Hybrid Methods for Fabric Defect Detection: Integrating Traditional Image Processing with Deep Learning Approaches

[1]Ms.Rutuja S. Patil, [2]Mrs.Shubhangi R. Patil,
[1]Student, [2]Assistant Professor
Department of Computer
Engineering
Shri Balasaheb Mane Shikshan Prasarak Mandals, Ashokrao Mane Group of Institute ,Vathar Tarf Vadgaon

Abstract - This paper reviews the development of fabric defect detection methods in terms of traditional image processing, deep learning techniques, and hybrid models. Traditional approaches, including edge detection and segmentation, are efficient but tend to fail in the case of complex textures and slight defects. Deep learning methods, especially CNNs, offer high accuracy but face challenges in data scarcity and computational costs. Hybrid models combining traditional techniques with deep learning seem to be promising in overcoming these limitations, improving detection accuracy and efficiency. Challenges remain, however, such as dataset limitations, model generalization, and the need for lightweight solutions. This paper addresses these issues and points out directions for future research on developing more robust, scalable, and efficient fabric defect detection systems in the textile industry.

Index Terms - Fabric defect detection, traditional image processing, deep learning, hybrid models.

I. Introduction

Quality control, reduction of waste, and productivity improve all due to fabric defect detection. According to authors such as [1], automated systems play a crucial role in maintaining advantages in competitive global markets while addressing shortcomings stemming from human inspections. Such methods like image segmentation are extensively used to detect defects using algorithms on anomaly detection for texture and patterns. However, such methods as used by [2] do not have efficiency because the light change sensitivity and complexity in the texture result in a loss of accuracy. With the discovery of deep learning, models such as CNNs have performed more effectively in defect detection, according to [3]. However, on the other side, deep learning also brings dependency on large data sets and more significant computational power, so there is an immense attraction toward its hybrid version.

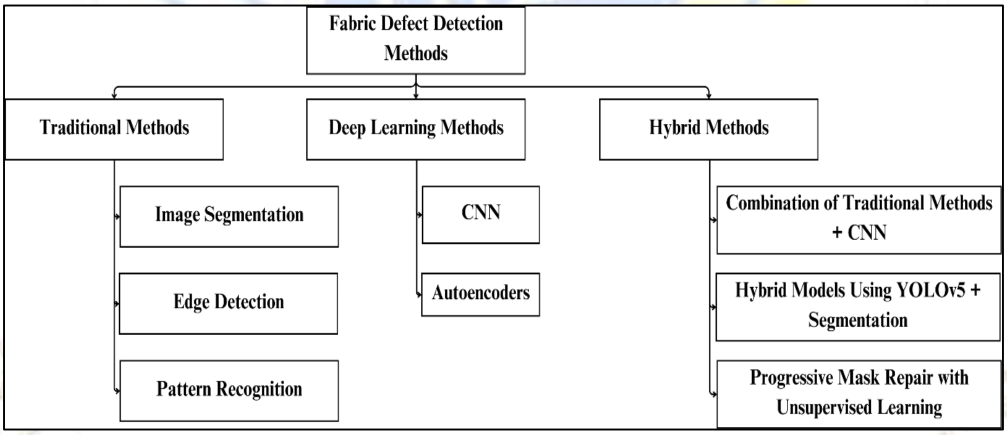

Fig 1: Fabric defect detection methods

Figure 1 shows the timeline summary of the development of fabric defect detection techniques from traditional ones to the present hybrid advanced techniques. A flowchart depicting this trend explains how each methodology addresses the specific limitation present, making hybrid models a more promising solution to the challenges presented by both traditional image processing and deep learning methods. One of the very promising approaches to avoid drawbacks of some methods is integrating traditional image processing techniques with deep learning methodologies. [4] proposed the multi-scale autoencoder in, which uses mixed-attention mechanisms to upscale the richness of spatial and channel information in order to enhance accuracy in the defect localization task. [5] also recently combined classic segmentation methods with the YOLOv5s framework, reporting large improvements on detection performance from defects against more complex backgrounds. Others, including [6], utilize unsupervised feature extraction, for example using pyramid structures that significantly reduce dependency on annotated data without sacrificing the high accuracy in detection. This will combine these complementary techniques, allowing researchers to enhance both robustness and efficiency simultaneously. [7] have demonstrated how a hybrid YOLOv4 model reduces false negatives while retaining computational efficiency.

The purpose of this review is to evaluate hybrid methods that combine the strengths of traditional and deep learning-based approaches to address the gaps in current defect detection systems. [8] have argued for modular approaches that utilize deep learning networks alongside analytical methods to overcome data limitations. In addition to this, [9] proposed a hybrid progressive mask repair model. The author showed how deep learning can be combined with traditional techniques so that better defect segmentation can be realized, making it possible to improve accuracy according to the requirement of industry. Improving accuracy and simultaneously meeting the operational feasibility, this paper creates a roadmap for advancing hybrid methodologies in fabric defect detection.

II. TRADITIONAL METHODS FOR FABRIC DEFECT DETECTION

Edges from the image detected, segmented into regions, filtered, and smoothed are the older techniques of fabric defect detection traditionally used due to their simplicity as well as computer efficiency. Recently, [10] developed the edge detection based method for automatic identification of fabrics defects on colored fabrics, validating its real time applicability. However, such traditional methods lack sensitivity to differences in texture and lighting and, hence are not that useful for patterned or multicolored fabrics, as authors such as [11] indicated. [12] thus developed adaptive segmentation techniques that make use of periodic patterns to improve detection accuracy. These methods are computationally efficient and relatively simple to implement. However, the dependence on specific image characteristics reduces their robustness against noise and complex fabric textures.

These limitations motivated the development of algorithms that utilize high-processing strategies in an attempt to increase detection accuracy. [11] constructed a saliency-based technique by applying Gaussian filtering and contrast enhancement. The method found the defects successfully with efficiency even in noisy images. [13] applied image pyramid matching as a technique in order to benefit from periodicity in fabric patterns to recognize and segment the defects with an accurate precision. Such improvements represent the capability to tune traditional methods toward increased precision and adaptability even under the complex conditions. However, as observed by [14] such methods often lack when slight or abnormal defects are involved where features are not clearly separable using conventional filters or segmentation methods.

Despite these disadvantages, traditional techniques are still worthwhile, especially in hybrid frameworks. For example, [15] have shown that hybrid models that couple refined filtering techniques with attention-based models outperform state-of-the-art approaches in both patterned and unpatterned fabric defect localization. Even more, [10] suggested that edge detection is also economical in terms of processing for simple kinds of fabric and thus is relevant to the said context. But in the contemporary textile industry with the continuously rising demand for strong and automatic solution, [11] urge hybrid solutions that blend the simplicity of old approaches with the potency of deep modern learning algorithms. The above research opens up new avenues for building more efficient, scalable, and adaptable systems in defect detection.

III. DEEP LEARNING APPROACHES FOR FABRIC DEFECT DETECTION

Deep learning has completely transformed the realm of fabric defect detection, in that models learn complex patterns and features directly from image data. Convolutional Neural Networks (CNNs) have been most prominent, with [7] presenting an improved YOLOv4 algorithm to increase the accuracy of defect detection with minimal computational cost. Similarly, [1] proposed a two-stage approach that uses the integration of U-Net and feature fusion techniques to detect defects with a higher degree of accuracy. These methods are based on the capability of CNNs to determine fine features and classification. They are used for the minor and irregular anomalies where they can detect anomalies. However, these high-accurate ones have large amounts of labeled data as mentioned in [4].

To mitigate the issue of lack of data, GANs have been employed to artificially create synthetic defect images for training purposes. [9] utilized GANs for creating highly realistic images of defects with their supplementation of the datasets and improvement of performance in the defect detection framework. Finally, attention mechanisms have been incorporated to further focus models on critical regions of defects. [5] proposed a mixed attention module inside the YOLOv5 architecture, which achieved a much higher accuracy in detection performance in complex backgrounds. However, authors such as [2] mentioned that the computational costs are still the major problem, since deep learning models require powerful hardware and longer training times.

Addressing the computational inefficiency of models has also led researchers to design optimal architectures and hybrid solutions. [15] improved RefineDet architecture with an incorporation of attention mechanism and path augmentation, showing improvements in real-time defect detection along with reducing the training time. Similar results are presented by [9] using progressive mask repair based on a balance between unsupervised deep learning and traditional image processing methods. The state-of-the-art performance and adaptability of deep learning techniques make it inevitable to adapt such techniques; however, a considerable number of obstacles like data scarcity and high computation have to be faced. Thus, the upcoming era of hybrid models and optimization techniques will prevail over fabric defect detection.

IV. HYBRID APPROACHES FOR FABRIC DEFECT DETECTION

This solution called for hybrid models, essentially coupled traditional image processing with deep learning models, capitalizing on the good from both approaches. The traditional approach is very efficient at extracting features such as edge detection and texture analysis. Deep learning models are better suited at learning complex patterns from data. To benefit from these advantages, [2] have proposed a hybrid method with improvement of images of fabric by means of the global and local transform domain-based algorithm followed by a CNN for defect classification. Similar research on developing saliency-based defect detection was given by [11], which combines Gaussian filtering with a deep learning-based segmentation model to gain higher accuracy. These methods show how the interpretability of traditional algorithms combined with the adaptability of deep learning improves overall detection performance.
Hybrid algorithms for solutions to specific challenges like noise and complex textures have been proposed, thereby depicting reliance on the needs of the textile industry. [1] propose a two-stage model, where they use traditional active contour methods to first segment the fabric images before finally using a deep feature fusion network to localize defects. This significantly improves accuracy over either approach applied in isolation. Another one by [4] investigated a hybrid autoencoder-based framework that merges multi-scale attention mechanisms with conventional frequency-tuned saliency detection, thereby allowing the model to better identify subtle defects in patterned fabrics. These kinds of solutions depict how hybrid approaches can be effective in dealing with complex detection tasks through the integration of complementary strengths. To overcome the challenges of computational ability in deep learning, authors [5], [9] heavily stressed the need for optimization within hybrid models. Kong integrated mixed attention mechanisms with the traditional image preprocessing steps of a YOLOv5 framework, which improved efficiency and accuracy. Meanwhile, a progressive mask repair model was introduced by [9] with an unsupervised learning paradigm while using conventional texture analysis in parallel, hence limiting the requirement of large-sized labelled datasets. This is another excellent example which represents the hybrid methods capable of offering excellent performance where there is always the trade-off between accuracy and efficiency in computations. Hybrid models provide promising avenues towards finding solutions in the fabric defect detection domain.

V. INTEGRATION AND OPTIMIZATION OF FABRIC DEFECT DETECTION APPROACHES

Fabric defect detection systems were developed from a need to provide both accuracy and computational efficiency. Traditional edge detection and segmentation of an image in the field have long been used for detecting defects in fabric. It is computationally efficient and easy for simpler fabrics like cotton and linens but mostly lacks in providing required results with complex textures and different lighting [10], [12]. Recent years have seen the optimization of defects localization in noisy environments, owing to research efforts that have enhanced conventional methods with features of Gaussian filtering and contrast enhancement [11] and image pyramid techniques [13]. However, even with these approaches, subtle or irregular defects are difficult to detect [14]. Deep learning techniques, especially the use of CNNs, have made a giant step forward. Models like YOLOv4 [7] and U-Net [1] are giving stunning accuracy in defect detection, especially subtle or irregularly shaped. Although such breakthroughs were made, issues remain; for example, a deep learning system requires large amounts of labeled data and significant computational resources [2]. In this regard, researchers tried to use the GAN framework in augmenting datasets [4] while incorporating attention mechanisms into models [5].

Table 1: Key contribution summarization

Paper	Methodology	Key Contribution
Khan & Akhter (2022)	Edge detection	Developed real-time defect detection for single-colored fabrics.
Wang et al. (2020)	Traditional segmentation	Noted limitations of traditional methods in handling texture and lighting variations.
Li et al. (2023)	Saliency-based approach	Combined Gaussian filtering and contrast enhancement for better localization.
Jing & Ren (2020)	Image pyramid matching	Used periodicity for accurate segmentation and defect localization.
Xiang et al. (2022)	Traditional methods	Identified limitations in detecting subtle or irregular defects.
Voronin et al. (2021)	Hybrid method (transform + CNN)	Combined traditional image enhancement with CNNs for defect classification.
Sizyakin et al. (2022)	Two-stage model with U-Net	Used active contour and deep feature fusion for defect localization.
Zhang et al. (2023)	Hybrid autoencoder with attention mechanisms	Integrated multi-scale attention with frequency-tuned saliency detection.
Kong (2024)	YOLOv5 with attention mechanisms	Enhanced efficiency and accuracy by combining attention with image preprocessing.
Tang et al. (2023)	Progressive mask repair model	Combined unsupervised learning with traditional image analysis to reduce dataset dependency.
Zhang & Lu (2023)	GAN-based data augmentation	Utilized GANs to generate synthetic defect images to overcome data scarcity.

Hybrid approaches that use deep learning along with traditional methods are promising to detect defects, with the approach focusing on using strengths from both paradigms in a way that would improve accuracy and maintain computational efficiency. Hybrid models that combine image preprocessing with CNNs are proposed in [2] and [11]. [1] and [4] have further combined traditional methods with deep learning-based segmentation and feature fusion to improve the accuracy of defect localization. Further enhancements of the scalability and efficiency of hybrid models have been done through integration of optimization techniques such as attention mechanisms [5] and unsupervised learning [9]. Table 1 summarizes this key contributions from various studies on fabric defect detection methodologies.

VI. Conclusion and Future Work

This paper discusses the evolutionary trends of techniques related to fabric defect detection, strengths and weaknesses of the conventional methods, deep learning approaches, and hybrid models. Traditional approaches like edge detection and segmentation are computationally efficient but do not tackle problems with complex textures and subtle defects. Deep learning techniques, especially CNNs, provide high accuracy and are limited due to the dataset and high computational costs. Hybrid models that combine the best of both worlds have been found to be promising in these challenges, increasing detection accuracy and efficiency.

However, there are still a few key challenges that remain in fabric defect detection systems. Future work should be aimed at overcoming the limitations of datasets since the lack of large, diverse public datasets limits model generalization across different types of fabrics and categories of defects. Model generalization and sample imbalance would be critical factors to improve robustness across different industrial environments. This includes bringing lightweight solutions that can be deployed on low-cost hardware without losing performance. Finally, the extension of models to be developed to be more general and broad in type handling defects and fabrics thus showing the scalability and versatility of such systems for defect detection in the textile industry.

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