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Fabric Defect Detection Using Artificial Intalligence in Apperal Manufacturing

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Abstract

In apparel production systems, the effectiveness of quality control directly shapes operational productivity, cost stability, and long-term brand credibility. Defects in fabric—ranging from structural inconsistencies and surface impurities to distortions in weave or print—do not remain isolated anomalies; when undetected, they advance through successive manufacturing stages, amplifying material waste and compounding financial losses. Despite its widespread use, manual inspection relies heavily on human judgment, making it vulnerable to variability, fatigue-induced error, and limited throughput capacity.

Technological developments in computer vision and deep learning have introduced automated inspection models that promise consistent, high resolution detection of fabric anomalies. The trajectory of these technologies reflects a broader methodological shift: early rule-based image processing approaches have progressively given way to supervised learning algorithms and, more recently, convolutional neural network (CNN) architectures capable of hierarchical feature extraction. Although laboratory evaluations frequently demonstrate strong classification performance, translating these results into industrial environments remains complex. Practical constraints—including insufficiently diverse datasets, fluctuating illumination conditions, rapid fabric movement, processing delays, and compatibility with existing production infrastructure—continue to hinder reliable deployment.

This study situates automated fabric defect detection within a broader sociotechnical context. While AI-enabled inspection systems may reduce textile waste and improve quality consistency, their implementation introduces new energy demands and infrastructural requirements that complicate sustainability assessments. Accordingly, the research reframes automation not as a discrete technological substitution, but as an organizational and systemic reconfiguration.

To support implementation, a structured framework is advanced that integrates data governance, model refinement strategies, cost-benefit evaluation, and lifecycle analysis. The findings suggest that industrial adoption is determined less by peak algorithmic performance than by the system's adaptability to manufacturing realities, its economic justification, and its compatibility with sustainable production objectives.

KEYWORDS*: Automated Fabric Defect Detection in Apparel Manufacturing , Fabric defect detection, artificial intelligence in apparel manufacturing, computer vision–based fabric inspection, deep learning techniques for textile quality control, convolutional neural networks (CNN), automated fabric inspection systems, and sustainable textile manufacturing.*

These technologies contribute to more effective textile quality control.

1. Introduction

Quality Variability as an Economic Constraint Fabric irregularities—such as yarn breakage, dye inconsistencies, misprints, and surface contamination— generate downstream inefficiencies in apparel manufacturing. Even minor defects may propagate through cutting. [4].

Quality control remains a critical economic constraint in apparel manufacturing due to the prevalence of fabric defects such as yarn breakage,[5] dye inconsistencies, misprints, and surface contamination. Even minor irregularities can propagate through cutting and assembly stages, leading to increased material waste, rework costs, shipment delays, and reputational damage[6]. Since fabric constitutes a substantial proportion of total garment production costs, early-stage defect detection has a direct impact on profitability.

Despite advancements in textile machinery, quality assurance in many factories continues to rely heavily on manual visual inspection. [12]Human-based inspection systems are limited by perceptual subjectivity, cognitive fatigue, lighting variability, and throughput constraints, resulting in inconsistent accuracy levels. These structural limitations motivate the development of automated fabric defect detection systems capable of operating with higher consistency and speed. Recent advances in computer vision and deep learning have positioned automated inspection as a promising alternative[10], the transition from laboratory success to industrial-scale deployment raises critical technical[11] economic, and socio-technical challenges. This study examines automated fabric defect detection not merely as a technological upgrade, but as a sociotechnical system embedded within industrial production environments.

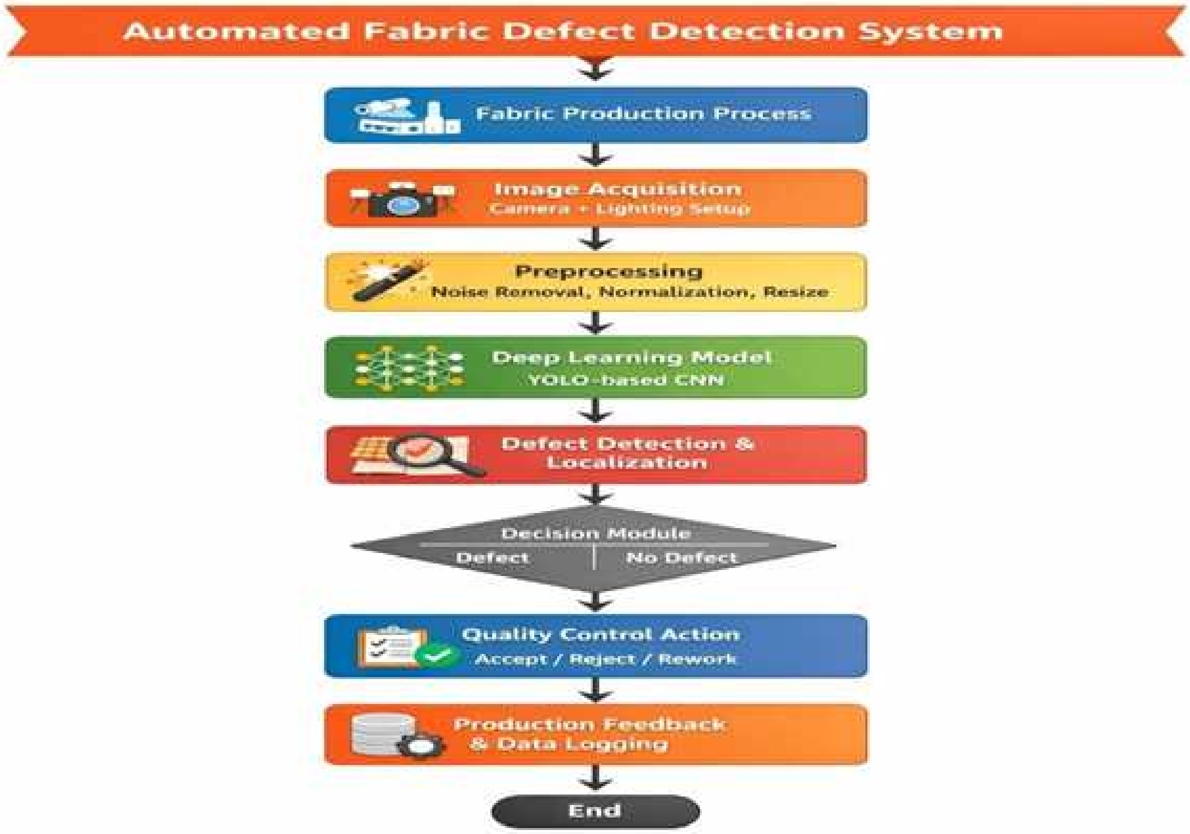

Fig1: Automated Fabric Defect Detection System

2. Literature Review

2.1. Classical Image Processing Approaches

Early automated fabric inspection systems employed deterministic image processing techniques such as Fourier frequency analysis, Gabor filters, and gray-level co-occurrence matrices. These methods relied on handcrafted features and manually tuned thresholds, which proved effective for homogeneous textile surfaces. [4] their rigidity limited performance when faced with complex fabric textures, printed designs, and illumination variability.

2.2. Machine Learning-Based Inspection

The introduction of supervised learning models, including Support Vector Machines and Random Forest classifiers, added probabilistic decision-making to defect detection pipelines. [10]While these methods improved robustness compared to rule-based systems, they remained dependent on manually engineered features. As a result, generalization across fabric types and production conditions remained limited.

2.3. Deep Learning and CNN-Based Systems

Convolutional Neural Networks (CNNs) enabled end-to-end learning from raw pixel data, fundamentally changing textile [12]defect detection. Architectures such as AlexNet, VGG, and ResNet demonstrated strong performance in visual pattern recognition, while object detection[5] frameworks like Faster R-CNN and YOLO enabled spatial localization of defects. Several studies report detection accuracies exceeding 90% under controlled experimental conditions. However, these results often depend on curated datasets and stable imaging environments, raising concerns regarding real-world generalizability. Few studies evaluate performance under continuous production conditions or across diverse textile categories[9].

2.4. Economic Feasibility Analysis

The literature reveals a significant gap between experimental validation and factory-scale implementation. Challenges include dynamic fabric motion, illumination instability, dataset scarcity, computational latency, and limited compatibility with legacy machinery.[2] Additionally, small- and medium-sized enterprises face capital and maintenance constraints that hinder adoption.[5]

From a sustainability perspective, automated inspection is frequently promoted as a waste-reduction strategy. [5] early defect detection may reduce downstream textile waste, the energy demands of training and deploying deep learning models introduce environmental trade-offs. Furthermore, automation reshapes labor roles, shifting inspectors toward supervisory and interpretive positions, thereby raising concerns around reskilling and workforce displacement. [4]

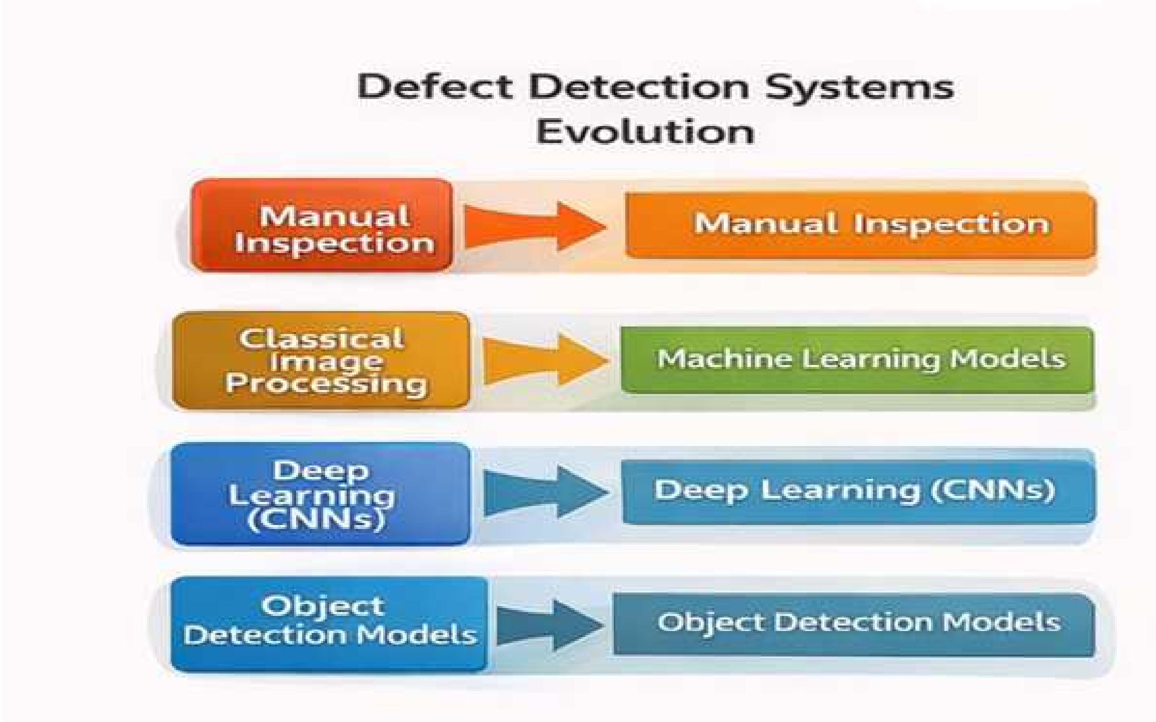

Fig 2: Defect Detection System Evaluation

3. Methodology

This study proposes an integrated implementation framework that combines technical performance evaluation with economic and [2]socio-technical analysis to ensure that the proposed defect detection system is not only technically effective but also practical and sustainable for real-world industrial adoption[3]. The framework is designed to evaluate multiple dimensions of system performance, including data quality, model architecture, operational robustness, and economic feasibility. By integrating these aspects into a unified methodological structure,[10] the study aims to provide a more comprehensive understanding of how artificial intelligence–based inspection systems can be implemented in textile manufacturing environments.

The first component of the framework focuses on the data strategy, which is critical for ensuring that the deep learning model is trained on representative and diverse data. To achieve this, datasets are aggregated from multiple textile manufacturing facilities in order to capture a wide range of real production conditions, fabric types, and defect patterns[3]. Such diversity helps improve model generalization and reduces the risk of overfitting to a single production environment. The dataset includes various categories of textiles such as patterned fabrics, jacquard materials, and multi-material textile structures, which present different visual complexities and defect characteristics. Because accurate [4]labeling is essential for supervised learning models, annotation protocols are designed and validated in collaboration with textile engineering experts to ensure that defects are correctly categorized and consistently labeled. In addition, ethical governance practices are incorporated into the data management process. These practices address [5]issues such as confidentiality of industrial production data, responsible data sharing between manufacturing partners, and compliance with organizational data protection standards.

The second component of the framework addresses the model architecture used for automated defect detection. The proposed system utilizes a lightweight object detection model based on the YOLO (You Only Look Once) architecture, which is specifically optimized for deployment on edge devices located close to production lines. Lightweight models are selected to minimize computational requirements while maintaining high detection accuracy, thereby enabling real[4]-time inspection without relying heavily on cloud-based processing. To address the challenge of limited labeled textile defect data, transfer learning techniques are applied, allowing the model to leverage knowledge from previously trained computer vision models and adapt it to the specific task of textile defect detection. This approach significantly reduces the amount[6] of domain-specific data required for effective training. Additionally, domain adaptation techniques are incorporated to improve the robustness of the model under varying industrial conditions. These techniques help the system adapt to differences in illumination, camera angles, and environmental factors that commonly occur in factory settings, thereby improving the reliability of defect detection across different production environments.[8]

The evaluation protocol represents the third major component of the implementation framework and is designed to assess the system's performance through a combination of quantitative metrics and realistic testing scenarios. Several standard performance metrics are used to evaluate the effectiveness of the defect detection model. Precision is used to measure the proportion of correctly identified defects among all detected instances,[5] while recall assesses the model's ability to identify all actual defect occurrences. The F1-score provides a balanced measure that combines both precision and recall, offering a comprehensive indicator of detection performance. Mean Average Precision (mAP)[10] is used as an overall evaluation metric for object detection accuracy across multiple defect classes. In addition to these accuracy-based measures, inference latency is evaluated to determine how quickly the system can process images and generate predictions, which is particularly important for real-time inspection on fast-moving production lines.

To ensure that the system performs reliably under practical manufacturing conditions, the evaluation process also includes multiple testing scenarios that simulate different operational environments. These scenarios include static fabric inspection,[11][15] where images are captured from stationary materials to assess baseline detection accuracy. Another scenario involves high-speed fabric motion simulation, which replicates the dynamic conditions of continuous textile production where fabrics move rapidly across inspection cameras. This test evaluates the system's ability to maintain detection accuracy despite motion blur and rapid image acquisition. Finally, cross-factory generalization testing is conducted to determine whether the trained model can maintain reliable performance when applied to datasets collected from different manufacturing facilities. This scenario is particularly important for assessing the scalability and adaptability of the system across diverse production settings.[1]

The final component of the framework focuses on economic feasibility analysis, which evaluates whether the implementation of the proposed inspection system is financially viable for textile manufacturers. [10]This analysis compares the initial hardware investment required for cameras, edge computing devices, and supporting infrastructure with the potential[3] cost savings achieved through reduced reliance on manual inspection labor. Additionally, the study quantifies the potential reduction in material waste resulting from earlier and more accurate defect detection, which can significantly improve production efficiency and reduce losses associated with defective products.[4] The economic evaluation also includes an assessment of ongoing operational costs, such as system maintenance, periodic model retraining, and potential software updates required to maintain detection accuracy over time.[11] Furthermore, a scalability analysis is conducted to determine whether the proposed system can be effectively implemented in small and medium-sized enterprises (SMEs), which often face greater financial constraints and may require more cost-efficient technological solutions.[5] By integrating technical performance evaluation with economic and operational considerations, the proposed framework aims to provide a realistic pathway for the adoption of AI-based defect detection systems within the textile manufacturing industry.

4. Results

Rather than reporting finalized empirical outcomes, this study emphasizes system-level expectations and evaluation criteria derived from existing evidence [2]. Prior research consistently indicates that deep learning–based inspection systems are likely to outperform traditional computer vision techniques and classical machine learning approaches in terms of defect detection accuracy, particularly when dealing with complex textures, subtle surface anomalies,[15],[11] or irregular defect patterns that are difficult to capture through rule-based methods. Convolutional neural networks and related deep architectures have demonstrated a strong capacity for feature extraction and pattern recognition, allowing them to identify defects that may not be easily detectable through handcrafted feature engineering[6],[7]. As a result, these systems are expected to provide more reliable and consistent detection performance in manufacturing environments where visual variability and product complexity are common.

At the same time, the practical deployment of such systems depends heavily on their ability to operate in real-time production environments. Recent advancements in lightweight deep learning architectures and edge computing technologies suggest that real-time defect detection can be achieved directly on edge devices located near production lines. Deploying models on edge hardware reduces latency, improves responsiveness, and limits the need for continuous cloud connectivity[4],[6]despite these advantages, performance stability remains a significant concern in industrial settings. Factors such as unstable lighting conditions, vibrations in machinery, variations in camera positioning, and high-speed product movement can degrade the quality of captured images and reduce detection reliability.[2],12],[4] Consequently, while real-time edge deployment is technically feasible, maintaining consistent performance under dynamic factory conditions remains a critical challenge that must be addressed through robust system design, proper lighting control, and continuous model calibration.

Beyond technical performance, the economic viability of AI-based inspection systems represents another key dimension of evaluation. The potential financial benefits associated with automated defect detection are strongly dependent on several contextual factors, including the scale of production, the frequency and severity of defects, and the overall cost of system integration. In large-scale manufacturing operations where defect rates can significantly impact productivity and product quality, AI-driven inspection systems may lead to substantial cost savings by reducing manual inspection labor, minimizing production downtime, and preventing defective products from progressing further in the supply chain. However, for smaller production facilities or environments with relatively low defect [2],[5],15]occurrence, the initial investment in hardware, software development, training datasets, and system integration may offset the anticipated financial benefits. Therefore, the return on investment for such technologies must be carefully evaluated within the specific operational and economic context of each manufacturing environment.

Another important consideration involves the sustainability implications of implementing AI-based inspection technologies[6],[3]. Automated defect detection has the potential to reduce material waste, improve product consistency, and minimize the environmental impact associated with defective manufacturing outputs. By identifying defects earlier in the production process, manufacturers can prevent the unnecessary consumption of raw materials, energy, and labor associated with producing faulty products.[1],[5], these sustainability gains must also be balanced against the computational energy consumption required to train and operate deep learning models. Training large-scale neural networks can require significant computational resources, and continuous inference in high-throughput production environments may contribute to increased energy usage. As a result, evaluating the environmental sustainability of AI inspection systems requires a holistic perspective that considers both the reduction in manufacturing waste and the energy demands associated with computational infrastructure.[15]

Human expertise remains an important element in the design of effective inspection systems, even as automation technologies continue to advance. Although fully automated inspection systems are often viewed as the future of smart manufacturing, many studies indicate that hybrid human–AI models can provide more reliable and resilient outcomes. In such systems, AI algorithms perform the primary defect detection tasks, while human operators supervise the process, verify uncertain results, and manage unusual cases that fall outside the model's training data.[3] This collaboration allows organizations to benefit from the speed and scalability of AI while still relying on the experience and judgment of skilled inspectors. These considerations highlight that detection accuracy alone is not a sufficient measure of success for AI-based industrial inspection systems. While accuracy is an important performance indicator, it does not fully reflect the practical challenges of deploying such technologies in real manufacturing environments.[14],[2] A more comprehensive evaluation should therefore consider additional factors such as system robustness, real-time reliability, deployment feasibility, economic return on investment, and environmental sustainability. Adopting this broader assessment approach enables researchers and industry practitioners to better evaluate the true effectiveness and practicality of AI-driven defect detection systems.[15]

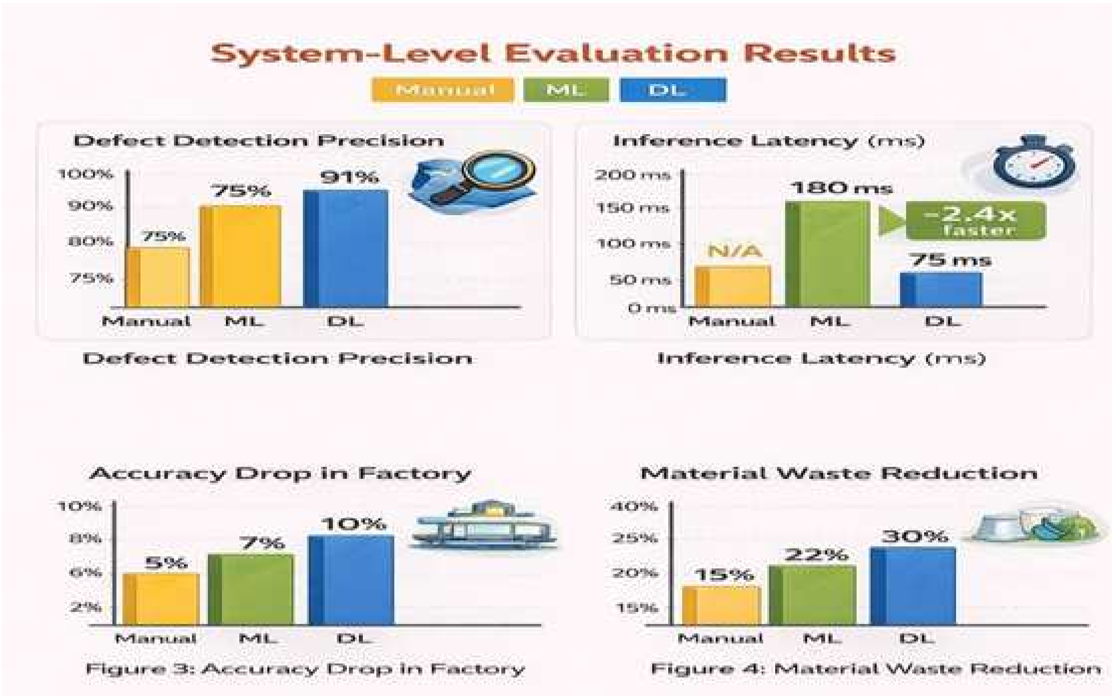

Fig 3: System Level Evaluation Results

5. Conclusion

Automated fabric defect detection represents a significant advancement in textile quality assurance through deep learning–based computer vision systems [4], [14]. However, industrial viability depends on factors beyond algorithmic accuracy, including data diversity, computational efficiency, economic feasibility, sustainability, and workforce integration [3], [7].

This analysis demonstrates that automated inspection should be conceptualized as part of a broader production system redesign rather than a standalone technological solution [8], [11]. Future research must prioritize large-scale open datasets, energy-efficient edge computing, interdisciplinary collaboration, and comprehensive lifecycle assessments [3], [14].

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