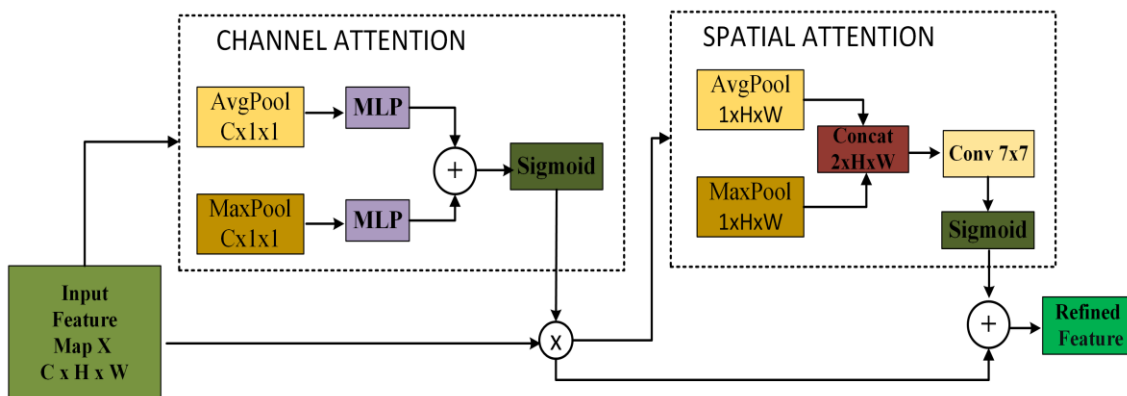


Fig. 2. Structure of the CBAM module for feature refinement

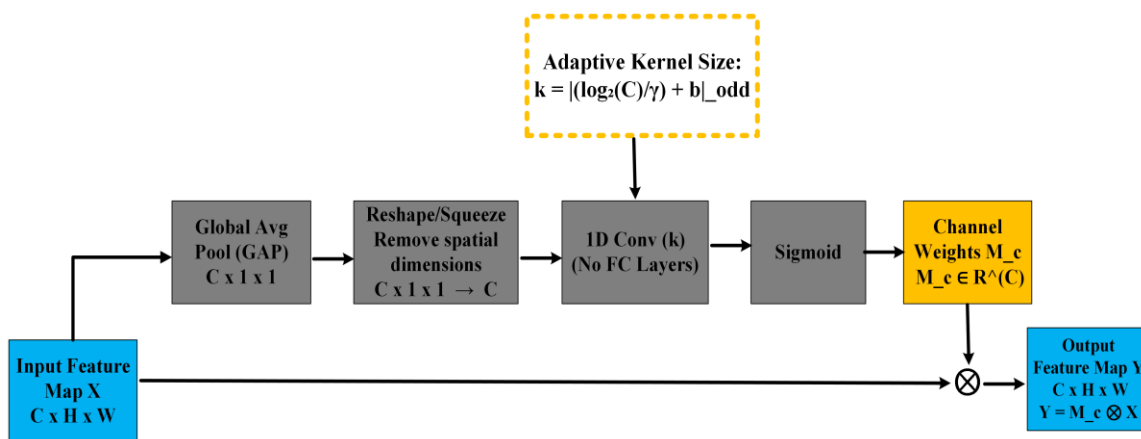


Fig.3. Structure of the ECA module for lightweight channel attention.

3.4 Efficient Channel Attention (ECA)

The ECA module is incorporated into the detection head to further refine feature representation with minimal computational overhead. Unlike traditional attention mechanisms that rely on fully connected layers, ECA uses a lightweight one-dimensional convolution to model local cross-channel dependencies efficiently. The structure of the ECA module is shown in Fig. 3.

ECA first applies global average pooling to compress spatial information into a channel descriptor. A one-dimensional convolution with an adaptively determined kernel size then captures channel-wise interactions, allowing the

model to emphasize defect-relevant features without introducing additional parameters. The resulting attention weights are applied to the feature maps via element-wise multiplication.

By integrating ECA into the detection head, the proposed model improves sensitivity to small-scale fabric defects while maintaining real-time inference performance suitable for industrial inspection systems.

3.5 Loss Function

To improve bounding box regression accuracy for small, thin, and irregular fabric defects, the proposed CBAM-ECA-YOLOv8

model employs a hybrid loss function combining **WIoU** and **NWD**.

WIoU introduces position-sensitive weighting that prioritizes high-quality predictions and reduces the impact of poorly aligned samples. This enhances localization precision in challenging fabric scenes with complex textures or low contrast.

NWD models predicted and ground-truth bounding boxes as Gaussian distributions and measures their spatial similarity. Unlike

traditional IoU-based losses, **NWD** provides smoother gradients and more stable optimization, which is particularly beneficial for detecting tiny or discontinuous fabric defects.

By combining **WIoU** and **NWD**, the proposed loss function improves both geometric accuracy and robustness, leading to more stable training

and superior fabric defect detection performance.



Fig. 4. Representative samples of spot defects from the **FabricSpotDefect** dataset.

4. EXPERIMENT SETUP

This section presents the experimental setup, including the dataset, implementation environment, training parameters, and evaluation metrics used to comprehensively assess and validate the proposed WCE-YOLOv8 model.

4.1 Dataset

The experiments in this study were primarily conducted using the publicly available **FabricSpotDefect** dataset [55], an annotated benchmark designed for spot defect detection in textile materials. The dataset consists of fabric images containing both defective and non-defective samples, covering various fabric types and surface textures.

The images were collected under diverse real-world conditions, including variations in illumination, texture patterns, and background appearance, providing a realistic and

challenging evaluation environment, as illustrated in Fig. 4.

To evaluate the generalization capability of the proposed model, additional experiments were conducted using the **Fabric Defects Dataset**, which contains different categories of fabric defects and visual characteristics not seen during training. This cross-dataset evaluation helps assess the robustness of the proposed approach under varying defect patterns and imaging conditions.

For experimental consistency, the datasets were divided into 70% training, 20% validation, and 10% testing subsets. Prior to training, all images were resized and normalized to ensure a uniform input resolution while preserving critical defect characteristics.

4.2 Implementation Details

The experiments were conducted on a system with an NVIDIA RTX 2070 GPU, Intel

Core i9 CPU, 32 GB RAM, 500 GB SSD, and 1 TB HDD, using PyTorch with CUDA acceleration.

The model was trained for 400 epochs with a batch size of 16, learning rate 0.01, momentum 0.937, and weight decay 0.0005. Dataset split: 70% training, 20% validation, and 10% testing. Data augmentation included random flipping, rotation, brightness and contrast adjustment, and Gaussian noise to improve robustness under varying lighting and texture conditions.

4.3 Evaluation Metrics

To evaluate the performance of the proposed WCE-YOLOv8 model, standard object detection metrics were employed. Precision, Recall, and F1-score were used to assess detection accuracy and the balance between missed and false detections. Mean Average Precision (mAP) served as the primary performance indicator and was computed as mAP@50 (IoU = 0.5) and mAP@50–95, averaged over IoU thresholds from 0.5 to 0.95,

reflecting localization accuracy and detection consistency.

Computational efficiency was assessed using the number of model parameters and inference time per image, providing insight into the model’s suitability for real-time fabric inspection. Together, these metrics offer a balanced evaluation of detection accuracy and computational efficiency.

5. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed WCE-YOLOv8 model, emphasizing its detection accuracy, robustness, and efficiency through quantitative metrics and comparative analyses.

5.1. Quantitative Results

Table 1 presents the ablation study results, illustrating the contribution of each proposed component, including the grayscale input channel, CBAM, ECA, and the combined WIoU with NWD loss, to the overall performance of the WCE-YOLOv8 model.

Variant	Precision	Recall	F1-score	IoU	Params (M)
Base YOLOv8	0.931	0.941	0.936	0.885	22.94
+ Gray Channel	0.940	0.950	0.945	0.892	23.12
+ CBAM	0.948	0.958	0.953	0.902	22.45
+ ECA	0.952	0.962	0.957	0.910	23.46
+ WIoU + NWD	0.956	0.968	0.962	0.918	23.52

Tab.1. Ablation study of the proposed WCE-YOLOv8 model with different module configurations.

As shown in Table 1, the baseline YOLOv8 model achieves a precision of 0.931, recall of 0.941, F1-score of 0.936, and IoU of 0.885. Adding the grayscale input channel improves texture contrast and leads to consistent gains across all metrics, increasing the F1-score to 0.945 and the IoU to 0.892. The introduction of CBAM further enhances feature representation, particularly improving recall and localization accuracy, resulting in an F1-score of 0.953 and an IoU of 0.902. Incorporating ECA yields additional improvements in

precision and overall stability, achieving an F1-score of 0.957 and an IoU of 0.910. Finally, the full model using the WIoU and NWD loss functions delivers the best overall performance, with a precision of 0.956, recall of 0.968, F1-score of 0.962, and IoU of 0.918, confirming the effectiveness of the proposed enhancements with only a modest increase in model parameters.

To further assess the effectiveness of the proposed WCE-YOLOv8 model, Table 2

compares its performance with other detection stability on the FabricSpotDefect dataset, highlighting its competitive accuracy and representative object detection frameworks.

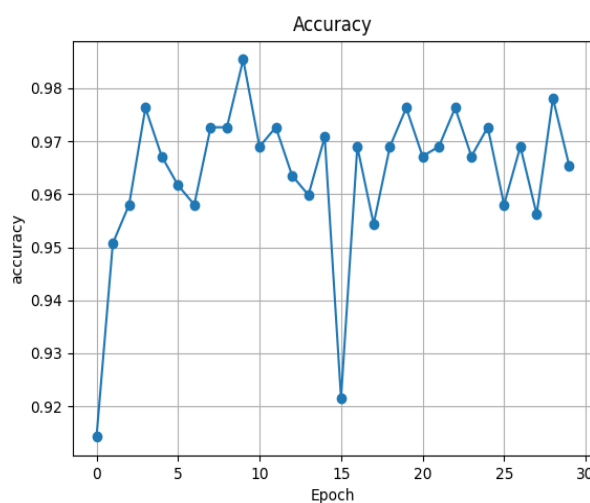
Model	Precision (%)	Recall (%)	F1-score (%)	mAP50 (%)	mAP50-95 (%)	Parameters (M)
YOLOv3	89.82	84.6	86.63	81.22	48.18	61.9
YOLOv5s	90.13	87.2	82.17	83.89	50.21	7.3
YOLOv7	88.12	85.4	85.29	82.63	47.25	6.9
YOLOv8s	92.56	88.1	88.33	86.17	51.44	11.1
Proposed	94.6	92.8	93.7	89.3	53.7	23.5

Tab. 2. Comparison of experimental results for various object detection models.

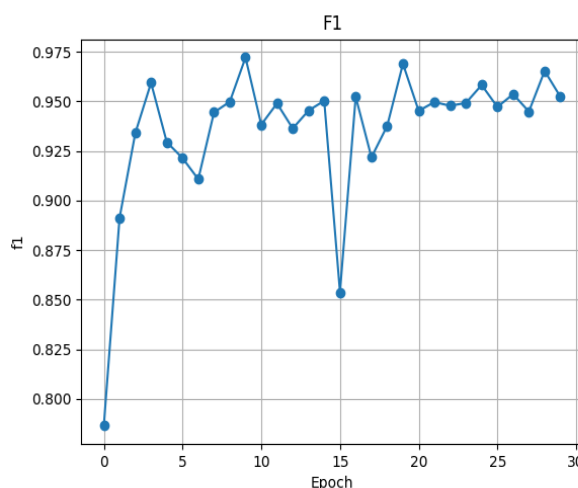
As shown in Table 2, the proposed WCE-YOLOv8 model consistently outperforms existing YOLO variants in overall detection performance. Compared with YOLOv3, YOLOv5s, YOLOv7, and YOLOv8s, it achieves the highest recall of 92.8% and F1-score of 93.7%, indicating improved detection of fine and subtle defects. Although YOLOv8s shows strong precision, its recall and overall balance remain inferior to the proposed method. WCE-YOLOv8 also attains superior mAP50 and mAP50-95 values of 89.3% and 53.7%, respectively, demonstrating robust performance across varying defect scales and complex backgrounds. While the proposed model has a higher parameter count, the resulting accuracy gains justify this increase, offering a practical trade-off between detection performance and computational complexity for fabric defect inspection.

5.2 Qualitative Results

This section visually compares baseline YOLO models and the proposed WCE-YOLOv8 on representative crack images, emphasizing improved accuracy, localization, and robustness under varying conditions.



(a)



(b)

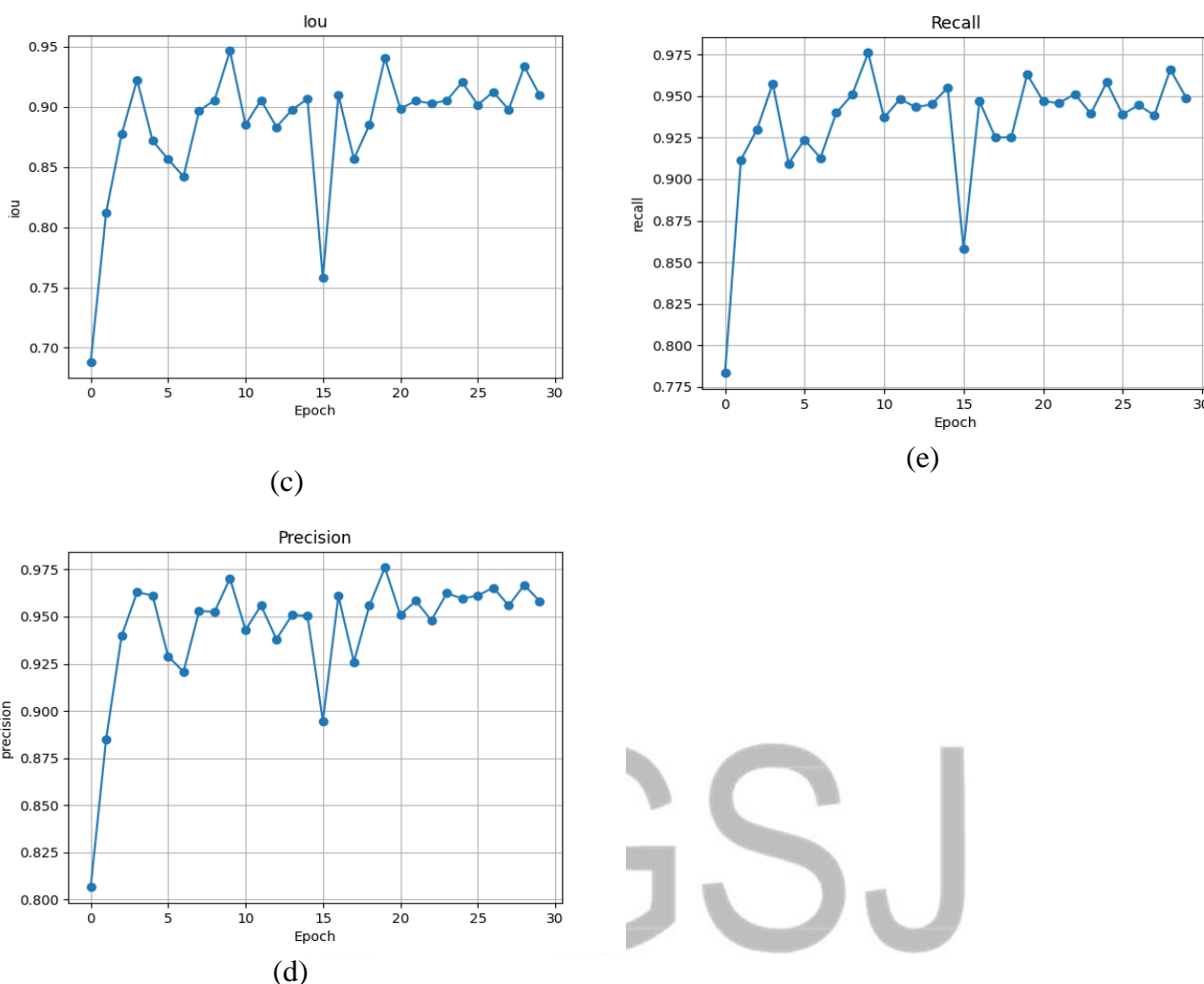


Fig. 5. Validation performance curves of the proposed WCE-YOLOv8 model on the FabricSpotDefect dataset, showing (a) Accuracy, (b) F1-score, (c) IoU, (d) Precision, and (e) Recall over training epochs. To avoid visual overcrowding, only a representative segment of the training process (first **30 epochs**) is shown; the complete **400-epoch** training exhibits a similar stable convergence trend.

As shown in Fig. 5, the proposed WCE-YOLOv8 model demonstrates stable convergence and strong generalization on the FabricSpotDefect dataset. For clarity, only the first 30 epochs are displayed, as the full 400-epoch training follows a similar stable trend. Validation accuracy remains above 96%, while precision and recall stay within 0.93–0.97 and 0.92–0.97, respectively. The F1-score stabilizes around 0.94–0.96, and IoU values remain within 0.88–0.94, indicating accurate localization and balanced detection performance. Minor mid-training fluctuations are rapidly corrected, suggesting effective regularization.



Fig. 6 presents a qualitative comparison using ground-truth bounding boxes. Earlier models such as YOLOv3 and YOLOv5 frequently miss thin or discontinuous defects, while YOLOv7 and YOLOv8 still produce fragmented detections under complex backgrounds. In contrast, WCE-YOLOv8 generates tighter and more continuous bounding boxes that better align with the ground truth, reducing false detections and improving localization consistency. These results confirm that CBAM and ECA integration enhances feature representation and spatial focus for fabric defect detection.

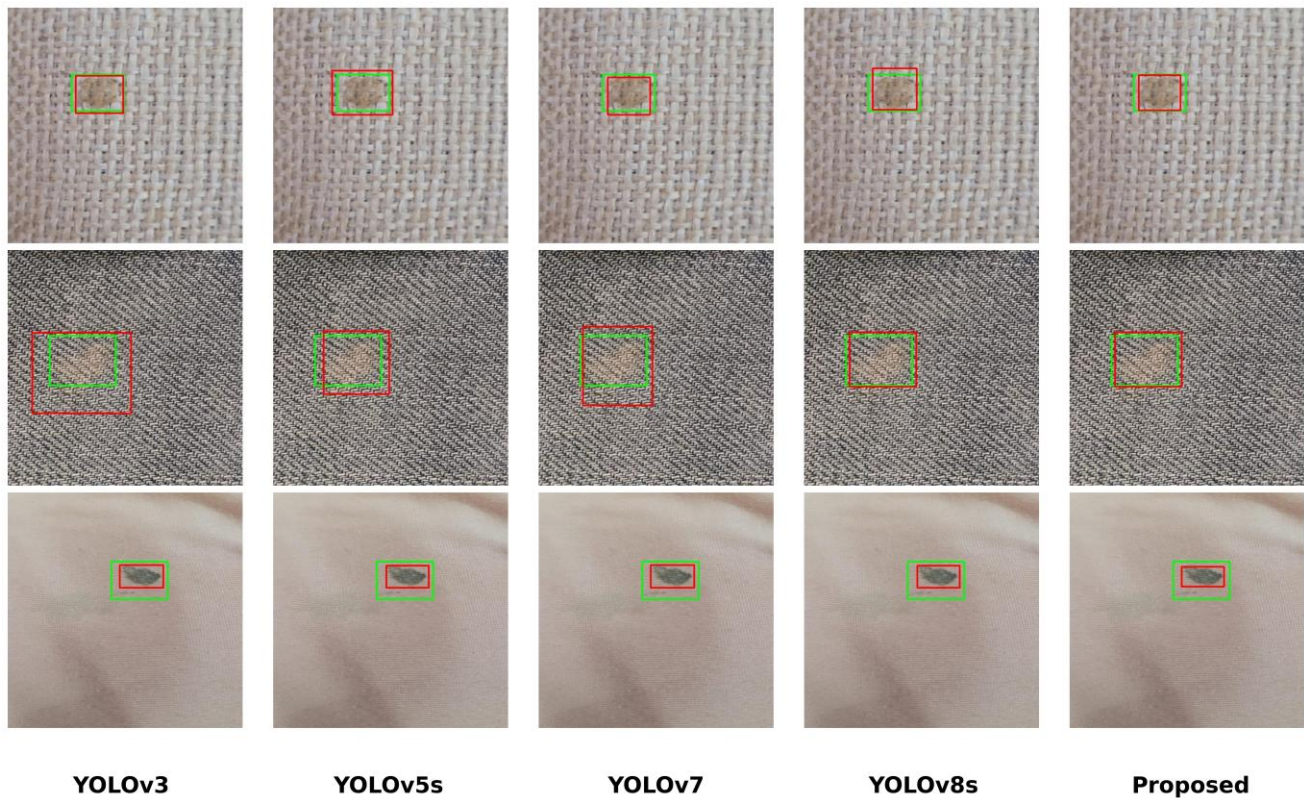


Fig. 6. Comparative visualization results of different YOLO-based models and the proposed approach on fabric defect detection.

5.3 CROSS-DATASET EVALUATION ON CrackSeg9k

To further evaluate the generalization capability of the proposed WCE-YOLOv8 model, a cross-dataset experiment was conducted using the CrackSeg9K dataset. Although CrackSeg9K focuses on concrete crack images rather than textile defects, it provides a challenging benchmark characterized by fine-grained and low-contrast structural patterns. The model trained on the FabricSpotDefect dataset was directly evaluated on CrackSeg9K without fine-tuning to assess robustness to unseen surface defect characteristics. As reported in **Table 3**, the proposed model consistently outperforms the baseline across all evaluation metrics,

demonstrating improved cross-domain generalization ability. In addition, **Fig. 7** presents qualitative results showing ground-truth and predicted bounding boxes under diverse surface textures and illumination conditions, further confirming the model’s ability to accurately localize crack regions despite significant domain differences.

Model	Precision (%)	Recall (%)	F1-score (%)	mAP50 (%)	mAP50-95 (%)
Baseline	80.8	86.9	83.7	84.6	48.9
Proposed	83.2	89.4	86.2	86.8	50.7

Tab.3. Cross-dataset quantitative performance on the CrackSeg9k dataset



Fig. 7. Ground-truth (green) and predicted (red) bounding boxes under diverse surface textures and illumination conditions.

CONCLUSION AND DISCUSSION

This study proposed an enhanced fabric defect detection framework, termed WCE-YOLOv8, which integrates a grayscale input channel, CBAM in the backbone, ECA in the detection head, and a hybrid WIoU–NWD loss to improve feature representation and localization of fine and low-contrast defects under complex textures and uneven illumination.

Experimental results on the FabricSpotDefect dataset demonstrate that WCE-YOLOv8 consistently outperforms standard YOLO variants across precision, recall, F1-score, and mAP metrics. Ablation studies verify that each component contributes to performance gains, while qualitative results show tighter and more continuous bounding boxes with reduced false detections in challenging backgrounds.

Cross-dataset evaluation on the CrackSeg9K dataset, conducted without fine-tuning, further confirms the robustness and generalization capability of the proposed framework under significant domain shifts.

Despite these advantages, the model introduces a higher parameter count of approximately 23.5 million and still exhibits occasional false positives under highly textured or extreme illumination conditions. Future work will focus on reducing model complexity through lightweight attention mechanisms and

extending the framework to broader industrial surface defect inspection scenarios.

DECLARATIONS

Availability of data and materials

The datasets used in this study are publicly available, including the FabricSpotDefect dataset and CrackSeg9k.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Salman Bhuyan¹ contributed to the conception of the study, dataset preparation, model development, experimentation, and manuscript drafting.

Tahmid Bin Sayed^{2*} supervised the research, contributed to methodology refinement and results analysis, and critically reviewed and revised the manuscript. All authors read and approved the final manuscript.

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REFERENCES

- [1] Dharma, F.P., Singgih, M.L. and Prastyo, D.D., 2025. Beyond Architecture: Hyperparameter Optimization for YOLOv8m in Multi-Class Textile Defect Detection. *Results in Engineering*, p.108356. DOI: 10.1016/j.rineng.2025.108356.
- [2] Thakur, R., Panghal, D., Jana, P. et al. Automated fabric inspection through convolutional neural network: an approach. *Neural Comput & Applic* 35, 3805–3823 (2023). <https://doi.org/10.1007/s00521-022-07891-1>
- [3] Shahrabadi, S., Castilla, Y., Guevara, M., Magalhães, L.G., Gonzalez, D. and Adão, T., 2022, April. Defect detection in the textile industry using image-based machine learning methods: a brief review. In *Journal of Physics: Conference Series* (Vol. 2224, No. 1, p. 012010). IOP Publishing. DOI: 10.1088/1742-6596/2224/1/012010
- [4] Koulali, I. and Eskil, M.T., 2021. Unsupervised textile defect detection using convolutional neural networks. *Applied Soft Computing*, 113, p.107913. doi: 10.1016/j.asoc.2021.107913.
- [5] Dong, X., Liu, H., Luo, Y., Yan, Y., Liang, J. (2025). Semi-supervised Lightweight Fabric Defect Detection. In: Lin, Z., et al. *Pattern Recognition and Computer Vision. PRCV 2024. Lecture Notes in Computer Science*, vol 15034. Springer, Singapore. https://doi.org/10.1007/978-981-97-8505-6_8
- [6] Soon, R.J. and Chui, C.K., 2024, June. Textile Surface Defects Analysis with Explainable AI. In *2024 IEEE Conference on Artificial Intelligence (CAI)* (pp. 1394-1398). IEEE. DOI: 10.1109/CAI59869.2024.00248
- [7] Kang, S. and Yang, M., 2025. FD-YOLO: An Attention-Augmented Lightweight Network for Real-Time Industrial Fabric Defect Detection. *Computers, Materials and Continua*, 86(2), pp.1-23. Doi: 10.32604/cmc.2025.071488
- [8] Anagnostopoulos, C., Vergados, D., Kayafas, E., Loumos, V. and Stassinopoulos, G., 2001. A computer vision approach for textile quality control. *The Journal of Visualization and Computer Animation*, 12(1), pp.31-44. Doi: 10.1002/vis.245
- [9] Goyal, A., 2018. Automation in fabric inspection. In *Automation in Garment Manufacturing* (pp. 75-107). Woodhead publishing. Doi: 10.1016/B978-0-08-101211-6.00004-5
- [10] Xu, C., Xu, L., Luo, K., Zhang, J., Sitahong, A., Yang, M. and Zhang, C., 2025. The essence and applications of machine vision inspection for textile industry: a review. *The Journal of The Textile Institute*, 116(10), pp.2286-2310. Doi: 10.1080/00405000.2024.2426257
- [11] Dal Forno, A.J., Bataglini, W.V., Steffens, F. and Ulson de Souza, A.A., 2023. Industry 4.0 in textile and apparel sector: a systematic literature review. *Research Journal of Textile and Apparel*, 27(1), pp.95-117. Doi: 10.1108/RJTA-08-2021-0106
- [12] Majumdar, A., Bhattacharyya, R. & Yadav, V.S. Deep Learning Applications in Textile Industry: A Systematic Review of Current Status and Delineating Future Research Agenda. *Arch Computat Methods Eng* (2025). <https://doi.org/10.1007/s11831-025-10366-w>.
- [13] Chen, Z., Zhu, Q., Zhou, X., Deng, J. and Song, W., 2024. Experimental study on YOLO-based leather surface defect detection. *IEEE Access*, 12, pp.32830-32848. Doi: 10.1109/ACCESS.2024.3369705

- [14] Dong, Y., Lu, N. and Li, X., 2025. Dense attention networks for texture classification. *Neurocomputing*, 634, p.129833. DOI: 10.1016/j.neucom.2025.129833
- [15] Ma, H., Li, Z., Fan, H., Zheng, X., Yan, J. and Hu, R., 2025. Phased noise enhanced multiple feature discrimination network for fabric defect detection. *Engineering Applications of Artificial Intelligence*, 149, p.110480. DOI: 10.1016/j.engappai.2025.110480
- [16] He, F., Xin, B., Zhan, Z., Yang, W. and Liu, J., 2025. A review of fabric defect detection in textile manufacturing. *The Journal of The Textile Institute*, pp.1-19. DOI: 10.1080/00405000.2025.2502188
- [17] Lu, B., Huang, B. A texture-aware one-stage fabric defect detection network with adaptive feature fusion and multi-task training. *J Intell Manuf* 35, 1267–1280 (2024). <https://doi.org/10.1007/s10845-023-02105-4>
- [18] Gerges, M. and Chen, X., 2022. Adaptive lighting for curved and nonuniform objects in optomechanical inspection systems. *IEEE/ASME Transactions on Mechatronics*, 27(6), pp.5792-5802. DOI: 10.1109/TMECH.2022.3189344
- [19] Cheng, G., Yuan, X., Yao, X., Yan, K., Zeng, Q., Xie, X. and Han, J., 2023. Towards large-scale small object detection: Survey and benchmarks. *IEEE transactions on pattern analysis and machine intelligence*, 45(11), pp.13467-13488. DOI: 10.1109/TPAMI.2023.3290594
- [20] Wu, H., Deng, Y., Meng, J. *et al.* Illuminance-Invariant Defect Detection for Multiform Fabrics Using Multiscale Feature Fusion Model. *Fibers Polym* 26, 4615–4634 (2025). <https://doi.org/10.1007/s12221-025-01090-0>
- [21] Wang, H., Peng, J., Zheng, X. and Yue, S., 2019. A robust visual system for small target motion detection against cluttered moving backgrounds. *IEEE transactions on neural networks and learning systems*, 31(3), pp.839-853. DOI: 10.1109/TNNLS.2019.2910418
- [22] Yu, Z., Wu, Y., Wei, B. et al. A lightweight and efficient model for surface tiny defect detection. *Appl Intell* 53, 6344–6353 (2023). <https://doi.org/10.1007/s10489-022-03633-x>
- [23] Ho, C.C., Chou, W.C. and Su, E., 2021. Deep convolutional neural network optimization for defect detection in fabric inspection. *Sensors*, 21(21), p.7074. DOI: 10.3390/s21217074
- [24] Talu, M.F., Hanbay, K. and Varjovi, M.H., 2022. CNN-based fabric defect detection system on loom fabric inspection. *Textile and Apparel*, 32(3), pp.208-219. DOI: 10.32710/tekstilvekonfeksiyon.1032529
- [25] Wang, H., Zhang, R., Feng, M., Liu, Y. and Yang, G., 2023. Global context-based self-similarity feature augmentation and bidirectional feature fusion for surface defect detection. *IEEE Transactions on Instrumentation and Measurement*, 72, pp.1-12. DOI: 10.1109/TIM.2023.3309374
- [26] Yu, K., Lyu, W., Yu, X., Guo, Q., Xu, W. and Zhang, L., 2024. FA-YOLO: A high-precision and efficient method for fabric defect detection in textile industry. *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences*, 107(6), pp.890-898. DOI: 10.1587/transfun.2023EAP1030
- [27] Dlamini S, Kao C-Y, Su S-L, Jeffrey Kuo C-F. Development of a real-time machine vision system for functional textile fabric defect detection using a deep YOLOv4 model. *Textile Research Journal*. 2021;92(5-6):675-690. doi:10.1177/00405175211034241
- [28] Mao M, Hong M. YOLO Object Detection for Real-Time Fabric Defect Inspection in the

- Textile Industry: A Review of YOLOv1 to YOLOv11. *Sensors* (Basel). 2025 Apr 3;25(7):2270. doi: 10.3390/s25072270. PMID: 40218782; PMCID: PMC11990965.
- [29] Li, C., Li, J., Li, Y., He, L., Fu, X. and Chen, J., 2021. Fabric defect detection in textile manufacturing: a survey of the state of the art. *Security and Communication Networks*, 2021(1), p.9948808. DOI: 10.1155/2021/9948808
- [30] Seçkin, M., Seçkin, A.Ç., Demircioglu, P. and Bogrekci, I., 2023. FabricNET: a microscopic image dataset of woven fabrics for predicting texture and weaving parameters through machine learning. *Sustainability*, 15(21), p.15197. DOI: 10.3390/su152115197
- [31] Madrigal, C.A., Branch, J.W., Restrepo, A. and Mery, D., 2017. A method for automatic surface inspection using a model-based 3D descriptor. *Sensors*, 17(10), p.2262. DOI: 10.3390/s17102262
- [32] Zhu, R., Xin, B., Deng, N. and Fan, M., 2024. Fabric defect detection using ACS-based thresholding and GA-based optimal Gabor filter. *The Journal of The Textile Institute*, 115(9), pp.1432-1446. DOI: 10.1080/00405000.2023.2231188
- [33] Sinchuk, Y., Kibleur, P., Aelterman, J., Boone, M.N. and Van Paepegem, W., 2021. Geometrical and deep learning approaches for instance segmentation of CFRP fiber bundles in textile composites. *Composite Structures*, 277, p.114626. DOI: 10.1016/j.compstruct.2021.114626
- [34] Yao, S., Zhang, Y., Xiao, Z., Ni, J. and Ding, S., 2025. A real-time fabric defect inspection based on improved multi-scale Gabor filter. *Journal of Computational Methods in Sciences and Engineering*, 25(1), pp.211-222. DOI: 10.1177/14727978241300076
- [35] Si, J., Kim, S. GRooUV: surface defect detection with Gabor filter using reconstruction-based blurring U-Net–ViT. *Int J Adv Manuf Technol* 141, 2663–2678 (2025). <https://doi.org/10.1007/s00170-025-16844-6>
- [36] Chen, M., Yu, L., Zhi, C., Sun, R., Zhu, S., Gao, Z., Ke, Z., Zhu, M. and Zhang, Y., 2022. Improved faster R-CNN for fabric defect detection based on Gabor filter with Genetic Algorithm optimization. *Computers in Industry*, 134, p.103551. DOI: 10.1016/j.compind.2021.103551
- [37] Cai, X., Chen, Y., Yao, Z. and Wang, Y., 2025. Defect Detection in Patterned Wafers Using Dynamic Local Adaptive Sensitivity Adjustment. *IEEE Transactions on Instrumentation and Measurement*. DOI: 10.1109/TIM.2025.3604128
- [38] Dlamini, S., Kao, C.Y., Su, S.L. and Jeffrey Kuo, C.F., 2022. Development of a real-time machine vision system for functional textile fabric defect detection using a deep YOLOv4 model. *Textile Research Journal*, 92(5-6), pp.675-690. DOI: 10.1177/00405175211034241
- [39] Geze, R.A. and Akbaş, A., 2023. Detection and classification of fabric defects using deep learning algorithms. *Politeknik Dergisi*, 27(1), pp.371-378. DOI: 10.2339/politeknik.1386458
- [40] Jing, J., Wang, Z., Rättsch, M. and Zhang, H., 2022. Mobile-Unet: An efficient convolutional neural network for fabric defect detection. *Textile Research Journal*, 92(1-2), pp.30-42. DOI: 10.1177/0040517520928604
- [41] Zhang, H., Wang, S., Lu, S., Yao, L. and Hu, Y., 2023. Attention-Gate-based U-shaped Reconstruction Network (AGUR-Net) for color-patterned fabric defect detection. *Textile Research Journal*, 93(15-16), pp.3459-3477. DOI: 10.1177/00405175221149450
- [42] Zhang, H., Meng, L., Lu, S., Song, Z. and Wu, L., 2025. A diverse embedding-based composite reconstruction encoder–decoder for

- color fabric defect detection. *Expert Systems with Applications*, 278, p.127261. DOI: 10.1016/j.eswa.2025.127261
- [43] Jun X, Wang J, Zhou J, Meng S, Pan R, Gao W. Fabric defect detection based on a deep convolutional neural network using a two-stage strategy. *Textile Research Journal*. 2020;91(1-2):130-142. doi:10.1177/0040517520935984
- [44] Lin, S., He, Z. & Sun, L. Self-Transfer Learning Network for Multicolor Fabric Defect Detection. *Neural Process Lett* 55, 4735–4756 (2023). <https://doi.org/10.1007/s11063-022-11063-6>
- [45] Rasheed, A., Zafar, B., Rasheed, A., Ali, N., Sajid, M., Dar, S.H., Habib, U., Shehryar, T. and Mahmood, M.T., 2020. Fabric defect detection using computer vision techniques: a comprehensive review. *Mathematical Problems in Engineering*, 2020(1), p.8189403. DOI: 10.1155/2020/8189403
- [46] Kahraman Y, Durmuşoğlu A. Deep learning-based fabric defect detection: A review. *Textile Research Journal*. 2022;93(5-6):1485-1503. doi:10.1177/00405175221130773
- [47] Jing J, Zhuo D, Zhang H, Liang Y, Zheng M. Fabric defect detection using the improved YOLOv3 model. *Journal of Engineered Fibers and Fabrics*. 2020;15. doi:10.1177/1558925020908268
- [48] Sharma, H., Durgasree, M.R., Jayasree, L., Hussain, S.J. and Babu, K.S., 2025. Enhanced YOLOv3 Model for Automated Fabric Defect Detection. *International Journal of Human Computations & Intelligence*, 4(3), pp.487-499. DOI: 10.5281/zenodo.15280482
- [49] Dlamini S, Kao C-Y, Su S-L, Jeffrey Kuo C-F. Development of a real-time machine vision system for functional textile fabric defect detection using a deep YOLOv4 model. *Textile Research Journal*. 2021;92(5-6):675-690. doi:10.1177/004051752111034241
- [50] L. Zheng, X. Wang, Q. Wang, S. Wang and X. Liu, "A Fabric Defect Detection Method Based on Improved YOLOv5," 2021 7th International Conference on Computer and Communications (ICCC), Chengdu, China, 2021, pp. 620-624, doi: 10.1109/ICCC54389.2021.9674548.
- [51] Yaohui, Z., Jia, R. & Yu, L. Yolov7-Tinier: Towards High-Precision and Lightweight Detection of Fabric Defects in Textile Plant. *Fibers Polym* 25, 3549–3562 (2024). <https://doi.org/10.1007/s12221-024-00662-w>
- [52] Yue, X., Wang, Q., He, L., Li, Y. and Tang, D., 2022. Research on tiny target detection technology of fabric defects based on improved YOLO. *Applied Sciences*, 12(13), p.6823. DOI: 10.3390/app12136823
- [53] Li, Y., Song, L., Cai, Y. et al. Research on fabric surface defect detection algorithm based on improved Yolo_v4. *Sci Rep* 14, 5537 (2024). <https://doi.org/10.1038/s41598-023-50671-7>
- [54] Zhou, L., Ma, B., Dong, Y., Yin, Z. and Lu, F., 2025. DCFE-YOLO: A novel fabric defect detection method. *PloS one*, 20(1), p.e0314525. DOI: 10.1371/journal.pone.0314525
- [55] Sumaya; Islam, Farzana; Monir, Md. Fahad; Islam, Ashraful (2024), "FabricSpotDefect: An Annotated Dataset for Identifying Spot Defects in Different Fabric Types", Mendeley Data, V1, doi: 10.17632/6574nhzm8x.1
- [56] Kulkarni, S., Singh, S., Balakrishnan, D., Sharma, S., Devunuri, S., Korlapati, S.C.R. (2023). CrackSeg9k: A Collection and Benchmark for Crack Segmentation Datasets and Frameworks. In: Karlinsky, L., Michaeli, T., Nishino, K. (eds) Computer Vision – ECCV 2022 Workshops. ECCV 2022. Lecture Notes in

Computer Science, vol 13807. Springer, Cham.
https://doi.org/10.1007/978-3-031-25082-8_12.

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