ADMI IJST International Journal Science and Technology
OPEN ACCESS
IJST Vol 5 No. 1 | March 2026 | ISSN: 2828-7223 (print), ISSN: 2828-7045 (online), Page 28-41

Industrial Artificial Intelligence Methods for Fabric Color-Defect Detection in Textile Manufacturing

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Article History
Received : February 14, 2026
Revised : February 26, 2026
Accepted : February 27, 2026
Published : March 01, 2026

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Cite This Article:
Kim, B.- ho, & Jae, H.-S. (2026). Industrial Artificial Intelligence Methods for Fabric Color-Defect Detection in Textile Manufacturing. *International Journal Science and Technology*, *5*(1), 28–41.

DOI:
https://doi.org/10.56127/ijst.v5i1.2600

Abstract: Color-related fabric defects such as shade variation, off-shade, discoloration, and color bleeding remain challenging to detect consistently in textile manufacturing because camera-based inspection is highly influenced by illumination variability, fabric reflectance, and domain shift across production batches. These limitations often reduce the reliability of automated inspection systems and highlight the need for a systematic synthesis of existing Industrial Artificial Intelligence approaches. **Objective**: This study aims to systematically review and synthesize Industrial Artificial Intelligence methods for fabric color-defect detection to identify methodological trends, evaluation practices, and research gaps, as well as to explain why these approaches are important for improving reliability in industrial quality control. **Method**: The research employs a Systematic Literature Review design, collecting peer-reviewed studies through structured database searches followed by PRISMA-guided screening and eligibility assessment. The selected studies are analyzed using comparative narrative synthesis and standardized coding of method types, color representation, illumination handling strategies, datasets, and evaluation metrics. **Findings**: The review reveals four dominant methodological groups: classical computer vision, supervised deep learning, reconstruction-based anomaly detection, and feature-space anomaly or hybrid approaches. Across these approaches, robust performance consistently depends on a triadic design principle consisting of color-consistent representation, illumination robustness, and learning strategies aligned with label availability. The study also identifies a key evaluation gap where conventional vision metrics are rarely complemented by perceptual color-difference measures. **Implications**: The findings suggest that future research and industrial implementation should focus on developing color-calibrated datasets, adopting dual-axis evaluation frameworks that include perceptual color metrics, and validating models under varying illumination and fabric conditions to enhance real-world reliability. **Originality/Value**: This study provides an original contribution by proposing a color-defect–focused operational framework that integrates color science principles with Industrial AI method selection and deployment constraints, offering clearer guidance than previous reviews that primarily addressed structural textile defects.

Keywords: Industrial Artificial Intelligence; Fabric Color Defects; Textile Inspection; Illumination Robustness; Systematic Literature Review.

INTRODUCTION

The textile industry is increasingly operating under stricter quality requirements: product variety expands, batch-to-batch color consistency is demanded by buyers, and production speed continues to rise. In this environment, fabric inspection that still relies heavily on human visual judgment becomes a critical bottleneck because it is vulnerable to fatigue, subjectivity, and inter-inspector variability. Reviews of automated textile inspection consistently emphasize that manual inspection struggles to maintain stable performance over long shifts and across diverse fabric textures, especially when defects are subtle or small (Hanbay, 2016). Consequently, computer-vision-based inspection is no longer framed merely as a technological upgrade, but as a practical quality assurance mechanism to reduce escape defects, improve repeatability, and lower downstream costs related to rework and claims (Hanbay, 2016).

The challenge becomes even more demanding when the target is color-related defects such as shade variation, off-shade, local discoloration, or dye/finish inconsistency because these defects can be perceptually significant while remaining visually ambiguous under changing illumination. Unlike structural defects (Li et al., 2015), that often-present sharp edges or distinct texture discontinuities, color defects may manifest as small chromatic shifts without strong spatial contrast, making them difficult to detect consistently through unaided observation. In color quality control, perceptually motivated color-difference measures particularly CIEDE2000 are widely used because they better reflect human color discrimination than earlier formulations. However, once color assessment is performed through cameras, the same fabric may appear different due to illumination spectra, sensor characteristics, and viewing geometry, which directly relates to the long-studied problem of color constancy and illumination dependence in imaging (Jing, 2020; Liu & Yang, 2021). This means Industrial AI for fabric color defects must address not only "defect detection," but also color-stable representation and illumination robustness as first-order requirements (Liu & Yang, 2021; Rahaman, 2024).

Early work on fabric inspection typically relied on handcrafted features and rule-based pipelines, including texture analysis (e.g., Gabor or wavelet features), statistical modeling, and "golden image" subtraction approaches. These methods contributed important building blocks for automated inspection, such as computational efficiency and interpretability, which made them attractive for industrial deployment. Nevertheless, major reviews highlight recurring limitations: performance can degrade substantially under variations in fabric weave, fiber orientation, surface reflectance, and nonuniform lighting conditions that are common on production lines (Hanbay, 2016). These weaknesses become more consequential in the context of color defects, where the discriminative signal may be a subtle chromatic change rather than a strong structural anomaly. As a result, classical pipelines that are effective for texture/structure defects may be less reliable when the defect signature is primarily chromatic and illumination-sensitive (Hanbay, 2016).

More recent research has shifted toward deep learning, covering supervised object detectors, segmentation networks, and unsupervised representation learning. Unsupervised multi-scale deep learning approaches have been reported to detect and localize fabric defects with reduced reliance on handcrafted feature engineering, supporting a broader move toward learned representations in textile inspection (Mei, 2018). Similarly, multi-scale CNN designs have been proposed to improve sensitivity to defects of different sizes while considering computational efficiency for practical inspection. For deployment-oriented systems, modern detectors have also been explored in fabric inspection scenarios, including architectures emphasizing scalability and performance (Song, 2021). Despite these advances, many deep-learning-based fabric inspection studies still focus more heavily on structural/texture anomalies than on color-specific defects, while cross-fabric generalization and domain shift (camera, lighting, and process variability) remain persistent barriers to stable industrial performance (Chen, 2020; Song, 2021; Wang, 2025)

Color-defect inspection literature points to two dominant challenges: (1) selecting an appropriate representation and metric for color differences, and (2) mitigating the effects of illumination and imaging variability. On the measurement side, CIEDE2000 provides a perceptually grounded way to quantify color differences and textile-focused studies have explored algorithmic approaches for fabric color-difference detection (Li et al., 2015) as well as image-processing strategies tailored to dyed fabrics (Wu, 2020). On the imaging side, color constancy and Retinex research explains why perceived object color can remain relatively stable for humans but not for cameras, motivating the use of illumination correction to approximate "consistent color" in captured images. Retinex-inspired optimization models, including total-variation-based formulations, have been used to separate illumination and reflectance components, which is directly relevant to stabilizing chromatic information for inspection tasks (Ng et al., 2011). A third issue is that labeled datasets of color defects are often scarce and imbalanced, because specific off-shade events may be rare or sporadic in production, making low-label or unsupervised strategies especially relevant for real manufacturing conditions.

Building on these three streams, this literature review aims to develop an operational synthesis of Industrial Artificial Intelligence for fabric color defect detection. Specifically, it will (a) organize methods into classical computer vision, supervised deep learning, and low-label/unsupervised paradigms; (b) analyze color representations and evaluation concepts grounded in perceptual color difference (e.g., CIEDE2000/ΔE) alongside illumination-robust preprocessing and correction (e.g., color constancy/Retinex); (c) summarize evaluation practices and deployment constraints (fabric diversity, lighting conditions, camera setup, speed requirements); and (d) identify research gaps that most strongly affect industrial feasibility and reliability. To anchor the discussion on label scarcity and industrial inspection settings, the review also leverages broader surveys of unsupervised anomaly detection for industrial images and widely used industrial visual inspection benchmarks (Cui et al., 2023; Bergmann et al., 2021).

The central argument (working hypothesis) of this review is that robust fabric color defect detection in manufacturing is most likely to be achieved by integrating three components: (1) a color-consistent representation linked to perceptually meaningful color-difference measures (Li et al., 2015), (2) illumination correction/normalization that reduces lighting-driven variance in production images ((Ng et al., 2011), and (3) learning strategies that remain effective under limited defect labels, including low-label or unsupervised anomaly detection approaches aligned with industrial inspection practice (Cui et al., 2023; Wang, 2025). Under this framing, the novelty of the review is not limited to comparing model architectures; rather, it synthesizes “color as the primary signal” and “industrial data constraints” (domain shift and label scarcity) as two coupled design axes for building reliable Industrial AI systems for fabric color quality control.

RESEARCH METHOD

This study uses peer-reviewed scholarly articles as the unit of analysis, specifically publications that address fabric color-defect detection in textile manufacturing. The scope focuses on chromatic defects such as off-shade, shade variation, discoloration, and color inconsistency, including studies that explicitly employ perceptual color-difference concepts (e.g., ΔE or CIEDE2000) or discuss color representation and stability in vision-based inspection systems. Each article is treated as an evidence unit from which methodological characteristics, color representation choices, illumination-handling strategies, evaluation metrics, and indicators of industrial applicability are systematically extracted.

The study adopts a Systematic Literature Review (SLR) design, reported in accordance with the PRISMA 2020 framework. This design is chosen because the objective is not to test a field-based hypothesis but to synthesize and critically evaluate existing evidence on Industrial Artificial Intelligence approaches for detecting fabric color defects. Given that research in this domain spans multiple disciplines including computer vision, color science, and industrial inspection a systematic review provides a transparent and reproducible procedure to consolidate findings, identify methodological patterns, and highlight research gaps relevant to real manufacturing environments.

The study relies on secondary data obtained from major academic databases widely used in engineering and computer-vision research: Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, and SpringerLink. The search covered publications from 2011 to 2025, with the final search conducted on 15 January 2026. To minimize the risk of omission, backward citation tracking was performed on included papers to identify additional relevant studies, benchmark datasets, and industrial inspection references frequently cited in the literature.

Data collection followed a structured literature search and screening process. Search queries combined three keyword clusters: (1) textile or fabric domain terms, (2) color-defect phenomena such as off-shade or discoloration, and (3) methodological terms including industrial AI, deep learning, anomaly detection, color constancy, and Retinex. All retrieved records were compiled, duplicates were removed, and screening was conducted in two stages: title–abstract screening followed by full-text assessment using predefined inclusion and exclusion criteria. The PRISMA process yielded 1,284 initial records, with 314 duplicates removed, 970 records screened, 158 full texts assessed, and 62 studies included in the final qualitative synthesis. Reasons for exclusion were documented to ensure transparency.

Data analysis employed a structured coding and comparative synthesis approach. Each study was coded according to inspection task type (classification, detection, segmentation, or anomaly detection), defect focus (color-specific or mixed), color representation (RGB, HSV, or CIELAB) and use of perceptual color-difference metrics, illumination-handling strategies, dataset characteristics, evaluation metrics (e.g., F1, AUROC, mAP, IoU, Pixel-

AUROC, and ΔE indicators), and industrial feasibility factors such as acquisition setup and processing speed. To strengthen interpretability, a 10-item quality appraisal checklist was applied to assess reporting completeness and reproducibility. The synthesized evidence was then organized into a method taxonomy and evaluated across dimensions of color robustness, label availability, and deployment constraints to derive research implications and future directions.

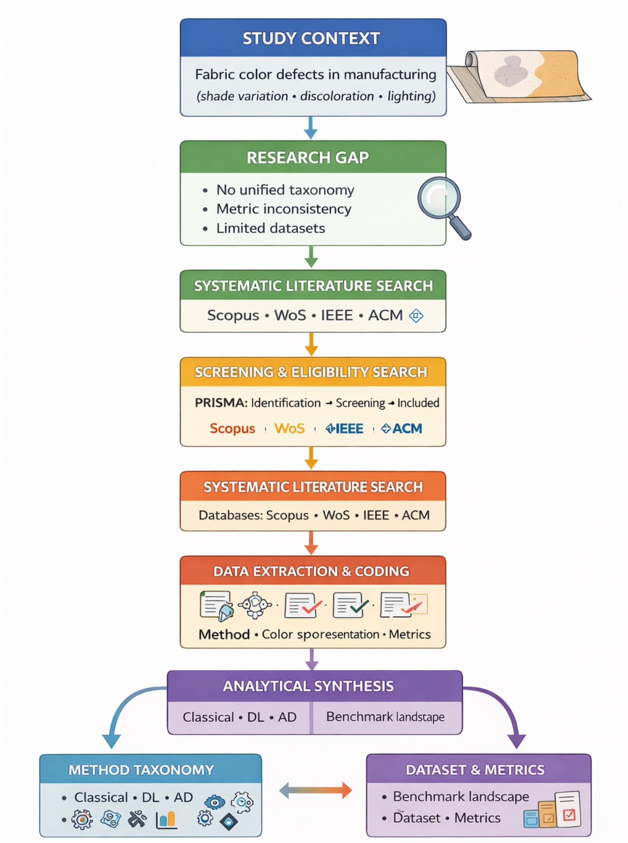

Figure 1. Research flowchart

RESULT

Method Taxonomy for Fabric Color-Defect Detection

The reviewed studies converge on a common methodological landscape: regardless of the specific algorithm, fabric inspection approaches with relevance to color-related defects can be clustered into a small number of recurring method families. First, classical computer-vision pipelines rely on handcrafted representations of color and texture (often combined with thresholding, similarity measures, or "reference/golden image" comparison). These approaches are attractive for industrial settings because they are interpretable and computationally efficient; however, they tend to be sensitive to illumination changes and surface reflectance, which is precisely what complicates chromatic inspection in production. Second, supervised deep learning (classification, object detection, and segmentation) dominates performance-oriented work when labeled datasets are sufficiently available, because learned features are generally more discriminative than handcrafted ones. Yet, domain shift across fabric types and camera–lighting configurations remains a recurring source of instability, and label requirements are often high relative to the frequency of rare color-defect events (Page et al., 2021). Third, anomaly-detection paradigms including reconstruction-based and feature-space methods appear frequently as a pragmatic response to label scarcity: instead of enumerating all defect types, they learn the distribution of "normal" fabric appearance and flag deviations. In color-defect scenarios, this strategy is conceptually aligned with production reality, but its success depends heavily on whether the captured color is stabilized (e.g., via normalization or illumination handling) so that the "normal" distribution is not dominated by lighting artifacts (Ng et al., 2011).

Across these families, one cross-cutting message emerges: robust color-defect inspection is rarely achieved by model choice alone. The literature repeatedly points toward a design triad that must be jointly addressed (i) color-consistent representation, ideally linked to perceptual color difference; (ii) illumination robustness through correction/normalization; and (iii) a learning strategy matched to label availability (supervised when labels are abundant; anomaly detection when defects are rare). This triangulation aligns with the broader principle that systematic reviews should synthesize not only "what works," but also the contextual conditions under which methods remain reliable.

Table 1. Method taxonomy and typical design choices for fabric color-defect inspection

Method family	**Typical task output**	**Color representation**	**Illumination handling**	**Label demand**	**Strength for color defects**	**Key limitation**
Classical CV (handcrafted)	Binary/multi-class	RGB/HSV/CIELAB; sometimes ΔE	Basic normalization	Low–Medium	Interpretable; fast	Highly lighting- and fabric-sensitive
Supervised deep learning	Class / bbox / mask	Mostly RGB; sometimes CIELAB	Augmentation/normalization (varies)	High	Strong recognition & localization with enough data	Costly labels; domain shift in production

Method family	Typical task output	Color representation	Illumination handling	Label demand	Strength for color defects	Key limitation
Reconstruction-based anomaly detection	Anomaly map + score	RGB/CIELAB	Normalization (common)	Low (normal-only)	Practical under rare defects	Subtle chromatic shifts may be missed without calibration
Feature-space anomaly / hybrid	Score + localization	RGB/CIELAB	Robustness modules (varies)	Low–Medium	Better under label scarcity & shift	Inconsistent benchmarking/reporting

Datasets, Benchmarking Practices, and Evaluation Metrics

When the literature is examined through the lens of evidence quality and comparability, datasets and evaluation practices become as important as algorithms. Studies in industrial visual inspection often draw from two broad sources: (1) domain-specific textile datasets curated for fabric defects and (2) general industrial anomaly detection benchmarks that support low-label evaluation. This split is consequential for color-defect research because many fabric datasets prioritize structural/texture defects, while chromatic defects require careful control of illumination and color measurement to remain meaningful across experiments. The color science literature explains why the same fabric can appear different across lighting spectra and camera settings, and why illumination–reflectance separation or color normalization is central to color-stable analysis (Ng et al., 2011). As a result, the validity of a reported "high accuracy" hinges on whether acquisition conditions are controlled and reported, and whether evaluation metrics actually reflect chromatic deviation rather than only spatial localization (Page et al., 2021).

A second consistent observation is the metric mismatch that often occurs in color-defect studies: computer vision reporting tends to emphasize classification (accuracy/F1/AUC) and localization (mAP/IoU), while industrial color QC is fundamentally concerned with perceptual color difference. Perceptual metrics such as ΔE (CIEDE2000) were explicitly developed to quantify color differences in a way that aligns more closely with human perception, making them theoretically well-suited for chromatic defect assessment. However, ΔE-type metrics are not consistently integrated into model evaluation, which limits the interpretability of results for industrial color control. This gap reinforces the need for dual-axis benchmarking, where localization/recognition metrics are paired with perceptual color-difference measures to ensure that detected "defects" correspond to meaningful color deviations.

Table 2. Evaluation metrics and what they capture in color-defect inspection

Metric group	Examples	What it measures	Fit for color defects	Typical risk
Classification	Accuracy, F1, AUROC	Correct defect/no-defect decision	Moderate	Can hide localization failure or subtle color drift
Localization	mAP, IoU	Correct location/shape of defect	High (if defect is spatially localized)	May ignore perceptual color severity
Pixel anomaly quality	Pixel-AUROC, PRO	Quality of anomaly maps	High (anomaly settings)	Threshold/reporting sensitivity
Perceptual color difference	ΔE (CIEDE2000)	Magnitude of perceptual color deviation	Very high	Not consistently reported with vision metrics

Industrial Deployment Constraints and Robustness Requirements

The synthesis of industrial constraints shows that color-defect inspection must be treated as a system-level problem rather than a model-only problem. In production, the same fabric can be observed under slightly different illumination intensities, spectra, and geometries, while textile surfaces may introduce specular reflections or texture-driven shading that visually resembles chromatic anomalies. These factors can cause false positives (e.g., highlights misread as discoloration) or false negatives (subtle shade shifts masked by lighting variation). The conceptual foundation for this instability is well captured in illumination and color perception research: camera-captured color is inherently entangled with illumination, motivating illumination-aware correction methods to approximate stable reflectance-based color information (Ng et al., 2011; Nguyen, 2024).

From an SLR perspective, another industrial issue is that studies often underreport acquisition conditions and deployment constraints, which weakens reproducibility and limits the external validity of "lab performance" claims (Iqbal, 2024; Li et al., 2015; Liu & Yang, 2021). When defects are rare or intermittent as is common for off-shade events label scarcity further pushes the field toward anomaly detection or low-label learning. Combined with real-time throughput requirements and maintainability considerations (ease of recalibration, monitoring drift, and updating models), the evidence indicates that the most industry-ready solutions are those that integrate acquisition control, color stabilization, and learning strategies designed for limited labels then evaluate outcomes using both spatial metrics and perceptual color measures.

Table 3. Industrial constraints and recommended robustness responses

Industrial constraint	Why it matters for color defects	Typical robustness response (from synthesis)
Illumination variability	Changes chromatic appearance	Color constancy / Retinex / normalization; reporting lighting setup
Fabric texture & reflectance	Highlights/shadows mimic color drift	Controlled lighting geometry; preprocessing to reduce specular effects
Domain shift (fabric types/batches)	Model fails across unseen fabrics	Diverse training/validation splits; domain-aware evaluation
Label scarcity for rare off-shade	Hard to build supervised datasets	Anomaly detection / semi-supervised learning; normal-only training
Real-time line speed constraints	Limits model complexity	Efficient architectures; edge deployment planning
Reproducibility gaps in papers	Hard to compare methods fairly	Minimum reporting checklist; PRISMA-consistent documentation

DISCUSSION

The findings of this systematic review indicate that although fabric inspection research has progressed significantly in algorithmic sophistication, color-related defects remain a distinct and comparatively under-standardized problem relative to structural or texture defects. Synthesizing the methodological taxonomy, dataset landscape, and industrial constraints reveals that robustness in color-defect detection does not arise primarily from model architecture, but from the interaction between color representation, illumination handling, and learning strategy. This reinforces the view that color inspection is fundamentally a system-level problem, where upstream imaging decisions and downstream evaluation criteria jointly determine reliability.

One key explanatory insight emerging from the synthesis is that color defects often exhibit low spatial contrast but high perceptual impact, which helps explain why many models achieve strong localization results for structural anomalies yet struggle with subtle shade variation. When illumination conditions are not controlled, chromatic shifts caused by lighting variation may be misinterpreted as defects or may mask true deviations, leading to both false positives and missed detections. The literature consistently shows that illumination and reflectance are tightly coupled in camera-based inspection, highlighting the importance of color constancy and normalization strategies to approximate stable reflectance-based color information (Liu & Yang, 2021).

Compared with earlier inspection approaches, the review confirms a clear methodological transition from handcrafted pipelines to data-driven representation learning. Classical computer-vision techniques remain relevant due to interpretability and efficiency but are sensitive to production variability, limiting their reliability for chromatic inspection tasks (Hanbay, 2016). Supervised deep learning approaches demonstrate strong performance when defect classes are well-defined and annotated, yet their dependence on labeled data constrains applicability in real manufacturing environments where color defects may be rare or continuous rather than categorical. This observation explains the growing prominence of anomaly-detection approaches, which align more closely with industrial conditions by modeling normal fabric appearance and detecting deviations (Cui et al., 2023).

The synthesis also highlights that evaluation practices remain inconsistent across studies. Conventional computer-vision metrics such as accuracy, F1-score, or mAP capture detection and localization performance but do not necessarily reflect the perceptual severity of color deviations. Perceptual metrics such as ΔE provide a theoretically grounded measure of chromatic difference, yet they are not consistently incorporated into evaluation protocols (Li et al., 2015). This discrepancy suggests that future benchmarking should adopt a dual-axis evaluation framework, combining spatial detection metrics with perceptual color-difference indicators to ensure alignment between algorithmic performance and industrial quality criteria.

From an industrial perspective, the implications of these findings extend beyond methodological optimization. Reliable color inspection directly influences material waste, production efficiency, and customer satisfaction, as over-rejection increases operational costs while under-detection risks quality claims. The evidence therefore supports the need for integrated inspection system design, where imaging setup, calibration, and model selection are considered jointly rather than independently. In addition, the limited reporting of acquisition conditions across many studies suggests that reproducibility remains a critical gap, hindering the transferability of research outcomes to real production lines (Iqbal, 2024; Nguyen, 2024).

Reflecting on both the functional and potential dysfunctional consequences of Industrial AI adoption, the review suggests that while AI-enabled inspection improves consistency and scalability, systems deployed without illumination robustness or drift monitoring may introduce systematic bias or performance degradation over time. Consequently, practical implementation should incorporate operational safeguards such as periodic recalibration, domain-shift validation, and clear acceptance thresholds aligned with perceptual color standards.

Based on the synthesized evidence, several future research directions emerge. First, the development of color-calibrated textile datasets with documented acquisition conditions is essential to improve comparability across studies. Second, evaluation frameworks should integrate perceptual color metrics alongside conventional vision measures. Third, research should prioritize methods that reduce dependence on extensive labeled data, including semi-supervised and anomaly-detection approaches, while validating them under cross-condition scenarios. Finally, closer alignment between algorithm outputs and quality-control decision rules is needed to translate technical performance into measurable industrial benefits.

Overall, this discussion reinforces the central proposition of the review: achieving reliable fabric color-defect detection requires the coordinated design of color representation, illumination robustness, and learning strategy within the constraints of real manufacturing environments. By framing color as the primary inspection signal and industrial variability as a co-determining factor, the synthesis provides a conceptual foundation for more reproducible and deployment-oriented research in Industrial AI-based textile inspection.

CONCLUSION

This systematic literature review shows that fabric color-defect inspection in manufacturing should be treated as a system-level challenge rather than a model-only problem. The most important lesson from the synthesized evidence is that reliable detection of shade variation and related chromatic defects depends on the coordinated design of (1) color-consistent representation (ideally aligned with perceptual color difference), (2) illumination robustness through acquisition control and/or correction and normalization, and (3) a learning paradigm matched to label availability, where supervised deep learning is effective under rich annotations while anomaly detection and low-label strategies are more realistic when color defects are rare and heterogeneous. In this sense, the review clarifies why strong results reported under controlled conditions may not translate directly to production lines if illumination and domain shift are not explicitly addressed.

The main scientific contribution of this review is a structured synthesis that consolidates dispersed findings into an operational framework for Industrial AI-based color-defect inspection. Specifically, the study contributes (i) a method taxonomy spanning classical computer vision, supervised deep learning, and anomaly/hybrid paradigms; (ii) an evaluation perspective that highlights the need to pair conventional recognition/localization metrics with perceptual color-difference indicators when defects are fundamentally chromatic; and (iii) a deployment-oriented interpretation that links methodological choices to industrial constraints such as lighting variability, fabric reflectance, domain shift, and limited defect labels. Together, these contributions provide a clearer roadmap for both researchers and practitioners to design, evaluate, and report color-defect inspection systems more consistently and transparently.

Several limitations should be acknowledged. First, the evidence base is constrained by inconsistent reporting of acquisition conditions and calibration procedures across studies, which limits reproducibility and makes cross-paper comparisons less definitive. Second, many datasets and benchmarks used in the broader fabric inspection literature emphasize structural defects, reducing the availability of directly comparable evidence for color-specific defects. Third, because this work synthesizes published findings, it cannot fully resolve performance trade-offs under real production variability without standardized cross-condition testing. Future research should therefore prioritize the development of color-calibrated textile datasets with documented lighting/camera configurations, adopt dual-axis evaluation protocols that include perceptual color-difference measures, and validate models under cross-fabric and cross-illumination scenarios. In addition, practical deployments would benefit from integrating drift monitoring and periodic recalibration strategies to sustain reliability over time in dynamic manufacturing environments.

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