
Fabric Defect Detection Textile Inspection Automated Quality Control and Image Processing: A Survey

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Abstract

Fabric defect detection is pivotal in ensuring quality control within the textile industry, traditionally challenged by inefficient manual inspection methods. This survey paper explores the integration of machine learning and image processing techniques, which have revolutionized automated defect detection. Key advancements include the use of computer vision, deep learning, and unsupervised learning, which collectively enhance the accuracy and efficiency of identifying fabric anomalies. Despite these technological strides, challenges persist in data acquisition, model adaptability, and real-time processing. The survey highlights the need for diverse training datasets to improve model robustness and suggests exploring methodologies that minimize reliance on extensive labeled data. Additionally, optimizing models for real-time applications and integrating tactile with visual information are identified as future directions to enhance system adaptability and accuracy. By addressing these challenges, the textile industry can improve quality control, reduce waste, and maintain competitive production standards. This survey underscores the transformative potential of advanced technologies in fabric defect detection, offering a roadmap for future research and development in this evolving field.

1 Introduction

1.1 Importance of Fabric Defect Detection

Fabric defect detection is essential for quality control in textile manufacturing. Traditional manual inspection methods are inefficient, often resulting in missed defects due to eye fatigue and subjective judgment. This reliance on human inspection not only leads to inaccuracies but also hinders global competitiveness. In contrast, automated systems employing advanced technologies such as computer vision can significantly enhance defect detection and classification, improving product quality and operational efficiency. The industry's modernization demands reliable automated inspection systems to reduce human error in quality assurance processes [1, 2, 3]. Automated defect detection is crucial for maintaining the aesthetic and functional standards of textiles while minimizing waste, a significant concern in the industry.

The complexity of automated inspection is amplified by the diversity of defect types and their variations in size, shape, and texture, which pose technical challenges [4]. Nonetheless, implementing advanced detection systems is vital to mitigate the substantial costs associated with fabric defects, which can profoundly affect the final product quality [5]. The high volume of fabric production, particularly in plain weave fabrics, further underscores the necessity for efficient defect detection systems [6].

Moreover, the limitations of human visual inspection methods in the textile and apparel industry highlight the urgent need for innovative defect detection approaches. A thorough understanding of various methods, including expert systems, is essential to meet the critical quality control requirements

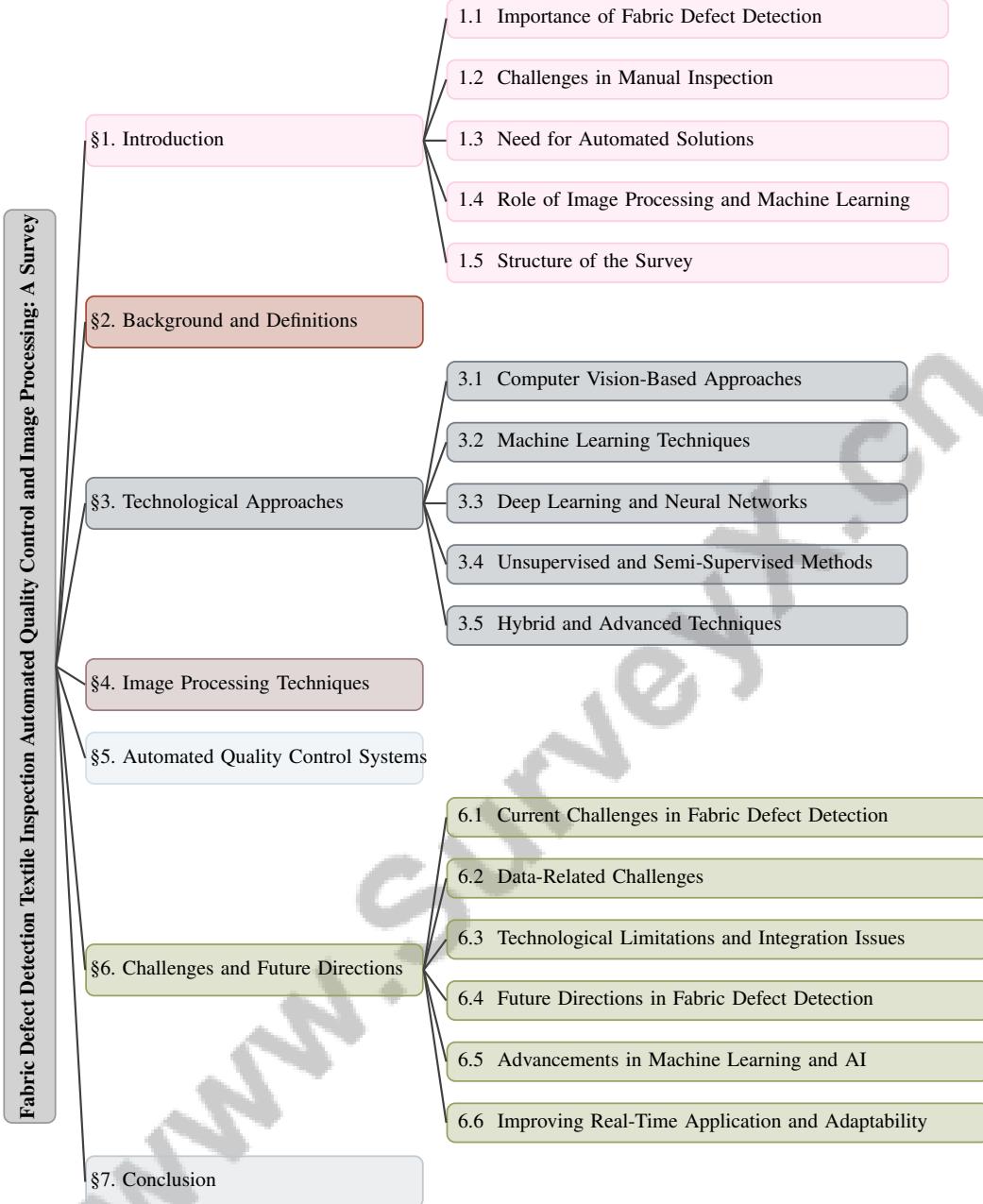


Figure 1: chapter structure

in textile manufacturing [3]. Accurate defect detection is pivotal for upholding quality standards, thereby ensuring manufacturers' reputations and consumer satisfaction [7].

1.2 Challenges in Manual Inspection

Traditional manual inspection methods in the textile industry are plagued by inefficiencies and inaccuracies, primarily due to their dependence on human vision, which is subjective and prone to fatigue [8]. The labor-intensive nature of these processes often leads to significant errors, especially during prolonged inspection tasks or with complex fabric patterns [9]. Inspectors frequently struggle to detect structural defects consistently due to the influence of fabric patterns and varying environmental conditions, further contributing to inaccuracies [10].

The time-consuming nature of manual inspection exacerbates these inefficiencies, as inspectors must meticulously examine vast quantities of fabric, resulting in inconsistent and costly processes. This inefficiency has spurred the demand for automated inspection solutions [11]. Additionally, traditional supervised deep-learning methods require extensive labeled datasets, which are resource-intensive to create, thus limiting their practical application in the textile industry [12].

Manual inspection is also challenged by the variability in fabric textures and defect types, complicating accurate detection [3]. Existing automated systems often necessitate manual tuning for each new fabric type, an impractical requirement in fast-paced industrial environments [6]. Furthermore, previous methods have faced challenges such as multi-scale, noisy, and blurred images, which underscore the need for effective automated systems that enhance accuracy, efficiency, and uniformity in fabric defect detection.

1.3 Need for Automated Solutions

The growing complexity and volume of textile production demand the adoption of automated solutions for fabric defect detection to overcome the limitations of traditional manual inspection methods [13]. Manual inspection is inherently subjective and error-prone, particularly when addressing the imbalanced nature of defect datasets, leading to inconsistent detection outcomes [14]. The need for automated systems is further driven by the necessity to uphold high-quality textile standards without incurring the substantial costs associated with manual methods [5].

Automated defect detection systems utilize machine learning and computer vision techniques to enhance the accuracy and efficiency of inspections [13]. These systems excel in environments with irregular fabric textures and varying ambient conditions, where traditional methods often fail [10]. The integration of lightweight convolutional neural network (CNN) models is crucial for balancing detection accuracy with computational efficiency, particularly in industrial settings with limited resources [8].

Additionally, developing methods that do not rely on extensive labeled datasets, such as those utilizing synthetic defect data or unsupervised learning approaches, is vital for reducing the computational costs and time associated with model training. Techniques that evaluate diverse fabric textures, including non-uniform patterns, are necessary to ensure the robustness and generalization of automated systems across different textile types [3]. Benchmarking plays a vital role in advancing research and improving the effectiveness of automated fabric defect detection solutions by facilitating the comparison of state-of-the-art methods [9].

Implementing automated solutions greatly enhances the accuracy and efficiency of textile inspection processes through advanced computer vision and machine learning techniques. These technologies effectively address manual inspection limitations, such as human error and time consumption, enabling early and precise defect detection. Furthermore, adopting automated systems supports the textile industry's goal of maintaining consistent production quality while simultaneously reducing operational costs, ultimately enhancing competitiveness in the global market [13, 1, 2, 3].

1.4 Role of Image Processing and Machine Learning

Image processing and machine learning are pivotal in advancing automated fabric defect detection, offering sophisticated techniques that overcome traditional inspection methods' limitations. Image processing enables the extraction and analysis of complex features from fabric images, enhancing defect identification accuracy and efficiency. For example, the Automated Visual Defect Detection Framework (AVDDF) employs fully convolutional networks to identify yarn float-points and detect anomalies, highlighting the role of image processing in this field [6].

Machine learning, particularly deep learning models, has revolutionized defect detection by facilitating the handling of intricate data patterns. Lightweight CNN architectures like FN-Net have been developed to optimize computational efficiency while preserving high detection accuracy, demonstrating the adaptability of machine learning solutions in industrial settings [8]. These architectures are crucial for environments with limited computational resources, ensuring that automated systems remain both practical and effective.

Unsupervised learning techniques further enhance fabric defect detection by analyzing fabric images based on their inherent features, thus reducing reliance on extensive labeled datasets. Recent

methodologies exemplify how unsupervised learning can evaluate diverse fabric textures without the constraints of traditional supervised frameworks [12]. Moreover, technical vision systems, combined with image and video processing methods, provide robust solutions for detecting defects on fabric surfaces, underscoring the effectiveness of integrating machine learning with image processing techniques [5].

The synergy of image processing and machine learning technologies streamlines the defect detection process in the textile industry, enhancing quality control by automating inspections and providing scalable, adaptive solutions. This integration addresses the complexities of textile structures and surface irregularities, improving accuracy in identifying over 70 distinct fabric defect types, which may arise from various manufacturing issues. By leveraging advanced techniques, such as novel algorithms and neural networks, the industry can achieve a higher detection rate compared to traditional methods, ensuring that the final product meets evolving quality standards [3, 5].

1.5 Structure of the Survey

This survey provides a comprehensive overview of the current state of fabric defect detection, textile inspection, and automated quality control, emphasizing the integration of image processing and machine learning technologies. It begins with an introduction that highlights the importance of defect detection in the textile industry and addresses the limitations of manual inspection methods, establishing the need for automated solutions. The introduction also sets the stage for subsequent sections by discussing the role of image processing and machine learning in this domain.

The second section offers essential background information, defining key concepts and tracing the evolution of fabric defect detection technologies. It examines the challenges inherent in traditional inspection methods and the significance of image processing in modern textile inspection practices.

The third section explores various technological approaches to fabric defect detection, including computer vision, machine learning, and deep learning techniques. It details the advantages and limitations of each approach, providing insights into their applications and effectiveness.

The fourth section delves into image processing techniques, discussing methods such as feature extraction, segmentation, and classification, with a focus on advanced algorithms and models like convolutional neural networks.

The fifth section examines automated quality control systems, detailing the integration of hardware and software components, real-time processing capabilities, and their impact on production efficiency. Case studies and experimental evaluations illustrate the practical applications of these systems.

The survey concludes with an in-depth discussion of prevailing challenges and prospective advancements in fabric defect detection. It emphasizes critical data-related issues, such as the need for diverse and comprehensive datasets to improve anomaly detection, alongside the technological limitations faced by current automated inspection systems that often require manual calibration for different fabric types. Furthermore, it highlights the potential advancements in machine learning and artificial intelligence, particularly the application of deep learning techniques like convolutional neural networks, which could significantly enhance defect detection processes in the textile industry [15, 6, 1, 9]. Strategies for improving real-time application and adaptability of detection systems are also considered.

This structured approach delivers a thorough analysis of the various technologies and methodologies utilized in fabric defect detection—ranging from expert systems and automated visual inspection to advanced machine learning techniques—while outlining a strategic framework for future research and development. It addresses key challenges such as defect detection accuracy, classification, and system adaptability to new fabric types in the rapidly evolving field of textile manufacturing [6, 1, 3]. The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Definitions and Key Concepts

Fabric defect detection is integral to ensuring quality in textile production by identifying and classifying imperfections that compromise the aesthetic and functional quality of fabrics [6]. Key to this

process is anomaly detection, which identifies deviations from normal patterns, a challenging task due to the infrequent occurrence of defects and variability in fabric textures [12]. Traditional methods often lack adaptability to new fabric types, highlighting the need for flexible solutions [5].

Unsupervised learning has emerged as a promising approach, effectively identifying defects without requiring labeled data, thus reducing the dependency on manual labeling [12]. Classification techniques for fabric defects are diverse, encompassing structural, statistical, spectral, model-based, learning, hybrid, and comparison studies, each offering unique advantages [3]. For example, Self-Feature Comparison (SFC) is an unsupervised method that segments anomalies in fabric images [12].

The integration of machine learning and computer vision has significantly improved real-time classification of fabric types and colors, enhancing inspection efficiency [8]. Automated systems employ various classification techniques to quickly and efficiently identify defect types, crucial for maintaining production quality and minimizing downtime [6]. These systems leverage methodologies such as expert systems and computer vision models, evaluated on detection accuracy, computational cost, and noise sensitivity, to enhance textile inspection [1, 11, 3].

2.2 Challenges in Traditional Inspection Methods

Traditional textile inspection methods face significant challenges, primarily due to the lack of comprehensive defect datasets, which limits their generalizability and leads to poor detection accuracy [13]. High false positive and negative rates are prevalent in manual inspections, which automated methods seek to address [14]. Traditional methods often fail to capture multi-scale information, relying on either global or local features, thus restricting their ability to detect intricate details necessary for accurate defect identification [7]. Manual adjustments required for different fabric types further complicate inspection, while the high computational costs and large model sizes of current CNN architectures hinder on-site deployment [8].

Traditional methods frequently overlook small defects, causing high false positive rates [5]. Benchmarks used to evaluate these methods often suffer from limited datasets and lack real-world applicability, impeding robust detection system development [9]. These challenges necessitate advanced automated systems that leverage image processing and machine learning to enhance defect identification accuracy, consistency, and efficiency across various fabric types and conditions. Automated systems address critical quality control challenges where manual inspection falters due to human error and textile complexity, improving image quality and defect classification [15, 1, 5, 3].

2.3 Evolution of Fabric Defect Detection Technologies

Fabric defect detection technologies have evolved from manual visual inspection to advanced automated systems. Early reliance on human inspection was inefficient and inaccurate due to subjective perception and physical limitations [13]. Tactile detection approaches marked a shift by enhancing defect identification through touch-based techniques [10]. The integration of machine learning algorithms, particularly CNNs, revolutionized defect detection, offering more accurate and efficient alternatives [2].

Recent advancements in image processing, such as the Sylvester Matrix-Based Similarity Measure, have improved detection accuracy and speed [16]. Statistical analysis and image processing frameworks have further enhanced detection capabilities, enabling precise identification across various fabric types [6]. The evolution of these technologies follows a structured approach, from image acquisition to classification, leading to robust systems adapted to specific fabric features [17].

Innovative methods, like cascaded mixed feature pyramids with guided localization, address previous limitations, providing novel solutions for complex inspection tasks [14]. The Cascaded Zoom-In Network employs A-HOG and SIFT features for improved detection precision [18]. This technological evolution reflects a commitment to enhancing inspection systems' precision, efficiency, and adaptability, driven by sophisticated algorithms and evaluation metrics tailored for batch processing. The shift from manual to automated systems, facilitated by computer vision, addresses significant challenges in defect detection and classification, improving quality control and mitigating fabric defects' impact on product quality [1, 17, 3].

2.4 Significance of Image Processing in Textile Inspection

Image processing techniques play a crucial role in modern textile inspection, offering advanced methods for precise and efficient defect detection and analysis. These techniques facilitate accurate defect identification and classification across various textile types by extracting detailed features from fabric images. The integration of image processing in inspection systems significantly enhances accuracy and efficiency compared to manual methods, which often suffer from human error and subjective judgment, with human inspectors identifying only 50-70% of fabric defects. Automated systems employ advanced digital image processing and machine learning algorithms for systematic defect classification, ensuring reliable evaluations of fabric quality and reducing production losses [1, 5, 17, 3].

Image processing techniques offer improved accuracy, reduced computational cost, and increased reliability. A comparative analysis by Kayumov et al. [3] emphasizes the importance of feature extraction and segmentation techniques for precise defect localization and classification. These techniques are vital for managing diverse and complex textile patterns, using algorithms like edge detection and texture analysis to differentiate between normal and defective regions. This capability is critical in industrial settings, where rapid and precise defect detection enhances production quality and minimizes waste. Automated systems, leveraging convolutional neural networks and image processing, identify a wide range of defects more reliably than human operators, reducing errors and improving profitability by conserving resources [15, 6].

Computational efficiency is essential for enhancing automated inspection systems, maintaining high-quality standards by enabling rapid and accurate defect detection. Techniques optimizing high-resolution image processing facilitate real-time detection, crucial for large-scale production. The ability to quickly process images ensures inspection systems meet modern textile manufacturing demands.

Integrating advanced image processing techniques into inspection practices represents a transformative industry leap, providing comprehensive solutions that significantly improve defect detection systems' accuracy, efficiency, and reliability. By utilizing digital image acquisition and sophisticated algorithms, these systems analyze fabric images to identify and classify over 70 defect types, critical for maintaining product quality and minimizing financial losses. Unlike manual inspections, which may miss up to 50% of defects, automated systems leverage computer vision and deep learning to enhance localization and detection, leading to higher quality textiles and reduced waste [15, 5, 17, 3]. By leveraging these techniques, the textile industry achieves higher quality standards and improved production efficiency.

3 Technological Approaches

Recent advancements in fabric defect detection have been driven by technological innovations that enhance inspection efficiency and accuracy, crucial for upholding quality standards in textile production. This section delves into the methodologies employed in fabric defect detection, focusing initially on computer vision-based techniques.

3.1 Computer Vision-Based Approaches

Computer vision-based methods have revolutionized fabric defect detection by automating the identification of textile imperfections with high precision and efficiency. Utilizing advanced image processing and machine learning, these techniques analyze fabric images to detect defects often overlooked in manual inspections, thereby improving real-time monitoring and scalable quality control across diverse fabric types, including complex patterns and textures. Transitioning from manual to automated systems reduces human error, minimizes fabric waste, and enhances product quality, ultimately boosting manufacturers' profitability [13, 6, 15, 5, 11].

A foundational approach involves extracting textural features from images and employing a sliding window technique for systematic surface examination [19]. Categorizing existing research into statistical, structural, and model-based approaches provides a comprehensive understanding of the methodologies [17]. Recent innovations, such as using generative adversarial networks (GANs), have enhanced defect detection capabilities. The CycleGAN architecture, for instance, generates fabric defects with segmentation guidance, offering a novel approach to simulating and detecting

imperfections [20]. Additionally, optimizing sparse coding processes, like grouped sparse dictionaries, has improved real-time inspection efficiency [21]. Tailored algorithms for specific fabric types, such as plain, twill, and striped, further enhance performance based on unique attributes [11].

Incorporating tactile sensors into systems allows for capturing tactile information from fabric surfaces, effectively identifying non-visible defects [10]. This multi-modal approach complements visual methods, providing a comprehensive framework for defect detection. As illustrated in Figure 2, the key techniques, innovations, and challenges in computer vision-based fabric defect detection are highlighted, showcasing the integration of image processing, machine learning, and tactile sensors, alongside innovations such as CycleGAN and sparse coding, while addressing challenges like texture variability and data requirements.

Weighted low-rank decomposition combined with deep hashing learning has advanced defect detection and classification across various fabric types [13]. Convolutional neural networks (CNNs) are crucial in segmenting fabric images into weft and warp float-points, enabling precise defect localization [6]. The Self-Feature Comparison (SFC) method exemplifies unsupervised learning techniques' effectiveness in detecting anomalies by comparing features from defect-free samples [12].

Overall, computer vision-based approaches have significantly transformed fabric defect detection by integrating advanced algorithms that automate inspections, enhance image quality, and improve accuracy. These systems leverage deep learning and hybrid methodologies to effectively identify and classify various fabric defects, addressing challenges posed by complex textile textures and ensuring high-quality control while minimizing waste and optimizing production efficiency [11, 13, 3, 5].

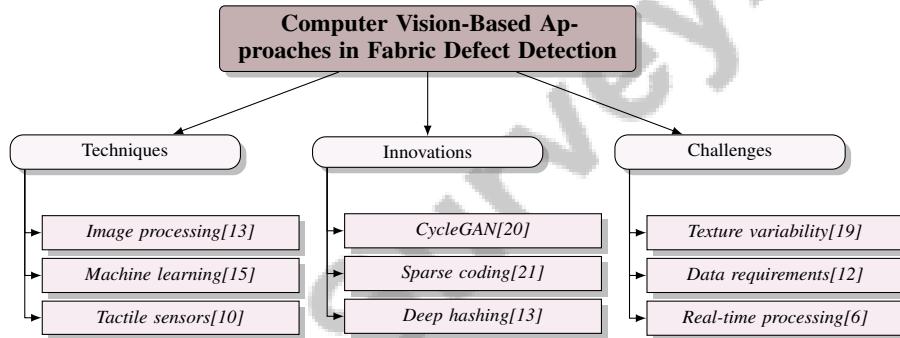


Figure 2: This figure illustrates the key techniques, innovations, and challenges in computer vision-based fabric defect detection. It highlights the use of image processing, machine learning, and tactile sensors, along with innovations like CycleGAN and sparse coding, while addressing challenges such as texture variability and data requirements.

3.2 Machine Learning Techniques

Machine learning techniques are pivotal in advancing fabric defect detection, offering sophisticated methods that enhance inspection accuracy and efficiency. These techniques employ various algorithms to analyze fabric images, identify defects, and improve quality control in textile production. For example, the Fabric Classification System leverages algorithms to automate fabric classification, significantly boosting detection accuracy [2].

Integrating computer vision enhances machine learning capabilities, with specific methods designed to automatically detect fabric defects by analyzing unique weave characteristics, streamlining the process [11]. The Cascaded Zoom-In Network (CZI-Net) uses A-HOG features for initial assessments and SIFT features for detailed examinations, enhancing detection accuracy [18].

The AVDDF framework exemplifies machine learning's application in tracking individual yarns and classifying float-points as defective or defect-free based on statistical measurements [6]. Advanced object detection frameworks, such as a two-stage system, further bolster detection accuracy and robustness, adapting to varying fabric textures and defect types [14].

Machine learning techniques provide powerful tools for automating and optimizing fabric defect detection, contributing to scalable and adaptive solutions that meet the textile industry's evolving demands. By integrating advanced technologies like computer vision and expert systems, traditional

textile manufacturing processes can significantly enhance quality control, reduce human error, and streamline production efficiency, ultimately improving competitiveness in a rapidly evolving global market [2, 3].

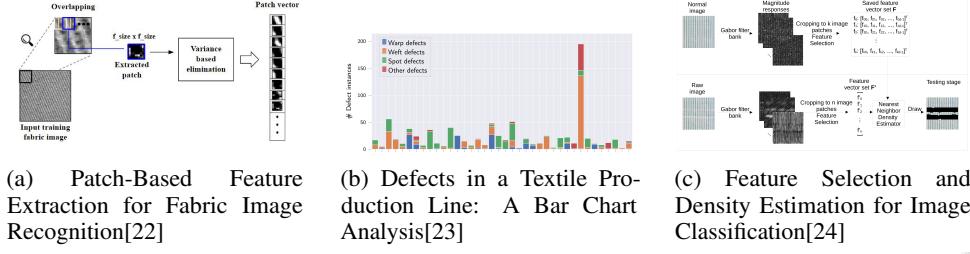


Figure 3: Examples of Machine Learning Techniques

As illustrated in Figure 3, the exploration of technological approaches, particularly machine learning techniques, reveals three illustrative examples highlighting their versatility in fabric image recognition and defect analysis. The first example, "Patch-Based Feature Extraction for Fabric Image Recognition," demonstrates a method where fabric images are divided into smaller, overlapping patches to enhance feature extraction and recognition precision. The second example, "Defects in a Textile Production Line: A Bar Chart Analysis," visually represents defect distribution within a textile production line, categorizing defects into warp, weft, and spot defects, aiding in identifying prevalent issues and optimizing quality control processes. Lastly, "Feature Selection and Density Estimation for Image Classification" details the stages of training and testing in image classification, emphasizing efficient feature processing for accurate classification. Together, these examples illustrate the diverse applications of machine learning in the textile industry, from enhancing fabric recognition to optimizing production quality [22, 23, 24].

3.3 Deep Learning and Neural Networks

Deep learning and neural networks have significantly advanced fabric defect detection by enhancing accuracy and efficiency through innovative methodologies. Techniques such as deep convolutional neural networks (CNNs) outperform traditional inspection methods by effectively addressing textile structures' complexities and accurately localizing defects. Modern approaches combine image enhancement algorithms with robust neural network architectures to achieve superior results, improving defect identification rates compared to human visual inspection, which typically detects only 50-70% of defects [15, 25, 5].

The PTIP method exemplifies a notable approach, decomposing fabric images into local patches and utilizing a pretrained deep CNN for defect detection [25]. This method leverages CNNs to analyze intricate patterns within fabric images, facilitating accurate defect identification across various textile types. Similarly, the Deep Convolutional Neural Network (DCNN) model provides an advanced framework for processing and analyzing images to detect defects in printed fabrics, underscoring the adaptability of deep learning techniques in different textile contexts [15].

Unsupervised learning approaches have also been explored, such as the architecture proposed by Koulali et al., which detects defects using a CNN without labeled data [22]. This approach reduces dependency on extensive labeled datasets, offering a practical solution for scenarios where labeled data is scarce.

The FabricNet model, a modified version of Faster R-CNN, exemplifies advanced techniques for feature extraction and loss calculation specifically tailored for fabric defect detection [4]. Additionally, the MSCRED model enhances defect detection by integrating temporal patterns through its convolutional long short-term memory (ConvLSTM) architecture, effectively capturing temporal dynamics and reconstructing correlation matrices for identifying anomalies. This approach is particularly valuable in fabric defect detection, where diverse colors, textures, and defect characteristics present significant challenges [22, 26, 15, 27, 9].

Furthermore, the Fab-ME framework combines the C2F-VMamba and EMCA modules to enhance defect detection while maintaining real-time processing capabilities, illustrating the balance between accuracy and computational efficiency in deep learning applications [7]. The FN-Net model, charac-

terized by its lightweight design and adaptive threshold-based class determination, further exemplifies advancements in deep learning aimed at minimizing computational load while maximizing detection accuracy [8].

Deep learning and neural networks provide powerful tools for improving fabric defect detection, offering scalable and adaptive solutions that meet the evolving demands of the textile industry. By incorporating advanced methodologies such as computer vision technology and anomaly synthesis strategies, the textile industry can significantly enhance quality control processes, reduce reliance on labor-intensive manual inspections, and ultimately achieve superior product quality and increased production efficiency. This digital transformation minimizes human error and enables more effective detection of fabric anomalies, improving the industry's competitiveness in the global market [20, 2, 28].

3.4 Unsupervised and Semi-Supervised Methods

Unsupervised and semi-supervised learning methods have emerged as powerful tools for fabric defect detection, offering innovative solutions to challenges posed by the need for extensive labeled datasets in traditional supervised learning approaches. These methods utilize distinctive characteristics of fabric images to detect anomalies, significantly minimizing reliance on labeled datasets. This reduction streamlines the defect detection process and enhances scalability, making systems more adaptable to various fabric types and defects. Techniques such as self-feature comparison and vicinal risk minimization enable effective defect identification, even in previously unseen fabrics, addressing critical limitations in traditional supervised learning [15, 6, 12, 23].

The Global and Local Anomaly co-Synthesis Strategy (GLASS) exemplifies unsupervised learning's potential by synthesizing anomalies through both global and local strategies, improving defect localization and detection in industrial applications [28]. Reverse Knowledge Distillation (RKD) represents a novel semi-supervised method that utilizes a teacher-student architecture to enhance anomaly detection capabilities by focusing on high-level features [27]. This technique underscores semi-supervised learning's adaptability in addressing conventional defect detection framework limitations.

Integrating unsupervised learning approaches, such as Self-Feature Comparison (SFC), further demonstrates the effectiveness of these methods in fabric defect detection [12]. SFC utilizes self-feature comparison to identify and segment anomalies in fabric images, offering practical solutions for scenarios with scarce labeled datasets.

Overall, unsupervised and semi-supervised methods provide robust and scalable solutions for fabric defect detection, enabling the textile industry to achieve higher quality standards and improve production efficiency. By employing advanced methodologies, including expert systems, fully convolutional networks, and automated image analysis techniques, the textile industry can effectively tackle data scarcity challenges and enhance defect detection system adaptability. This improvement is crucial for meeting increasing and diverse textile inspection demands, allowing for accurate identification of over 70 distinct types of fabric defects and ensuring higher quality control while reducing the risk of significant financial losses associated with undetected defects [6, 1, 9, 3].

3.5 Hybrid and Advanced Techniques

Hybrid and advanced techniques in fabric defect detection integrate a diverse array of methodologies, including structural, statistical, spectral, model-based, learning, and comparative approaches, significantly improving the accuracy and robustness of defect identification systems. This convergence enhances automated inspection efficiency and addresses critical challenges in defect detection and classification, ultimately contributing to higher quality control standards in textile manufacturing [1, 3]. These approaches combine various machine learning, image processing, and data synthesis methods to address traditional systems' limitations and improve detection capabilities across diverse textile environments.

The multi-scale convolutional recurrent encoder-decoder (MSCRED) method exemplifies an advanced approach by leveraging underlying temporal patterns in the data to enhance defect detection. This technique integrates convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to analyze fabric images, capturing both spatial features, such as yarn arrangement, and temporal

features, such as patterns over time. This comprehensive approach enhances detection accuracy for fabric defects while significantly minimizing false positives, improving quality control in textile manufacturing processes [15, 6].

The introduction of a one-class classification paradigm, as highlighted by Carrilho et al., advances the field by allowing models to detect anomalies using datasets consisting solely of normal fabric images [9]. This approach eliminates the need for labeled defect data, enabling the development of robust detection models that generalize well across different fabric types and conditions. By focusing on normal fabrics' characteristics, these models can effectively identify deviations indicating defects, enhancing inspection system reliability.

Hybrid techniques in anomaly detection often combine various detection methods—such as neural networks, clustering algorithms, and statistical models—to enhance performance and improve defect identification accuracy across diverse backgrounds, including fabrics and medical images. By leveraging multiple approaches, hybrid techniques can effectively address the complexities of different anomaly detection scenarios, optimizing detection thresholds and minimizing false positives through rigorous noise and anomaly analysis in residual images [9, 23]. For instance, combining supervised and unsupervised learning approaches can leverage both paradigms' strengths, utilizing labeled data where available and unsupervised methods to explore unlabeled datasets. This integration allows for a more flexible and adaptive defect detection framework capable of addressing diverse challenges encountered in textile inspection.

Hybrid and advanced techniques in fabric defect detection present innovative solutions that significantly enhance quality control processes in the textile industry. These methods leverage a combination of computational techniques, including automated visual inspection and machine learning algorithms, to improve detection accuracy and efficiency while minimizing human error. By offering scalable and adaptive approaches, these techniques address the challenges posed by the diverse range of fabric defects—over 70 distinct types—stemming from various production issues. Furthermore, implementing these systems streamlines inspection workflows, ensures consistent product quality, reduces waste, and increases competitiveness in the global market [3, 6, 1, 9, 11]. By incorporating these innovative approaches, the industry can achieve higher accuracy and efficiency in defect detection, ultimately leading to improved production standards and reduced waste.

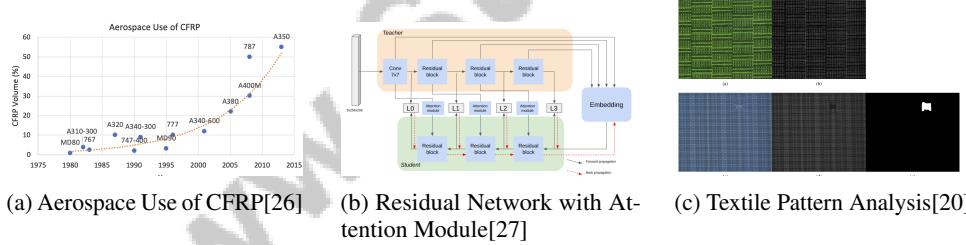


Figure 4: Examples of Hybrid and Advanced Techniques

As shown in Figure 4, the examples highlight the diverse applications of cutting-edge technology across various industries, illustrated through three distinct visual examples. The first image, "Aerospace Use of CFRP," presents a scatter plot tracking the increasing use of Carbon Fiber Reinforced Polymer (CFRP) in the aerospace sector from 1975 to 2015, showcasing advanced materials' integration in aircraft design. The second image, "Residual Network with Attention Module," illustrates a sophisticated neural network architecture featuring teacher and student networks enhanced by attention modules, demonstrating advancements in machine learning techniques for improved data processing and analysis. Lastly, the "Textile Pattern Analysis" image compares various textile patterns, employing visual analysis to highlight design differences, underscoring the intersection of technology and textile manufacturing for innovative pattern recognition and design automation. Together, these examples underscore the transformative potential of hybrid and advanced technological approaches in driving innovation across multiple fields [26, 27, 20].

In the realm of fabric defect detection, a comprehensive understanding of the various image processing techniques is crucial. As illustrated in Figure 5, the hierarchical structure of these techniques is categorized into several key areas: feature extraction, segmentation, advanced algorithms, and comparative analysis. Each of these categories is further subdivided into specific methods and

techniques, which collectively emphasize their significant roles in enhancing detection accuracy, efficiency, and quality control in textile inspection. This structured approach not only facilitates a clearer understanding of the methodologies employed but also underscores the importance of each technique in the overall process of defect detection.

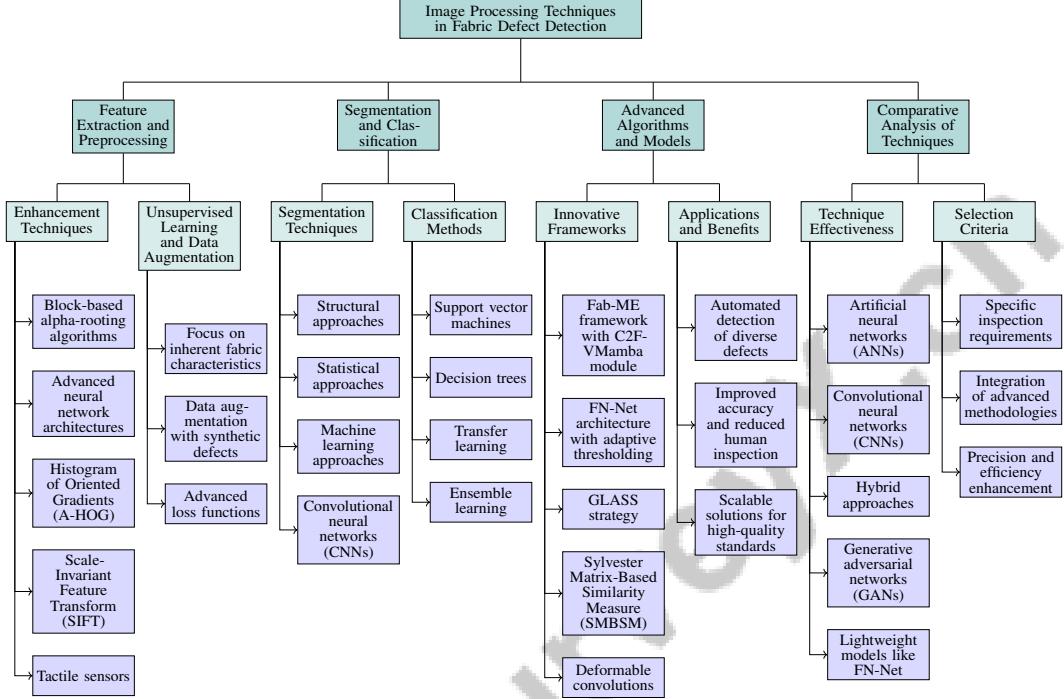


Figure 5: This figure illustrates the hierarchical structure of image processing techniques in fabric defect detection, highlighting key categories such as feature extraction, segmentation, advanced algorithms, and comparative analysis. Each category is further divided into specific techniques and methods, emphasizing their roles in enhancing detection accuracy, efficiency, and quality control in textile inspection.

4 Image Processing Techniques

4.1 Feature Extraction and Preprocessing

Feature extraction and preprocessing are pivotal in fabric defect detection, enhancing image characteristics to facilitate anomaly identification. Techniques such as block-based alpha-rooting algorithms enhance image quality, ensuring consistent scaling crucial for accurate detection [5]. Advanced neural network architectures, as demonstrated by Mo et al., optimize feature extraction and classification, underscoring deep learning's role in capturing intricate textile patterns [13]. Texture analysis is further refined through methods like Histogram of Oriented Gradients (A-HOG) and Scale-Invariant Feature Transform (SIFT), which facilitate defect localization by capturing surface textures [18]. Tactile sensors provide a novel approach, detecting subtle defects through tactile images [10].

Unsupervised learning techniques enhance feature extraction by focusing on inherent fabric characteristics without extensive labeled data [29]. Data augmentation and advanced loss functions, combined with diverse datasets, improve models' generalization by training them to recognize a wider range of anomalies through synthetic defects [9]. These integrated techniques establish a robust framework for improving fabric defect detection accuracy and efficiency, leveraging computer vision and automated detection to enhance quality control while minimizing human error [13, 3, 1, 2, 11].

4.2 Segmentation and Classification

Segmentation and classification are essential for precise defect identification in textiles. These processes involve segmenting fabric images into distinct regions and classifying these segments to enhance defect identification accuracy and quality control. Various methodologies, including structural, statistical, and machine learning approaches, facilitate monitoring and quality improvement by categorizing over 70 types of fabric defects [3, 1, 15, 17, 11]. Advanced algorithms, like convolutional neural networks (CNNs), excel in pixel-wise segmentation, isolating defects from background textures [6]. Classification methods refine detection by categorizing segments based on predefined defect types, utilizing machine learning models like support vector machines and decision trees [2]. Deep learning techniques, including transfer learning, enhance classification by leveraging large datasets for robust classifiers adaptable to diverse textile characteristics [25]. Ensemble learning approaches further improve accuracy, providing reliable outcomes that enhance defect detection robustness [12]. Integrating advanced segmentation and classification techniques enhances quality control processes, minimizing waste and ensuring compliance with stringent standards [13, 3, 1, 17, 11].

4.3 Advanced Algorithms and Models

Method Name	Technological Innovations	Application Context	Performance Enhancement
FCS[2]	Convolutional Neural Networks	Real-time Applications	Increased Accuracy
FM[7]	Fab-ME Framework	Textile Industry	Detection Accuracy
FN-Net[8]	Fn-Net	Textile Production	Adaptive Thresholding
GLASS[28]	Gradient Ascent	Industrial Applications	Classification Accuracy

Table 1: Overview of advanced algorithms and their technological innovations, application contexts, and performance enhancements in fabric defect detection systems. The table highlights the contributions of convolutional neural networks, the Fab-ME framework, FN-Net architecture, and the GLASS strategy, showcasing their impact on accuracy and application in various industrial contexts.

Advanced algorithms and models significantly enhance fabric defect detection systems' precision and robustness. Table 1 provides a comprehensive summary of the advanced algorithms and models employed in fabric defect detection, detailing their technological innovations, application contexts, and the resulting performance enhancements. Convolutional neural networks (CNNs) lead this advancement, effectively analyzing visual data and reducing manual inspection subjectivity [2]. The Fab-ME framework, featuring the C2F-VMamba module, exemplifies innovation by enhancing global context understanding and detail preservation [7]. The FN-Net architecture, with adaptive thresholding, supports real-time applications with minimal hardware [8]. Techniques like the GLASS strategy, combining global and local anomaly synthesis, highlight the importance of multiple strategies for improved localization and classification [28]. The Sylvester Matrix-Based Similarity Measure (SMBSM) and deformable convolutions enhance detection accuracy and robustness [16, 14]. These innovations facilitate automated detection of diverse defects, improving accuracy and reducing reliance on human inspection [6, 25, 15, 9, 23]. Such advancements provide scalable solutions to meet the textile industry's evolving demands, ensuring high-quality standards and efficient production processes.

4.4 Comparative Analysis of Techniques

A comparative analysis of image processing techniques in fabric defect detection reveals variations in effectiveness and efficiency. Artificial neural networks (ANNs) are favored for their accuracy, model complexity, and training time [1]. Convolutional neural networks (CNNs) excel in automatic detection by analyzing both low-level and high-level features, though their computational demands require optimized implementations for real-time applications [15, 6, 8, 25]. Hybrid approaches, integrating multiple techniques, enhance flexibility and adaptability, improving performance across varied textile characteristics [9, 23]. Generative adversarial networks (GANs) simulate defects, enhancing model training and addressing variability challenges [28, 6, 9, 23, 20]. Lightweight models like FN-Net balance detection accuracy and computational efficiency, suitable for resource-constrained environments. This analysis underscores the importance of selecting techniques based on specific inspection requirements, integrating advanced methodologies to enhance precision and efficiency, ultimately reducing waste and increasing competitiveness [6, 13, 2, 3].

5 Automated Quality Control Systems

The efficacy of automated quality control systems in the textile industry is contingent upon the seamless integration of hardware and software, enhancing operational efficiency and defect detection processes. This section delves into the synergy of these components, which is pivotal for optimizing automated quality control systems in textile production.

5.1 Integration of Hardware and Software Components

Integrating hardware and software components is fundamental in developing robust automated quality control systems in the textile sector. These systems utilize sophisticated image processing and machine learning to accurately identify defects, such as weave inconsistencies and surface irregularities, thus improving production quality and minimizing waste [3, 6, 1, 15, 17]. Key hardware components include cameras and sensors, which, when combined with advanced software algorithms, enable real-time data processing and analysis.

A prominent implementation is the Fabric Classification System, which exemplifies the seamless hardware-software interaction by capturing and processing images for real-time classification [2]. Utilizing digital color cameras, the system employs machine learning algorithms for defect classification and detection.

The Texas Instruments TMS320DM642 Evaluation Module highlights the significance of hardware in processing images frame-by-frame, with digital color cameras capturing detailed fabric areas [19]. This setup underscores the importance of selecting appropriate hardware to meet the computational demands of real-time defect detection.

Incorporating tactile sensing technology enhances quality assessment by providing tactile feedback from fabric surfaces, complementing visual inspection methods [10]. This multi-modal approach enhances defect detection capabilities.

Software components are crucial for data processing and analysis. Synthetic data improves training processes, addressing traditional quality control challenges and enhancing model robustness [30]. The MSCRED method, which integrates hardware and software, exemplifies the potential for utilizing temporal patterns to enhance defect detection.

Vision-based systems designed for real-time inspection demonstrate the effectiveness of integrated quality control solutions by minimizing manual intervention and reducing human error [21, 6].

The construction of large-scale fabric defect datasets for training underscores software's role in developing accurate detection models [13]. Leveraging these datasets enhances detection accuracy and reduces false positives through advanced image processing and deep learning algorithms [5].

Successful implementation of automated quality control systems depends on the effective integration of hardware and software components. This synergy facilitates the transition from manual inspections to advanced technologies like computer vision, enhancing defect detection and classification across various fabric types and streamlining production processes [13, 1, 2]. By merging advanced technologies and methodologies, these systems improve detection accuracy, efficiency, and reliability, raising production standards and reducing waste.

5.2 Real-Time Processing and Optimization

Real-time processing and optimization are critical for enhancing the efficiency and accuracy of automated fabric defect detection systems. These systems enable real-time analysis and defect identification during production, significantly reducing downtime and improving efficiency. Expert systems employing sophisticated computational techniques accurately identify numerous fabric defects caused by machine malfunctions and defective yarns, streamlining inspection processes and ensuring high-quality standards, maintaining competitiveness in the global textile market [1, 3].

Key advancements include algorithms capable of processing fabric at high speeds, with some systems achieving rates of up to 20 meters per minute [21]. This capability is crucial for modern textile production lines that require rapid and accurate defect detection to prevent delays and minimize waste.

Optimizing real-time systems involves employing advanced image processing techniques and machine learning models to efficiently handle large data volumes. Techniques such as feature extraction, segmentation, and classification are utilized for real-time analysis, enabling swift anomaly identification. Lightweight convolutional neural networks (CNNs), like FN-Net, significantly enhance computational efficiency, functioning effectively in resource-limited environments. FN-Net demonstrates training speeds 3 to 33 times faster than traditional models such as VGG16 and EfficientNet while maintaining lower memory consumption [15, 6, 8, 4].

Advanced hardware components, such as high-resolution cameras and sensors, capture detailed fabric images, supporting real-time processing. This integration enables the identification of numerous fabric defects, facilitating immediate corrective actions and enhancing quality control, minimizing the risk of producing substandard products [6, 1, 17, 3].

Ongoing algorithm enhancements focus on improving detection accuracy and minimizing false positives. Advanced techniques, including unsupervised anomaly detection methods analyzing residual images, establish rigorous detection thresholds, crucial in domains like industrial quality control and medical imaging [28, 29, 2, 23]. Leveraging large-scale datasets and advanced machine learning techniques, these systems adapt to diverse patterns and textures in modern textiles, ensuring reliable defect detection across various fabric types.

Real-time processing and optimization capabilities are vital for maintaining high production standards and achieving efficient quality control. By integrating advanced technologies such as computer vision and machine learning, the textile industry can enhance operational efficiency, automate quality control processes, reduce manual inspection errors and labor costs, and facilitate real-time defect detection, minimizing waste and ensuring consistent product quality across various fabric types, ultimately improving competitiveness in the global market [13, 11, 2, 3].

5.3 Impact on Production Efficiency

Automated quality control systems significantly impact production efficiency and output quality in the textile industry by enhancing defect detection accuracy and reducing inspection times. Advanced methods, such as the Sylvester Matrix-Based Similarity Measure (SMBSM), achieve 93.4

Innovative techniques within automated systems, such as those in the Fab-ME framework, capture intricate details and global context, significantly improving detection accuracy and real-time performance [7]. This capability is essential for maintaining high production standards and ensuring timely defect resolution, minimizing waste and enhancing quality control.

Systems like FabricNet demonstrate significant speed advantages, operating at 17 frames per second (fps), making them suitable for real-time applications [4]. This high-speed processing enables continuous monitoring of fabric quality, ensuring defects are detected and corrected without interrupting production flow. The effectiveness of these systems is further highlighted by their ability to achieve an 85

Lightweight architectures such as FN-Net illustrate that automated systems can achieve high detection speeds and lower computational costs, making them feasible for deployment in resource-limited industrial environments [8]. This efficiency enhances the scalability of quality control systems and supports the industry's goal of maintaining consistent production standards cost-effectively.

The adoption of automated quality control systems results in substantial improvements in production efficiency and output quality. By offering higher accuracy in defect detection compared to manual inspection and traditional methods, these systems play a crucial role in reducing waste and enhancing quality control [15]. The implementation of advanced methods achieves a mean Average Precision of 72.6

Integrating automated quality control systems in the textile industry significantly enhances defect detection precision and speed while improving overall production efficiency and final output quality. These systems utilize advanced computer vision and machine learning techniques to systematically classify and detect a wide range of fabric defects arising from various manufacturing issues, such as machine malfunctions and material inconsistencies. By automating the inspection process, these technologies reduce reliance on labor-intensive manual inspections—often subject to human error and fatigue—and facilitate the identification of defect types, enabling manufacturers to address underlying production problems more effectively. This shift toward automation is essential for maintaining

competitiveness in a rapidly evolving global market [1, 13, 2, 3]. By leveraging these advanced technologies, the industry can achieve higher quality standards, reduce waste, and ensure consistent product quality.

5.4 Case Studies and Experimental Evaluations

Benchmark	Size	Domain	Task Format	Metric
Lusitano[9]	36,000	Fabric Defect Detection	Anomaly Detection	AUC, mAP

Table 2: This table presents a representative benchmark used in the evaluation of automated quality control systems for textile inspection. The benchmark dataset, Lusitano, encompasses 36,000 samples in the domain of fabric defect detection, employing anomaly detection task formats. Key performance metrics for this benchmark include the Area Under the Curve (AUC) and mean Average Precision (mAP).

Case studies and experimental evaluations of automated quality control systems provide valuable insights into their effectiveness and adaptability in real-world textile inspection scenarios. A notable study demonstrated the efficacy of an unsupervised method, achieving a 100

The VRM-FAD method significantly contributes by enhancing defect detection models' generalization to unseen fabrics through diverse datasets [23]. This study emphasizes dataset diversity's critical role in developing robust automated systems capable of adapting to varied and complex textile patterns. Findings suggest that incorporating a wide range of fabric types in training datasets can significantly improve defect detection models' performance and reliability.

Experiments utilizing the TILDA textile texture database and real fabric samples from apparel companies demonstrated the superiority of proposed detection models over traditional methods [11]. These experiments provided a comprehensive evaluation of the models' capabilities in handling diverse fabric textures and patterns, reinforcing the importance of leveraging advanced image processing and machine learning techniques in automated quality control systems.

A benchmark study evaluated two state-of-the-art models, DBFAD and RD4AD, employing one-class classification techniques [9]. This benchmark highlighted these models' effectiveness in identifying fabric defects, showcasing their potential to enhance defect detection accuracy and reduce false positives. Table 2 provides a detailed overview of the Lusitano benchmark, which is integral to assessing the effectiveness of automated systems in fabric defect detection. This evaluation underscores one-class classification approaches' advantages in scenarios where labeled defect data is scarce or unavailable.

These case studies and experimental evaluations illustrate significant advancements in automated quality control systems, demonstrating their ability to improve defect detection accuracy and efficiency in textile inspection processes. By incorporating various advanced methodologies and utilizing extensive datasets, these systems provide scalable and adaptive solutions that effectively address the complex challenges of fabric defect detection in the textile industry. This is particularly crucial given the industry's reliance on manual inspection, which is labor-intensive and prone to errors, and the need for automation to keep pace with evolving fabric varieties and defect characteristics. Recent innovations, such as the introduction of a novel dataset that includes a wide range of fabrics and defect types, further enhance the performance of state-of-the-art machine learning techniques in ensuring high-quality textile production [2, 9].

6 Challenges and Future Directions

The textile industry faces significant challenges in fabric defect detection, necessitating a thorough understanding of current limitations and potential advancements. Addressing these challenges requires a multifaceted approach, as detailed in the following subsections.

6.1 Current Challenges in Fabric Defect Detection

Fabric defect detection is challenged by the inefficiencies of traditional manual inspections, which are prone to human error and inconsistencies [2]. Automated systems, while advanced, often depend

on high-quality training datasets that are limited by data imbalance and insufficient representation of diverse fabric types and defects. Performance variability across different fabrics, especially when their structures differ from the training set, presents another challenge [6]. High computational costs of deep learning models further complicate real-time industrial applications [5]. Although lightweight models like FN-Net offer efficiency, they may degrade in performance with extreme data imbalance [8]. The critical need for comprehensive datasets remains a hurdle, as they are often lacking in coverage of all defect types and fabric structures [5]. Detecting subtle defects, as shown by the Fab-ME framework, may require further tuning for diverse datasets [7]. Techniques like the SFC method detect defects without extensive labeled datasets, offering cost-effectiveness for the industry [12], but may struggle with certain defect types or texture variations [4]. The complexity of modern fabric designs necessitates model refinement, as noted by Mo et al. [13]. Variability in detection performance highlights the need for robust methodologies that generalize well across diverse textile environments [6]. The challenges underscore the need for ongoing innovation to ensure precise identification of defects caused by machine malfunctions and material inconsistencies, prompting exploration of automated systems leveraging computer vision and deep learning [1, 9, 3].

6.2 Data-Related Challenges

Data acquisition, quality, and diversity are significant challenges in fabric defect detection, impacting the development and performance of automated systems. High-quality, diverse datasets are essential for training robust models capable of detecting a wide range of fabric defects. However, the manual labeling of defects is labor-intensive and prone to human error [14], compounded by the limited availability of comprehensive datasets covering the full spectrum of defect types and textures [5]. Training data quality is crucial, as models trained on imbalanced datasets may struggle to generalize across different fabrics and defect patterns [9]. This is particularly problematic when certain defect types are underrepresented, leading to biased models [8]. The imbalance complicates model training, necessitating sophisticated techniques to address these disparities [12]. The diversity of fabric types and defect patterns presents a challenge for detection systems. Variability in textures, colors, and patterns necessitates adaptable models, often difficult to achieve with limited data [6]. Techniques like data augmentation and synthetic defect generation enhance dataset diversity but may not fully capture real-world complexities [13]. The reliance on high-quality datasets underscores the need for innovative approaches that operate effectively with limited labeled data. Unsupervised and semi-supervised learning methods present promising solutions to data-related challenges [12], although these require further refinement for robustness across diverse environments [4]. Addressing data-related challenges is crucial for advancing defect detection technologies, enhancing data acquisition techniques, and implementing adaptive learning algorithms to improve accuracy and efficiency. This advancement is vital for quality control, mitigating the limitations of manual inspection methods subject to human error and fatigue. Integrating advanced computational methods and machine learning can facilitate the recognition of a wide range of defects, leading to higher production standards and a more competitive market position [6, 2, 9, 3].

6.3 Technological Limitations and Integration Issues

Implementing automated fabric defect detection systems faces several technological limitations and integration challenges. A primary limitation is the high computational cost of advanced deep learning models, such as CNNs, which demand substantial processing power and memory [5]. This poses a barrier for real-time applications in settings with limited resources. Integrating automated systems with production lines requires seamless communication between hardware components like cameras and sensors, and software algorithms for real-time analysis [10]. Ensuring compatibility and interoperability is crucial for maintaining efficiency and reliability. The variability in fabric types and defect patterns complicates integration, as models trained on specific datasets may struggle to generalize across different environments [6]. The lack of standardized benchmarks and evaluation metrics further complicates performance assessment [9]. Additionally, the dependency on high-quality labeled datasets for training machine learning models is a significant challenge, as collecting and annotating such data is labor-intensive [14]. This highlights the need for innovative approaches, such as unsupervised and semi-supervised learning methods, which can reduce reliance on labeled data and enhance adaptability [12]. Integrating tactile sensing technology into automated systems offers a promising solution to enhance capabilities by capturing tactile information from surfaces [10]. However, incorporating such technologies requires careful consideration of costs and impacts

on workflows. Addressing technological limitations and integration issues is essential for advancing the effectiveness and scalability of automated systems. By overcoming manual inspection and data management challenges, the industry can leverage advanced technologies such as computer vision and AI to enhance quality control processes. This transformation promises greater accuracy and efficiency in detection and classification across various fabric types, facilitating a competitive production environment and reducing waste [13, 2].

6.4 Future Directions in Fabric Defect Detection

The future of fabric defect detection technologies is set for evolution through innovative pathways aimed at enhancing system robustness and efficiency. Integrating tactile and visual information to create comprehensive detection systems that address both structural and color defects is a promising direction [10]. This multimodal approach could significantly enhance capabilities to identify a wide range of defects. Expanding the diversity of training datasets remains critical. Incorporating a broader variety of defects and fabric types can enhance models' robustness and generalization capabilities, addressing variability in production. Enhanced dataset diversity will also improve adaptability to new fabric types and defects, a key challenge in current methodologies [9]. Future research could explore enhancements in model architecture, such as incorporating advanced attention mechanisms and expanding datasets to improve accuracy and efficiency [14]. Developing more inclusive databases and exploring the relationship between yarn and fabric defects will further advance automated methods [3]. Optimizing existing methods for real-time applications and exploring additional defect types will be crucial for practical applicability [5]. Furthermore, expanding methods like the SFC to a broader range of industrial surfaces beyond fabrics will enhance versatility [12]. Refining classification methods and exploring emerging trends in machine learning and AI are essential for advancing technologies. Future research should consider integrating semi-supervised learning techniques to leverage unlabeled data, reducing dependency on extensive datasets and improving performance [8]. Future directions could also focus on enhancing robustness against a wider variety of defects and exploring optimizations to improve speed without sacrificing accuracy [4]. Pursuing these advancements will enable the industry to achieve significant improvements in quality control and production standards, leading to more efficient and reliable detection technologies.

6.5 Advancements in Machine Learning and AI

Advancements in machine learning and AI have significantly transformed fabric defect detection, enhancing accuracy and efficiency while reducing labor costs. These improvements are evident in fabric classification systems, where machine learning algorithms automate classification, improving detection capabilities [2]. AI-driven techniques, such as deep learning models, have enabled sophisticated systems capable of processing complex images and identifying defects with high precision. CNNs have been instrumental in capturing intricate patterns within textile images, facilitating accurate identification across various fabric types. These models utilize extensive, diverse datasets specifically designed for detection, resulting in robust classifiers adaptable to a wide range of colors, textures, and defect types, ensuring consistent and reliable outcomes [6, 22, 9, 23]. Moreover, machine learning applications extend beyond traditional supervised approaches. Investigating unsupervised and semi-supervised techniques has advanced the field by minimizing reliance on large labeled datasets, traditionally expensive and labor-intensive. These innovative methods enable anomaly identification without extensive manual annotations, streamlining the process and enhancing adaptability to diverse types and characteristics [22, 12, 9, 23]. By employing these methodologies, systems can effectively analyze images based on inherent features, offering scalable solutions that enhance adaptability. AI advancements have also led to hybrid models that combine multiple paradigms to optimize performance. These models integrate the strengths of different approaches, such as combining supervised and unsupervised techniques, to provide comprehensive analysis. This integration significantly enhances accuracy and optimizes efficiency, making them highly effective for real-time applications in industrial settings. Utilizing advanced techniques such as fully convolutional networks and automated yarn tracking allows these systems to adapt to new types autonomously, minimizing human error and improving quality while reducing waste [6, 15, 30, 9, 19]. Recent advancements have transformed detection in the industry, introducing sophisticated automated systems that enhance quality control processes. These systems employ various techniques, including image analysis, expert systems, and deep learning algorithms, to accurately identify and classify over 70 distinct defect types arising from machine malfunctions and material inconsistencies. Automating the detection process not

only improves inspection accuracy and efficiency—overcoming human operators' limitations, who may miss up to 50% of defects—but also reduces production costs and minimizes waste, ultimately leading to higher quality finished products and increased profitability for manufacturers [3, 6, 1, 15, 5]. Leveraging these technologies enables the industry to achieve higher accuracy standards, reduce labor costs, and improve production efficiency, leading to more reliable and effective inspection systems.

6.6 Improving Real-Time Application and Adaptability

Enhancing real-time application and adaptability of defect detection systems is crucial for meeting the industry's dynamic demands. Developing lightweight models that maintain high accuracy while minimizing computational overhead is key, making them suitable for environments with limited resources [8]. By optimizing architectures and employing efficient algorithms, these systems can achieve rapid processing speeds necessary for real-time applications. Integrating advanced techniques, such as adaptive thresholding and transfer learning, further enhances adaptability. Adaptive thresholding allows dynamic adjustment of parameters based on real-time data, improving the ability to handle variations in textures and defect types [8]. Transfer learning leverages pre-trained models to quickly adapt to new types and patterns, reducing the need for extensive retraining and enabling faster deployment in diverse settings. Moreover, implementing real-time processing capabilities is supported by high-resolution cameras and sensors that capture detailed images of surfaces. These hardware components work in tandem with algorithms to provide continuous monitoring of quality, ensuring prompt detection and resolution of defects [10]. Exploring unsupervised and semi-supervised methods offers promising solutions for improving adaptability. These approaches reduce reliance on extensive datasets by analyzing images based on inherent features, allowing systems to adapt to new scenarios with minimal intervention [12]. To enhance effectiveness in real-time applications, a comprehensive strategy is essential. This strategy should integrate lightweight CNN architectures, such as FN-Net, which offers rapid training and lower resource consumption compared to traditional models like VGG16 and EfficientNet. Additionally, incorporating advanced techniques, including fully convolutional networks for yarn tracking and anomaly detection, is crucial for adapting to various types without extensive retraining. Finally, efficient hardware integration is necessary to ensure that these sophisticated algorithms can operate effectively on limited resources typically available in industrial settings. Such a multifaceted approach will significantly improve both accuracy and adaptability in textile manufacturing [6, 8, 3]. Pursuing these strategies will enhance detection accuracy and efficiency, ultimately improving quality control and production standards.

7 Conclusion

This survey comprehensively examines the evolution of fabric defect detection technologies, emphasizing their essential role in enhancing quality assurance within the textile industry. By integrating machine learning and image processing, these technologies have revolutionized defect detection, offering automated solutions that surpass the limitations of traditional manual inspection methods. The discussed models demonstrate superior performance in identifying various fabric defects, proving their effectiveness in industrial contexts.

The convergence of computer vision, deep learning, and unsupervised learning techniques has facilitated the development of robust systems capable of handling the complex and varied patterns found in contemporary textiles. These advancements not only improve detection accuracy but also optimize the inspection process, ensuring uniform quality in mass production.

Despite these innovations, challenges remain, particularly in the areas of data acquisition, model flexibility, and real-time processing. Future research should focus on expanding training datasets to enhance model resilience and exploring novel methods that reduce dependence on large labeled datasets. Additionally, refining model architectures for real-time deployment and creating hybrid systems that integrate tactile and visual data will improve the adaptability and precision of defect detection technologies.

Overcoming these obstacles while advancing fabric defect detection will allow the textile industry to achieve significant enhancements in quality control, minimize waste, and maintain competitive production standards.

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