SYSTEMATIC REVIEW OF THE COMPUTATIONAL EVOLUTION OF TEXTILE QUALITY ASSURANCE

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Abstract
Effective quality control is central to textile manufacturing, yet conventional fabric inspection remains slow, labor-intensive, and prone to human error and fatigue. This study traces the evolution of fabric defect detection, from conventional image-processing methods to Artificial Intelligence (AI)-based approaches. Following PRISMA guidelines, it systematically reviews 25 studies, examining the factors that affect, defect detection in fabrics and tracking the shift from conventional to computational methods of textile quality assurance.

The findings show that modern deep learning models detect fabric defects more accurately than conventional methods, and that hybrid approaches combining attention mechanisms with optimization techniques perform best. Recent work increasingly applies AI to real-time inspection and uses explainable AI (XAI) to make automated decisions more transparent and trustworthy. Class imbalance and limited training data remain the main obstacles to fully automated, reliable defect detection.

Keywords:
Fabric Defect Detection, Deep Learning, Systematic Literature Review, Industry 4.0, Computer Vision, Textile Quality Inspection.

1. Introduction

1.1. The Economic Importance of Textile Quality Control

The textile industry is a major contributor to global manufacturing and to India's economy, generating employment and supporting economic growth. High product quality improves competitiveness, cuts material waste, and increases export capacity, in line with the Atmanirbhar Bharat Abhiyan initiative. Fabric defects lower product quality and customer satisfaction, damage brand reputation, and cost manufacturers money. Fabric defect detection matters exactly these reasons: it protects quality, cuts waste and keeps production running efficiently.

1.2. Limitations of Conventional Manual Inspection

Textile manufacturing has become highly automated, but fabric inspection still depends mainly on people checking cloth by eye. This does not scale well to high-speed production lines. Inspectors get tired and need breaks, and their judgment varies from person to person, so defects get missed and quality assessments are inconsistent. Complex fabric patterns make this worse: the more intricate the weave or print, the harder it is to catch defects reliably by eye.

1.3. Objectives

To get past the limits of manual inspection, the textile industry has increasingly turned to machine vision and Artificial Intelligence (AI) for automated fabric defect detection. This systematic review traces the shift from conventional image-processing methods to deep learning techniques. Following PRISMA guidelines, it analyzes 25 studies to assess detection accuracy, real-time applicability, and the role of Explainable Artificial Intelligence (XAI). It also identifies current challenges and outlines future directions for reliable, efficient automated textile quality inspection.

2. Methodology

This review follows the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines for a transparent and reliable process, structured around four stages: identification, screening, eligibility, and inclusion. This structure helps select relevant, high-quality studies and limits selection bias.

2.1. Database Selection and Search Strategy

The search was conducted in the Scopus database, chosen for its broad coverage of engineering, materials science, and computer science research. It included studies published between January 2000 and May 2026, spanning the development of fabric defect detection methods from conventional image processing to deep learning.

2.2. Search String Construction

The search strategy combined keywords related to textiles, fabric defects, and detection techniques using Boolean operators (AND/OR), including terms such as fabric defects, outlier detection, YOLO, and transfer learning. Results were limited to peer-reviewed journal articles, conference papers, and review articles, yielding an initial set of 752 records.

2.3. Eligibility inclusion and exclusion Criteria

Inclusion and exclusion criteria were set before the review began, to keep study selection consistent and unbiased. Only English-language, peer-reviewed studies on fabric defect detection that reported quantitative performance measures, such as accuracy, precision, recall, or F1-score, were included. Studies on non-textile applications, duplicate records, and non-peer-reviewed publications were excluded.

2.4. Study Selection Process

Study selection followed the PRISMA 2020 flow diagram through a step-by-step screening process. Of the 752 records initially identified, 533 were excluded after screening titles, abstracts, and keywords. The remaining 219 studies underwent full-text review, which excluded a further 194. In the end, 25 studies were included in the review.

2.5. Prisma Flow Diagram

Identification	Records identified from Scopus Database (n = 752)	Advanced search: Title-Abs-Key Keywords: included ("Fabric Defect" OR "textile fabric defect detection" OR "fabric inspection" OR "defect classification" OR "fabric defect identification" OR "Indian textile industry" OR "textile manufacturing in India" OR "textile sector India") AND ("deep learning" OR "machine learning" OR "computer vision" OR "real-time detection" OR "embedded systems" OR "Multi-Resolution" OR "CNN" OR "YOLO" OR "Res Net" OR "LSTM" OR "GLCM" OR "DCT" OR "FFT" OR "ANN" OR "SVM" OR "GRU" OR "real-time fabric inspection" OR "defect detection systems" OR "curvelet" OR "wavelet" OR "DSP" OR "FPGA" OR "TILDA" OR "HKBU" OR "Ministry of Textile" OR "Industrial Images") Excluded: (n = 0) No duplicate records were identified
Screening	Records screened (n = 752)	Reason: Failed to jointly satisfy specific textile and defect detection criteria. Excluded: (n = 533)
Eligibility	Full text articles assessed for eligibility (n = 219)	Reason: Global studies, off domain (e.g. involving sectors such as welding, structural composites, 3D printing, PCB inspection) Excluded: (n = 194)
Inclusion	Studies included in synthesis (n = 25)	Final core corpus: studies focused on the Indian textile industry, forming the primary evidence base for tracing the evolution of quality assurance in this sector.

3. Thematic Analysis

The selected studies show a clear shift toward automated fabric inspection using Artificial Intelligence (AI). Deep learning has become the focus of recent research, overtaking traditional machine learning as the leading method for fabric defect detection. Two major thematic areas emerge from this analysis, reflecting the current direction of research in the field.

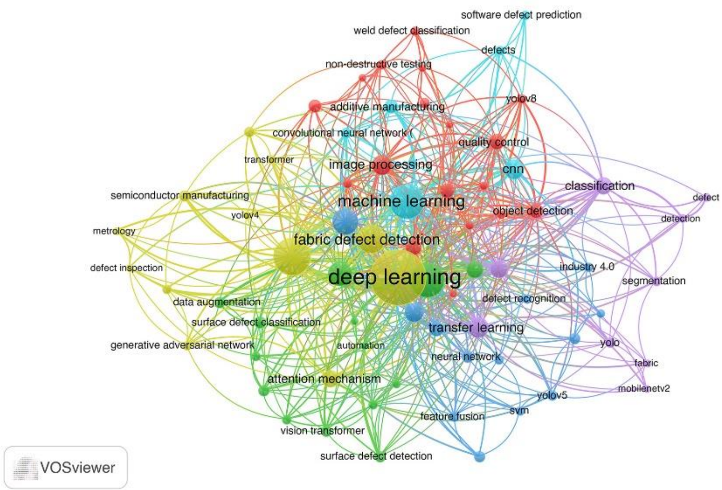

figure 1 convolutional neural networks (cnn)

The first theme centers on Convolutional Neural Networks (CNNs), transfer learning, and image processing. These approaches use pre-trained models to improve fabric defect detection while reducing the need for large training datasets and heavy computation.

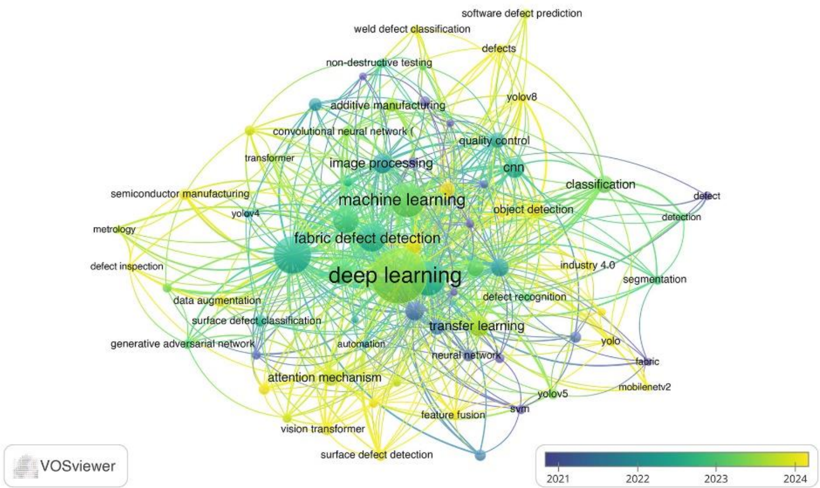

figure 2 important defect regions and improve detection accuracy.

The second theme concerns attention mechanisms in quality control, which let models focus on the regions most likely to contain defects and improve detection accuracy.

Recent research has moved from simple pass/fail classification toward more advanced defect detection and traceability. Rather than just flagging a fabric as defective, modern methods can classify the type of defect and help trace its likely cause. This reflects a growing emphasis on inspection systems that are accurate, efficient, and explainable.

4. Taxonomy of Fabric Defect Detection Paradigms

Fabric defect detection has moved from manual inspection to deep learning techniques. This taxonomy groups the major detection approaches by their underlying methods and feature extraction strategies.

4.1. Statistical Texture Analysis and Second-Order Feature Extraction

Statistical methods are among the earliest approaches to automatic fabric defect detection. They analyze the spatial distribution of pixel intensities to describe fabric texture and are typically classified as first-order, second-order, or higher-order methods (Anandan & Sabeenian, 2018). The Gray-Level Co-occurrence Matrix (GLCM) is widely used to capture texture patterns by measuring relationships between pixel intensities (Patil & Deshmukh, 2022) and is often combined with Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) for better feature representation (Juneja & Dudy, 2026). These methods are computationally efficient, but they require manual parameter tuning and struggle with fabrics that have complex texture variations (Pooja & Soma, 2024).

4.2. Spectral and Signal Processing Approaches (Fourier, Wavelet, and Curvelet Transforms)

Spectral and signal processing methods were introduced to address a key weakness of spatial-domain techniques: sensitivity to noise and lighting variation. These approaches analyze fabric images in the frequency domain, where defects show up as changes in texture patterns (Patil & Deshmukh, 2022). The Fourier Transform is commonly used to detect global defects, while the Wavelet Transform allows multi-scale analysis by preserving both spatial and frequency information (Sandhya et al., 2021). The Discrete Curvelet Transform goes further, capturing curved edges and directional features in complex fabric structures (Anandan & Sabeenian, 2018). These methods hold up well in noisy environments but perform worse on fabrics with irregular or non-periodic textures.

4.3. The Deep Learning Shift: Convolutional Neural Networks (CNN) and Transfer Learning

Convolutional Neural Networks (CNNs) marked a major advance in fabric defect detection, learning features directly from images and removing the need for handcrafted feature extraction (Pooja & Soma, 2024). To work around the limited availability of textile datasets, researchers have widely adopted transfer learning with pre-trained models such as VGG16, ResNet50, and AlexNet, which improve detection accuracy even with smaller datasets (Malathi & Aiswarya, 2025; Sandhya et al., 2021). For real-time applications, YOLO-based models, including YOLOv3 and YOLOv4, detect and classify fabric defects quickly and accurately (Sujee et al., 2020; Das & Deka, 2025).

4.4. Emerging Architectures: Generative Adversarial Networks (GANs), Transformers, and Attention Mechanisms

Recent research has turned to more advanced architectures that improve detection accuracy and address problems such as class imbalance and limited interpretability. Generative Adversarial Networks (GANs), including TGANet, detect defects by comparing fabric images against reconstructed defect-free versions (Agnes & Agees, 2024).

Vision Transformers (ViTs) capture global fabric patterns more effectively than conventional CNNs (Swapno et al., 2026). Attention mechanisms improve detection further by focusing on likely defect regions and filtering out background noise (Shen et al., 2024). Explainable Artificial Intelligence (XAI) adds visual explanations that help engineers understand and verify AI-based decisions (Swapno et al., 2026).

5. Data Synthesis and Performance Evaluation

This section summarizes how automated fabric defect detection methods perform across different datasets and testing environments and traces the shift from relying on classification accuracy alone to broader evaluation metrics that account for class imbalance and real-time performance in industrial settings.

5.1. Analysis of Benchmark Datasets

Model performance depends heavily on the quality and diversity of the training data. The TILDA dataset is a widely used benchmark for texture-based defect detection (Asha, 2022). More recent studies draw on the Kaggle Fabric Defect Dataset and repositories such as ZJU-Leaper, which offer larger and more diverse annotated images for training deep learning models (Juneja & Dudy, 2026; Malathi & Aiswarya, 2025; Sajitha & Priya, 2024). Researchers are also turning to real-world datasets such as SAR-CLD-2024 and Cotton Fabric Image BD to test model performance under practical conditions, including uneven lighting and environmental noise (Swapno et al., 2026). Models trained on industrial datasets often need image pre-processing, such as Contrast Limited Adaptive Histogram Equalization (CLAHE) and bilateral filtering, to reach acceptable detection accuracy (Das & Deka, 2025; Sajitha & Priya, 2024).

5.2. Methodological Frameworks, Performance Metrics, and Computational Platforms

This section summarizes the methodologies, performance metrics, and computational platforms reported across the 25 selected studies, tracing the shift from conventional statistical methods to deep learning techniques for fabric defect detection.

5.3. Quantitative Comparison of Performance Metrics

Accuracy alone is not enough to evaluate fabric defect detection systems, because industrial datasets tend to contain far more defect-free samples than defective ones. Measures such as the Matthews Correlation Coefficient (MCC), Kappa Statistic, F1-score, and mean Average Precision (MAP) give a more reliable picture. Hybrid models such as the MRMR-based Bayesian Random Forest reached an MCC of 0.9906 and a Kappa Statistic of 0.98 (Juneja & Dudy, 2026), while traditional GLCM-based methods performed worse on complex fabric textures (Asha, 2022; Patil & Deshmukh, 2022). More recent approaches, including Vision Transformers (ViT) and improved YOLO models with attention mechanisms, achieved high F1-scores and MAP scores while supporting real-time detection and better model interpretability (Shen et al., 2024; Swapno et al., 2026).

6. Discussion

6.1. Integration of Heuristic and Bayesian Optimization in Model Selection

Optimization techniques have improved automated fabric defect detection by reducing the need for manual parameter tuning. Recent studies apply Bayesian Optimization (BO) to tune Random Forest and Convolutional Neural Network (CNN) models, improving classification performance (Juneja & Dudy, 2026). Combining Minimum Redundancy Maximum Relevance (MRMR) feature selection with Bayesian-optimized Random Forests has produced strong results on complex datasets (Juneja & Dudy, 2026). Metaheuristic algorithms such as Cuckoo Search and Moth Flame Optimization (HMFO) have also been used to tune deep learning models like ResNet50, making them more adaptable to different fabric textures (Mewada et al., 2024; Malathi & Aiswarya, 2025).

6.2. Transition from Handcrafted Features to Automated Hierarchical Feature Learning

Fabric defect detection has moved from handcrafted feature-based methods to automated deep learning approaches. Early techniques used the Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and the Histogram of Oriented Gradients (HOG) to extract texture and structural features (Patil & Deshmukh, 2022; Sajitha & Priya, 2024). These methods were computationally efficient but performed poorly on complex fabric patterns and changing lighting. Transfer learning with models such as VGG16 and ResNet34 improved detection accuracy by reusing pre-trained networks on limited textile datasets (Malathi & Aiswarya, 2025). More recently, hybrid CNN–Vision Transformer (ViT) models combine local and global feature learning to detect subtler fabric defects (Swapno et al., 2026; Malathi & Aiswarya, 2025).

6.3. Real-Time Deployment Constraints: DSP, FPGA, and Edge Computing Platforms

Real-time fabric defect detection has to balance accuracy against processing speed. Early systems used Digital Signal Processors (DSPs) and Field Programmable Gate Arrays (FPGAs) for efficient real-time inspection (Raheja et al., 2013; Pattern classification..., 2016). With the growth of Industry 4.0, Edge AI has become a preferred solution for on-site defect detection: lightweight models such as MobileNetV2 and YOLOv3-Tiny detect defects quickly and accurately at low power, which suits real-time industrial use (Burra et al., 2023; Sujee et al., 2020). These systems let fabric inspection happen directly on production machines, without relying on centralized computing.

6.4. Interpretability and XAI in Industrial Diagnostics

As AI models grow more complex, Explainable Artificial Intelligence (XAI) has become important for building transparency and trust in automated fabric inspection. Techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) generate heatmaps showing which regions influenced a model's prediction, helping engineers check whether detected defects are genuine (Swapno et al., 2026). These visual explanations build confidence in AI-based decisions and support wider adoption of automated inspection in the textile industry (Swapno et al., 2026).

7. Limitations and Future Study

Automated fabric defect detection has made real progress, but several challenges still limit how widely industry has adopted it. These gaps point to the need for further research toward more accurate, reliable, and practical inspection systems.

7.1. Challenges of Class Imbalance and Small-Sample Learning

One major challenge is the imbalance between defective and non-defective samples. Since most fabric is defect-free, gathering enough annotated images of rare defects is difficult, and this can hurt model performance on uncommon defect types (Das & Deka, 2025; Malathi & Aiswarya, 2025). Data augmentation and Generative Adversarial Networks (GANs) have been used to address this, though they do not always reproduce real defect patterns accurately (Swapno et al., 2026). Limited training data also remains a problem for advanced models such as Vision Transformers, which need large datasets to perform reliably (Swapno et al., 2026; Malathi & Aiswarya, 2025).

7.2. Scalability to Complex Weave Patterns and Multi-Color Fabrics

Automatic fabric inspection gets harder with complex weave structures and multi-colored fabrics. Many conventional methods work well on simple fabrics but struggle with complex weaves, such as twills, jacquards, and handloom textiles, where texture patterns are highly irregular (Das & Deka, 2025; Pooja & Soma, 2024). Printed and multi-colored fabrics make it harder still to tell real defects from design variation (Sujee et al., 2020; Malathi & Aiswarya, 2025). Advanced models improve detection accuracy, but they typically need more computational power, which limits their use in real-time industrial settings (Das & Deka, 2025; Sujee et al., 2020).

7.3. Future Directions: Edge AI, XAI, and Open-Access Repositories

Future research is likely to focus on three areas. First, Edge AI should let lightweight models run real-time fabric inspection directly on production machines (Burra et al., 2023; Malathi & Aiswarya, 2025). Second, Explainable Artificial Intelligence (XAI) should make AI-based decisions more transparent through visual explanations, such as Grad-CAM heatmaps, that support quality engineers (Swapno et al., 2026). Third, building large-scale, open-access fabric defect datasets would support training more accurate and reliable models for diverse textile applications (Rasheed et al., 2020).

8. Conclusion

This review shows that fabric defect detection has evolved from manual inspection and conventional feature-based methods to Artificial Intelligence (AI) and deep learning approaches. Early methods, such as the Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), laid the groundwork for automated texture analysis but performed poorly on complex fabrics. More recent advances, including Convolutional Neural Networks (CNNs), YOLO-based models, and optimization techniques, have markedly improved detection accuracy and real-time performance. Hybrid models that combine Vision Transformers (ViTs) with advanced feature selection have achieved Matthews Correlation Coefficient (MCC) values above 0.99. The future of fabric defect detection lies in combining AI with inspection systems that are both efficient and transparent. Edge AI should enable real-time defect detection directly on production machines, while Explainable Artificial Intelligence (XAI) should improve the transparency and reliability of AI-based decisions. Future research may focus on building large, standardized, open-access datasets to address challenges such as class imbalance and limited training data. Together, these advances should support fully automated, accurate, and reliable quality inspection systems for the textile industry.

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