IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 26 March 2024, accepted 28 April 2024, date of publication 2 May 2024, date of current version 10 May 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3396053*

SURVEY

# Intelligent Quality Control of Surface Defects in Fabrics: A Comprehensive Research Progress

**PEIYAO GUO[1], YANPING LIU[1], YING WU[1,2,3,4], R. HUGH GONG[5], AND YI LI[6,7,8]**

[1]School of Fashion Design and Engineering, Zhejiang Sci-Tech University, Hangzhou 310018, China
[2]School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China
[3]Zhejiang Sci-Tech University Shengzhou Innovation Research Institute, Hangzhou 312400, China
[4]Clothing Engineering Research Center of Zhejiang Province, Zhejiang Sci-Tech University, Hangzhou 310018, China
[5]Department of Textiles, School of Materials, The University of Manchester, M13 9PL Manchester, U.K.
[6]Green and Low-Carbon Technology and Industrialization of Modern Logistics, Zhejiang Engineering Research Center, Wenzhou 325100, China
[7]Youngor Group Postdoctoral Workstation, Tsinghua University, Ningbo 315000, China
[8]Fashion Department of Iinternational United Faculty between Ningbo University and University of Angers/Faculty of Tourism and Culture Ningbo University, Ningbo 315211, China

Corresponding author: Ying Wu (ying012688@zstu.edu.cn)

This work was supported in part by the Zhejiang Provincial General Scientific Research Projects Fund of China under Grant Y202352846, in part by Zhejiang Sci-Tech University Shengzhou Innovation Research Institute under Grant SYY2023B000003, and in part by the Fundamental Research Funds of Zhejiang Sci-Tech University under Grant 22076229-Y.

**ABSTRACT** Fabric defect detection is a crucial step of quality control in textile enterprises. The use of computer vision inspection technology in the textile industry is key to achieving intelligent manufacturing. This study sought to determine the progress made and future research directions in intelligent fabric surface defect detection by comprehensively reviewing published literature in terms of algorithms, datasets, and detection systems. Initially, the detection methods are classified as traditional and learning-based methods. The traditional methods are subdivided into model, spectral, statistical, and structural approaches. Learning-based methods are categorized into classical machine learning methods and deep learning methods. The principles, model performance, detection rate, real-time performance, and applicability of deep learning methods are highlighted and compared. In addition, the strengths and weaknesses of all the approaches are elaborated. The use of fabric defect datasets and deep learning frameworks is analyzed. Public datasets and commonly used frameworks are collated and organized. The application of existing fabric inspection systems on the market is outlined. Fabric defect types are systematically named and analyzed. Finally, future research directions are discussed to provide guidance for researchers in related fields.

**INDEX TERMS** Computer vision inspection, deep learning, fabric defect detection, machine learning.

## I. INTRODUCTION

Computer vision is crucial in quality control in the automation industry. It has been successfully applied to inspect defects, such as the size, shape, and other characteristics of industrial products. Textile manufacturing involves complicated procedures including spinning, weaving, and finishing. Textile product quality is influenced by some factors such as raw materials, equipment, operating procedures, and environmental conditions. These factors can lead to varying degrees of damage or defects in the fabric, such as holes, broken yarns, and incorrect patterns [1]. These defects not only impact the quality and appearance of fabrics but also result in significant resource waste, increased production costs, reduced market competitiveness, and substantial economic losses.

Traditional fabric defect detection is mainly manual which suffers from many problems. The accuracy of manual detection is only 60-75% [2]. Small defects are often overlooked, resulting in significant product price reductions. In addition, visual fatigue among workers can occur after extended periods of work. In contrast, computer vision-based inspection addresses these problems and facilitates high-speed, efficient, and precise detection of fabric defects [3].

With the rapid development and application of computer vision technology, intelligent textile defect detection has experienced the transformation from traditional manual detection to automated detection. Using computer vision

The associate editor coordinating the review of this manuscript and approving it for publication was Filbert Juwono.

technology, textiles can be detected and classified with high speed, high efficiency, and high precision, and this greatly improves production efficiency and product quality. Compared with manual defect detection, intelligent textile defect detection has fewer errors and lower cost and improves the safety and stability of the production line. However, despite progress in intelligent fabric defect detection technology, several challenges and issues remain, primarily in the following aspects:

1) Insufficient datasets. Intelligent detection of fabric defects requires a large number of labeled datasets for model training. However, publicly available datasets are limited in quality, which can restrict the accuracy and the ability of models to generalize.
2) Complex defects. Fabrics can exhibit a wide range of detects with complex morphologies. Some defects such as yarn breakages, wrong yarns, and holes, are challenging to distinguish.
3) Inadequate detection speed and efficiency. There is a high demand for enhanced speed and efficiency in automatic defect detection, particularly for high-speed production line applications that require faster detection speed and higher efficiency.
4) Higher costs. Implementing intelligent fabric defect detection requires substantial investments in hardware and manpower, leading to increased costs. This may present challenges for some companies in terms of affordability.

To examine the above four challenges for the intelligent detection of fabric defects and identify further directions of research. Algorithms are suggested for researchers, and deployment problems are addressed for practitioners. Below is a summary of the main contributions of this article:

1) Provides a general overview of fabric defect detection algorithms, with emphasis on the latest research findings in deep learning approaches.
2) Compares the strengths, weaknesses, and applications of existing deep learning methods, and a quantitative comparison of detection effectiveness of deep learning methods.
3) Summarizes and collates commonly used open datasets of fabric defects and defect types.
4) Introduces the implementation of various detection systems.

The rest of the article is structured as follows, Section II specifies the methodology of the systematic review used. Section III reviews the progress of research on fabric fault detection algorithms using traditional methods. Section IV focuses on recent research on fabric defect detection using learning-based methods. Section V outlines relevant applications for fabric defect detection, including a collection of 12 commonly used open datasets of fabric defects and a comparison of the strengths and weaknesses of commonly used fabric inspection machines. Section VI summarizes and discusses the strengths and weaknesses of the methods in the literature. Finally, section VII presents a future outlook for textile defect detection.

## II. METHODOLOGY

To address the aforementioned challenges in intelligent fabric defect detection and explore future research directions, we followed the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines to conduct a comprehensive literature search and improve the rigor of the review process. This allowed us to conduct a thorough literature search and enhance the robustness of the review process. Our study employed the systematic literature review (SLR) approach as outlined by Kitchenham, which involves collecting, critically evaluating, integrating, and presenting the findings of multiple studies on a specific research question or related topic. The steps of the SLR approach are detailed below.

### A. RESEARCH QUESTIONS

To clarify the scope and objectives of this paper, we first pose the following questions for this review:

**RQ1** What is the most frequently used defect type for fabric detection?

**RQ2** What are the most commonly used publicly available fabric defect datasets?

**RQ3** In what ways are deep learning methods effective in detection compared to traditional methods?

**RQ4** What are the differences in detection performance between supervised, unsupervised, and semi-supervised learning methods?

**RQ5** What are the strengths and weaknesses of two-stage and one-stage object detection algorithms, respectively?

### B. SEARCH PROCESS

Establish the initial structure of the article and identify relevant keywords. Based on the literature review conducted by previous researchers, fabric defect detection algorithms are classified into traditional and learning based methods, with a focus on the topic of ''fabric defect detection method based on computer vision inspection''. The literature on traditional methods is analyzed following the same organizational structure as Hanbay et al. [4]. Relevant keywords include ''model-based'', ''spectral-based'', ''statistical-based'', and ''structural-based''. The keywords ''machine learning'' and ''deep learning'' were used for the literature on learning-based methods. Initially, we searched for the topic ''fabric defect detection method based on computer vision inspection'' and then refined the search results by manually searching for the specified keywords.

### C. ELIGIBILITY CRITERIA

Once the search strategy is established, the next step involves defining inclusion and exclusion criteria for evaluating the findings.

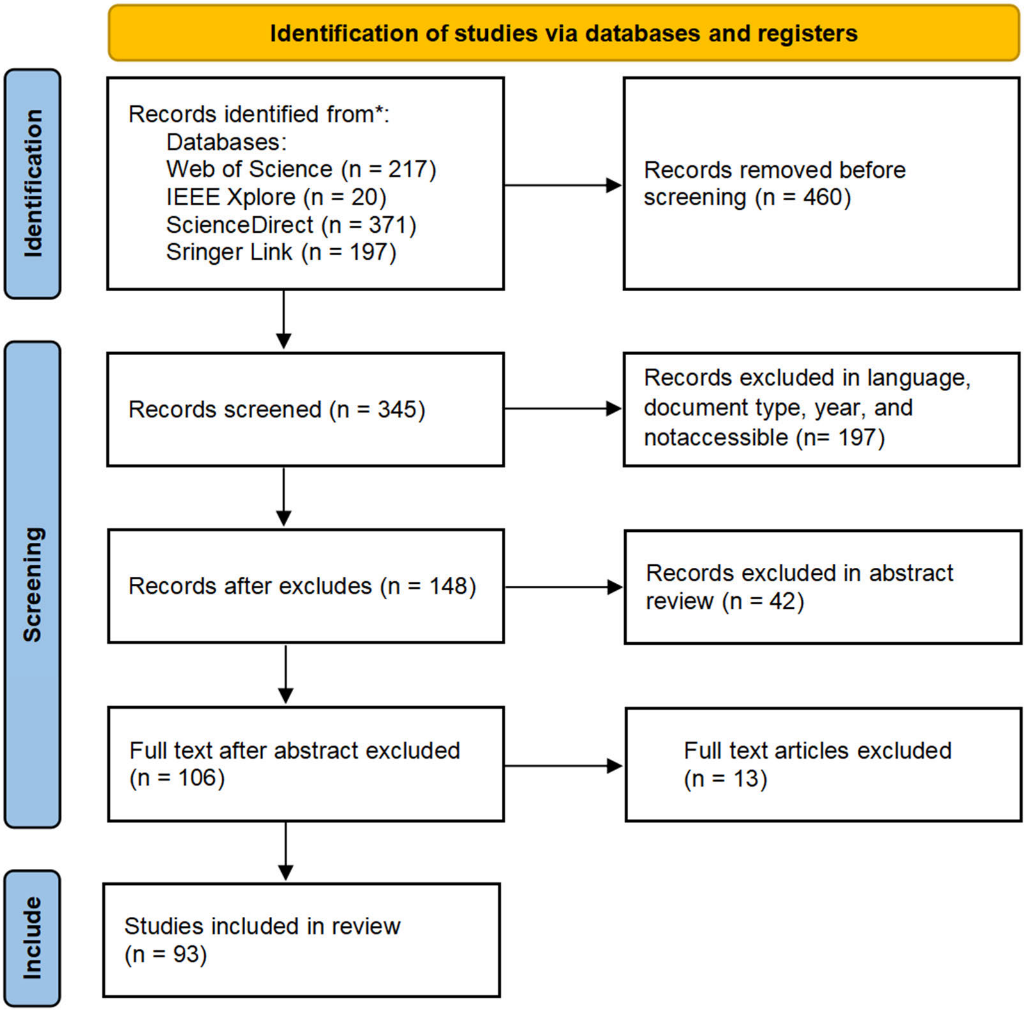



**FIGURE 1.** PRISMA flowchart of the study selection process.

Inclusion criteria:

- Research articles on fabric surface defect detection utilizing computer vision inspection techniques.
- Published scholarly journals, conference papers, and conference proceedings.
- Journal impact factors and citation rates are relatively significant.
- Papers retrieved with the keyword "deep learning" are studies conducted from 2018 to 2023.
- Composed in the English language.
- Complete full-text access is provided.

Exclusion criteria:

- A study focused on applying computer vision to identify flaws on non-textile surfaces.
- Reviewing survey articles.
- Studies that do not rely on image datasets.
- Conference papers containing only abstracts.

Deep learning methods are the focus of this paper. We briefly summarize the main development history of traditional methods, including literature that initially used each traditional method for fabric defect detection, literature with outstanding contributions to the detection results, and literature that uses only traditional methods, excluding the combination of traditional and deep learning methods. Representative literature on classical machine learning methods is also briefly overviewed. Deep learning methods are the primary focus of this research, with a selection of papers published within the last 6 years to reflect the current dominant research techniques. This ensures the rigor and value of the paper.

### D. ELIGIBILITY CRITERIA

The study selection process for this review is shown in Fig. 1. We used four scientific databases, Web of Science, IEEE Xplore, ScienceDirect, and Springer Link, to identify 805 articles by entering subject terms, and the remaining 345 studies entered the screening stage after excluding duplicate articles in each database, and 93 studies were eventually selected in the review after screening and analysis according to the developed inclusion and exclusion criteria.

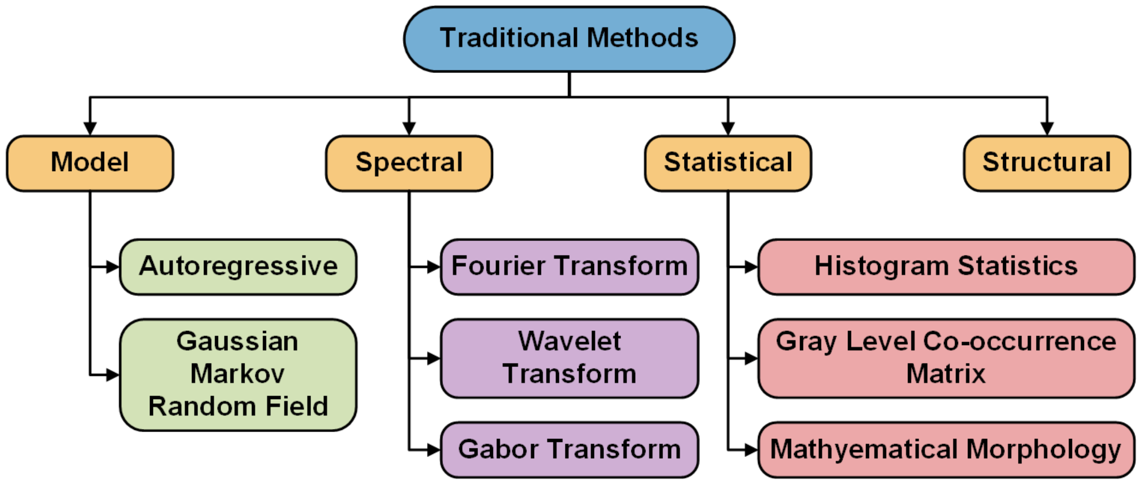



**FIGURE 2.** Traditional methods of fabric defect detection.

The following section of this review provides a detailed analysis of the methods, underlying models, datasets, types of defects, and evaluation metrics used in the relevant literature, based on the exclusion and inclusion criteria of the reviewed papers. We discuss the underlying models, enhanced algorithms, and their applications for both traditional and learning-based methods.

## III. TRADITIONAL FABRIC DEFECT DETECTION METHODS

The key to the intelligent detection of textile defects online lies in the detection algorithm. Numerous related industries have enhanced the effectiveness of automated textile defect detection by continuously designing and improving algorithms in the past decades. Currently, available algorithms for fabric defect detection can be classified into two main categories namely traditional methods and learning-based methods. Traditional methods based on image processing have been developing since the 1980s [5]. Hanbay et al. [4] classify traditional methods further into four categories: model approach, spectral approach, statistical approach, and structural approach. The traditional methods of textile defect detection are illustrated in Fig. 2.

### A. THE MODEL APPROACH

The model approach represents the fabric texture as a random procedure and assumes that the texture can be considered as a sample created by this procedure in the image space. This approach identifies faults by modeling the typical fabric texture and assessing whether the inspection image adheres to the model [6]. Notable approaches in this category include the Autoregressive model [7] and the Gaussian Markov Random Field model [8].

The Autoregressive (AR) model is a one-dimensional model that captures the association between each pixel of the fabric texture in the image. Alata and Ramananjarasoa [6] proposed a 2-D Quarter Plane Autoregressive (2-D QP AR) model based on four predictive supports. It focused on parametric modeling of the texture and probabilistic criterion during parameter estimation. The designed model achieved a segmentation error rate of 0.357% on images containing natural textures from the Brodatz album. Based on the theory that texture periodicity can be used as a fabric quality parameter, Vaddin and Subbaraman [9] utilized one-dimensional DCSFSS data as a signal to conduct experiments on non-parametric and parametric periodic modeling of plain fabrics. It proved that the AR (32) models could simulate the fabric periodicity for the u/v direction of DC Suppressed Fourier Power Spectrum Sum (DCSFPSS) and finally distinguish the defective fabrics from the normal plain fabrics. The AR model has the advantage of low computational requirements, low complexity, and high accuracy. However, this algorithm has limitations in detecting a diverse range of defects and extracting the features of fine defects.

The Gaussian Markov Random Field (GMRF) modeling algorithm measures the density value of an image in a specific local area by utilizing the dependency between each pixel and every other pixel in a noiseless fabric image. In 1991, Cohen et al. [10] used a GMRF model to capture the texture content of different fabrics and designed a simple ring structure to compute sufficient statistics to classify it into defective and non-defective windows by calculating the maximum likelihood estimate (MLE) of the model parameters in each window. The proposed means effectively extracts texture information from a wide range of fabric images. Yang [11] distinguished between normal fabric texture and statistically characterized aberrant defective texture using distance statistics constructed from parameters of the GMRF model for automatic defective fabric detection. However, this algorithm was not effective for defects with a relatively small area or impurities that resemble scattering noise. Table 1 provides a summary of the model-based approaches used for fabric defect detection.

The model approaches are preferred for fabrics with noise (such as protruding fibers and brushed surfaces) or fabrics lacking regular texture and exhibiting randomness. However, these approaches are more complex and computationally

**TABLE 1. A summary of model approaches.**

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| O. Alata and C. Ramananjarasoa [6] | Image with synthetic textures; Image with Brodatz natural textures | | Percentages of segmentation errors | Unsupervised image segmentation algorithm using the 2-D QP AR model |
| H. G. Bu *et al.* [12] | Created dataset (Solid color plain fabrics; Solid color twill fabrics) | Weft crackiness; Tight thread; Dirt; Scrape marks; Foreign matter; Knots; Slubs | False positive rate (FAR); Missing rate (MR) | Methods based on the modern spectral analysis of a time series |
| J. Zhou *et al.* [13] | Created dataset | Thin bar; Foreign matter; Missing pick; Wavy face; Holes; Shrinked weft; Loose warp | Three AR features | Defect feature extraction method based on one-dimensional projection series of fabric image |
| J. Vaddin and S. Subbaraman [9] | Plain weave fabric | Loose weft | AR model, values of predicted frequencies; the value of fit function | Modeling periodicity of a plain weave fabric based on DCSFPSS |
| F. S. Cohen *et al.* [10] | Created dataset (sueded denim; chambray; oxford shirting; piece dyed denim; oxford shirting; chambray) | Mispick; Dropped picks; Broken pick; Harseness breakdown; Burl mark | Detection results chart | Markov Random Field (GMRF) modeling system for textile inspection |
| S. Ozdemir and A. Ercil [7] | White wool fabric | | Execution times | Model-based approach with Markov Random Fields(MRF) as the texture model and a new method based on Karhunen-Loeve Transforms |
| X. B. Yang [11] | Created dataset | Skipping; Thinning and dense road; Rough yarn; Broken warp | Each sub-window distance | Gauss-Markov Random Field (GMRF) texture model for automatic identification of fabric defects with different kinds of statistical feature aberrations |
| Y. Zhang *et al.* [14] | Jacquard warp-knitted fabric | | Classification accuracy (P) and Ratio of true boundaries to segmented boundaries (Pa) | A new approach to intelligently segment jacquard warp-knitted fabric images by combining wavelet texture decomposition, multiresolution Markov random field (MRF) modeling, and Bayesian parameter estimation |

intensive, making them unsuitable for real-time detection requirements. In addition, the approaches are less capable of detecting defects in smaller areas.

### B. THE SPECTRAL APPROACH

Approaches based on spectral analysis take advantage of the strong periodicity in fabric images. These approaches involve transforming the spatial domain image to the frequency domain image and using an energy criterion for fabric defect detection [7]. The Fourier Transform [15], Wavelet Transform [16], and Gabor Transform [17] are widely applied in spectral approaches.

The Fourier transform algorithm is useful for monitoring the spatial spectrum of fabrics. Defects in fabric images cause changes in the regular structure, which correspond to changes in the spectrum at specific frequencies. In 2000, Chan and Pang [18] proposed a model based on the Fourier spectrum to understand the relationship between fabric structure (referred to as the center spatial spectrum) and extracted seven characteristic parameters. The results showed that these seven parameters can be used to classify the different types of fabric defects. To address the issue of real-time defect detection, Pan et al. [19] designed a Fast Fourier Transform (FFT) algorithm based on Computer Unified Device Architecture (CUDA). This algorithm employed multithreaded parallel implementation of the FFT algorithm to detect fabric defects, which has a four times faster detection rate compared to the CPU-based FFT algorithm. This algorithm can significantly shorten the time of detection on the basis of ensuring the correct detection rate. The Fourier Transform offers the advantage of lower computation requirements, but it is constrained by the changes in fabric structure. It captures the global fabric characteristics instead of the local texture. Overall, this algorithm is not ideal for detecting small local defects either.

The Wavelet Transform, on the other hand, can analyze fabric images at multiple scales and analyze the local information of fabric images efficiently. In 1997, Lambert and Bock [20] applied the multiscale wavelet algorithm to study the problem of fabric defect localization. They divided the fabric image into three layers and combined the wavelet coefficients of each layer with a feature vector. This improved the selectivity of extracting local features and thus enabled defect detection. In addition, the fast dyadic Wavelet Transform had low complexity and low computational cost. Combined with previous research on Wavelet Transforms, Li et al. [21] proposed an improved direct thresholding segmentation method based on high-frequency coefficients. They utilized the Wavelet Transform to denoise and reconstruct the image, and then segmented the new image based on the Gaussian mixture model of the expectation maximization (EM) algorithm. This algorithm effectively detected and localized fabric defects on the TILDA Dataset. To address the issue of multichannel Gabor Wavelet data redundancy and low arithmetic, Li and Zhou [22] proposed a Defect Direction Projection Algorithm (DDPA) based on the characteristics of Gabor Wavelets and Radon Transforms, their experiment results achieved 96.97% detection accuracy with an average detection speed of 0.2186s. The designed algorithm struck a balance between detection accuracy and speed, outperforming other algorithms in the process. The Wavelet Transform overcomes the limitations of the Fourier Transform, which relies on univariate representation of signals. It efficiently acquires fabric image information, making it suitable for local defect detection. However, the Wavelet Transform may fail to detect defects in the presence of color changes and edge smoothing. Furthermore, the choice of wavelet base affects the detection effectiveness.

The Gabor filter directly segments defects in fabric images from the filtered images without the need for feature extraction. In 2002, Kumar and Pang [23] proposed a fabric defect detection algorithm based on multichannel filtering using Bernoulli's rule of combination to fuse different channel images combined with low spatial sampling to perform supervised defect detection using optimized Gabor filters. Their algorithm significantly improved detection performance and validated a certain level of generalization. To address the limitations of previous algorithms that could not completely separate patterns, textures, and defects in fabrics, Zhang and Tang [24] utilized frequency filtering, the distance matching function and similarity coefficient to achieve automatic detection to address the difficulty of defect detection in yarn-dyed fabrics. This algorithm could quickly and accurately detect different types of defects in different types of patterns. Kim et al. [25] investigated the complexity and diversity of fabric pattern defects by optimizing the parameters of the 2D Gabor filter using a hybrid Beetle Antennae Search Algorithm (BAS) and Gravitational Search Algorithm (GSA) method. This created defect-free fabric images that were used to train the model in a semi-supervised manner. This proposed algorithm provided a detection rate of 98% and was suitable for industrial production. The Gabor filter is particularly suitable for describing and analyzing the texture structure of fabrics due to its strong practicality. However, selecting the optimal filter parameters becomes more challenging with the use of the Gabor Transform. Table 2 provides an overview of the spectrum-based approaches utilized for fabric defect detection.

Spectrum approaches effectively detect subtle defects such as color changes and are not influenced by noise. However, they can only be applied to fabrics with a high periodicity in texture and cannot handle fabrics with random textures. Moreover, the success of these approaches is strongly contingent on the filter bank selection, and they may not perform effectively when dealing with low-contrast situations between defective and defect-free areas or when the defects are very small.

### C. THE STATISTICAL APPROACH

Statistical approaches involve the calculation of statistical properties in both defect-free and defective areas of fabrics to detect defects. These approaches are simple and easy to implement, but their results can be influenced by the texture pattern and shape of the defects, which may make them unavailable for inspecting small defects [35]. Furthermore, designing different statistical indicators for defects of varying complexity can be expensive, and this limits the practical usefulness of statistical approaches in fabric defect detection. The commonly used statistical approaches for fabric defect detection include Histogram Statistics, Gray Level Co-occurrence Matrix, and Mathematical Morphology.

Histogram Statistics compute gray values to distinguish statistical differences between the defective and non-defective regions in a fabric image. Gao et al. [36] used straight-line texture features of fabric images to generate histograms. They extracted characteristic waveforms, and set the detection threshold $\lambda$ to identify and locate fabric defects. Filtering results showed that the eigenvalues of abnormal texture structures with fabric defects were efficiently identified. Since the low-rank decomposition method can decompose an image into redundant parts (background) and sparse parts (defects), Li et al. [37] developed an effective second-order direction-aware descriptor called GHOG by combining Gabor and histogram of gradient-oriented (HOG) features. They incorporated a spatial pooling strategy based on human vision mechanisms and constructed a low-rank decomposition model to accurately localize defects. Compared to other optimal methods, this approach greatly improved detection accuracy, detection speed, and adaptive capability. The Histogram Statistics algorithm offers fast computation speed and low cost, but it is sensitive to noise and prone to high false detection rates. Therefore, it is better suited for detecting the warp and weft defects.

The Gray Level Co-occurrence Matrix (GLCM) calculates image texture features by analyzing the correlation properties between two pixels in the image space [38]. In order to implement Fabric Defect Detection System (FDDS), Raheja et al. [39] proposed an automatic implementation of FDDS based on GLCM and compared it with the Gabor filtering algorithm. The GLCM was utilized to extract the statistical information of the texture and to map the signals based on the inter-pixel distance of the texture; on the other hand, Gabor filters of different scales and orientations were generated to filter the fabric images. Experimental results in the same environment showed that the proposed GLCM algorithm has higher defect detection accuracy and computational efficiency, with the disadvantage that it only worked under constant environmental conditions. Arnia and Munadi [40] used only a limited number of Discrete Cosine Transform (DCT) coefficients generated by DCT-based Compressed Image (DCTb-I) to calculate energy and contrast. They specifically selected images with high energy and low contrast for defect detection. To reduce computational costs, they substituted the frame grabber with the Moving Picture

**TABLE 2. A summary of spectral approaches.**

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| C.-H. Chan and G. Pang [18] | Created dataset(plain white fabrics) | Double yam; Missing yarn; Webs or broken fabric; Yarn densities variation | Seven salient features used to characterize defects P1 to 7 | Fourier transform the fabric model to understand the relationship between fabric structures |
| S. Q. Guan and X. H. Shi [26] | Created dataset(Plain and twill fabrics) | Defects of small size and large size | Accuracy (ACC) | A method based on wavelet lifting transform with one resolution level |
| K. Sakhare *et al.* [27] | Created dataset | Missing warp; Missing weft; Hole; Tom out | ACC | Spectral-domain and spatial domain approach for fabric defect detection |
| Z. L. Pan *et al.* [19] | Created dataset | Jump flower; Hook broken | Image eigenvalue; Detection time-consuming | Detection of fabric defects using CUDA-based fast Fourier transform methods |
| L. Di *et al.* [28] | FID Dataset | Broken end; Hole; Thick bar; thin bar; Netting multiple | True positive rate (TPR); FPR; Positive predictive value (PPV); Negative predictive value (NPV); f value | Fabric defect detection method based on the combination of illumination correction and visual salient features |
| G. Lambert and F. Bock [20] | Fine and periodic texture | Higher frequency structures; Lower frequency structures; Local brightness shifts | Distance images | Exploit multiscale wavelet methods for texture defect detection |
| Y. X. Zhi *et al.* [29] | Created dataset | Wrong Draw; Broken End; Mipick; Thin Bar; Slack End | Ratio of wavelet transform energy between defects area and the background | Adaptive-based nonsubsampled wavelet transform method |
| P. Li *et al.* [21] | TILDA Dataset | | Detection and localization results | A method based on multi-scale wavelet transform and Gaussian mixture model |
| Y. H. Li and X. Y. Zhou [22] | Textile factory collection | Bamboo-pick; Double-weft; Mispick; Looped-weft; Cracked ends | ACC; Speed | Optimal Gabor wavelet algorithm for directional projection of defect(DDPA) |
| M. Moezzi *et al.* [30] | Geometric folds | | Wrinkle parameters; Poisson's ratio | Combining non-destructive characterization and numerical analysis for predicting fabric folds |
| A. Kumar and G. Pang [23] | Textile factory collection(Twill and plain fabrics) | Most common defects | Binarized segmented image | Fabric defect detection algorithm based on multi-channel filtering |
| V. Agilandeswari *et al.* [31] | Created dataset | Defective yarns; Colour bleeding; Pores | Binary detection result | Filter-based method for automatic detection of fabric defects |
| B. Zhang and C. Tang [24] | Yarn-dyed fabric | Weft-lacking; Holes; Manually added | Speed; ACC | Novel automatic detection algorithm based on frequency domain filtering and similarity measurement |
| Y. Li *et al.* [32] | Standard Fabric Defect Glossary | Wild filling; Broken pick; Foreign fiber; Coarse end; Kinky filling; Knots; Knots with halos; Oil spot | ACC; Precision (P); Recall (R); F-score | Instead of a Gabor filter bank, an optimal Elliptical Gabor filter (EGF) |
| S. Ma *et al.* [33] | Created dataset | Weft missing; Hole-breaking; Oil pollution | Detection rate ($D_R$) | Improved algorithm by using the optimized Gabor filter with the two-dimensional image entropy and the loss evaluation function |
| M. Boluki and F. Mohanna [34] | TILDA Dataset; Fabric Stain Dataset | Ink; Oil; Dirt stains | R (Sensitivity); Specificity; ACC | Automatic algorithm for real-time inspection of textile fabrics based on the optimal Gabor filters |
| J. C. Kim *et al.* [25] | TILDA Dataset | Broken warp; Broken weft; Sparse weft; Double weft; Oil stains; Holes; Cross-stitching; Other | Undetected; Specificity; ACC | The method for detecting defects in fabric surface is presented using an optimal Gabor filter based on hybrid BAS-GSA(Beetle Antennae Search Algorithm–Gravitational Search Algorithm) |

Experts Group (MPEG) encoder for real-time monitoring of textile defects, including holes, stains, and missed stitches. Sorting problems with Troso fabrics, Gustian et al. [41] used the GLCM and the Principle Component Analysis (PCA) algorithm for feature extraction. The multiclass Support Vector Machines (SVM) used are Ones Against All (OAA) and Ones Against One (OAO) with the type of Gaussian kernel or Radial Basis Function (RBF) as a classification method. The results showed that the GLCM algorithm is superior in extracting features for Troso fabrics, achieving accuracies of 90% and 86.7% for SVM OAA and SVM OAO classifications, respectively. However, due to its significant computational requirements, the GLCM algorithm is generally unsuitable for analyzing high-resolution fabric images.

Mathematical Morphology has been widely employed in tasks such as image segmentation, edge extraction, and image denoising. Zhang and Bresee [42] investigated and compared the performance of grayscale statistics and morphological algorithms for detecting and classifying knots and slubs. Both algorithms utilized an autocorrelation function to identify the presence of duplicate units in the fabric, which were then statistically or morphologically computed. The results showed that the proposed algorithm takes a longer time to detect and has a high false alarm rate, but has better

**TABLE 3. A summary of statistical approaches.**

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| X. D. Gao *et al.* [36] | Created dataset | Slub yarn; Thick warp | Rectangular wave characteristic parameters | Detection of fabric defects using Histogram Statistics |
| S. Ding *et al.* [44] | Created dataset | Split seam; Mispick | Graph of the detection result | Novel fabric defect detection scheme based on HOG and SVM |
| G. Gao *et al.* [45] | Dataset of Dot, box, and star patterned fabrics | Thin bar; Thick bar; Netting multiple; Broken ends; Hole etc | Saliency map; Receiver operating characteristic curve (ROC) | Novel patterned fabric detection algorithm based on Gabor-HOG (GHOG) and low-rank recovery |
| C. L. Li *et al.* [37] | FID Dataset(Star, box, and dot pattern fabrics) | Broken end; Hole; Netting multiple; Thick bar; Thin bar; Knots | Saliency map; ACC; TPR; FPR; PPV; NPV | Defect detection method for patterned fabrics based on GHOG and low-rank decomposition |
| J. L. Raheja *et al.* [39] | Dataset of different sources(Plain, twill, and denim fabrics) | Common defects | Energy feature | Fabric defect detection system using GLCM for real-time detection with embedded DSP platform is proposed |
| F. Arnia and K. Munadi [40] | TILDA Dataset | Holes; Stains; Drop stitches | $D_R$; FPR; False negative rate (FNR) | Framework for textile defect detection based on energy and contrast features of the GLCM |
| P. Banumathi and G. M. Nasira [46] | Industrial Camera Capture(100% cotton flat woven fabric) | Stain; Hole; Warp float; Weft float | ACC; CPU time | A method to detect the defects in woven fabric based on the changes in the intensity of fabric |
| D. D. Zhu *et al.* [47] | Yarn-dyed fabric | Holes; Weft crackiness; Broken weft; Wrong weft; Oil stain; Stretched warp | Euclidean distances | New detection algorithm for yarn-dyed fabric defect based on autocorrelation function and GLCM |
| P. Anandan and R. S. Sabeenian [48] | Created dataset(Spot texture, star texture, and box texture) | Broken end; Thick bar; Thin bar | P; R; ACC | A defect detection method combining GLCM and Curvelet transform (CT) projection |
| D. A. Gustian *et al.* [41] | Three troso fabrics | | ACC | An SVM-RBF multiclass approach combined with GLCM and PCA feature extraction for classification of Troso fabrics |
| Y. F. Zhang and R. R. Bresee [42] | Textile factory collection(Twill and plain fabrics) | Knots; Slub | Ability to correctly detect and classify; Number of false positives | Two methods based on gray-scale statistics and based on morphological operations for detection and classification are studied and compared |
| K. L. Mak *et al.* [49] | 《Manual of Standard Fabric Defects in the Textile Industry》(Plain, twill, denim fabrics, etc.) | Common defects | True detection (TD); False alarm (FA);Missed detection (MD); Overall detection (OD) | Novel defect detection scheme based on morphological filters |
| J. L. Raheja *et al.* [50] | | | TD; FA; MD; OD | New fabric defect detection algorithm based on local homogeneity and mathematical morphology |
| P. Bandara *et al.* [51] | Cotton Incorporated created dataset | Knot; Dropped Stitches; End Out; Oil defect | Feature extraction map | Detection of defects in uniformly woven fabrics using a combined thresholding and morphological approach |
| L. W. Song *et al.* [43] | Textile factory collection | Miscellaneous defects; Dirty defect; Burnt defect; Flash defect; Hole defect | Average runtime; ACC | Improved fabric defect detection method based on the membership degree of each fabric region (TPA) |

detection accuracy for small defects and different types of defects. Song et al. [43] combined the ideas of density map of extreme points of an image and affiliation function to construct the saliency mapping of regional features, adopting threshold iteration and morphological algorithms. The proposed method achieved higher than 92% detection accuracy for different types of defects and satisfied the requirements of online detection. In addition, it could suppress the interference of noise and background texture. The Mathematical Morphology algorithm has lower requirements and better efficiency compared to certain spectral analysis-based algorithms. However, the Mathematical Morphology algorithm cannot be applied to detect fabric images with periodic textures. Table 3 provides a summary of the statistical-based approaches utilized for fabric defect detection.

Statistical approaches are effective in detecting large-size defects. However, they face challenges in distinguishing fuzzy and small defects because these defects may not alter the average gray level of the fabric image significantly. In addition, these approaches are less effective in detecting fabrics with complex defect distributions.

### D. THE STRUCTURAL APPROACH

The structural-based fabric defect detection approach views texture as a composite of texture elements. The underlying texture structure of the fabric is extracted from the image using an S-extraction technique to obtain structural features [52]. This approach is reliable for recognizing fabric defects with highly regular patterns. In 2005, Abouelela et al. [53] employed images captured by a camera

**TABLE 4.** A summary of structural approaches.

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| A. Abouelela *et al.* [53] | Created dataset | Missing yarns in the warp direction; Knots; Cut | Detection success rate (DACC); Detection error rate; Failure rate of defect location | A system for automated visual inspection of textiles is discussed |
| H. Y. T. Ngan *et al.* [55] | Patterned Jacquard fabric | Broken end; Holes; Knots; Netting multiple; Oil stain; Dirty yarn | DACC | A method called direct thresholding (DT) based on WT detailed subimages; Method of wavelet preprocessed golden image subtraction (WGIS) |
| L. Jia *et al.* [54] | FID Dataset (Star, box, and dot pattern fabrics) | Broken end; Hole; Netting multiple; Thick bar; Thin bar | True positive (TP); False positive (FP); True negative (TN); False negative (FN); ACC; TPR; FPR; PPV; NPV | A novel method, LSG, which integrates image decomposition and lattice segmentation for patterned fabric inspection |
| X. Chang *et al.* [56] | FID Dataset (Star, box, and dot pattern fabrics) | Broken end; Hole; Netting multiple; Thick bar; Thin bar; Knots | TP; FP; TN; FN; ACC; TPR; FPR; PPV; NPV; $f$ value | Template-based defect detection method for periodic structural fabrics |
| B. H. Shi *et al.* [57] | FID Dataset (Star, box, and dot pattern fabrics) | Broken ends; Holes; Reticular multiple; Thick rods; Thin rods; Nodules; Knots | TPR; FPR; PPV; NPV; $f$ value | Fabric defect detection method based on low rank decomposition of gradient information and structured graph algorithm |

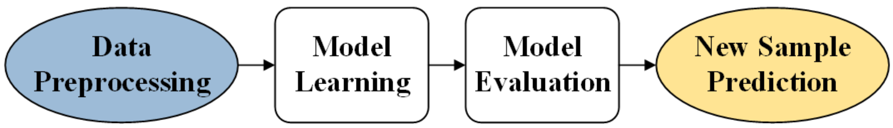



**FIGURE 3.** The basic process of classical machine learning method.

and simple texture features (mean, variance, median) for fault detection in an online real-time inspection system. Experimental results demonstrated 91% accuracy in detecting defects such as missing warp, knotting defects, and cuts. To achieve high quality detection of surface defects in patterned fabrics, Jia et al. [54] utilized Morphological Component Analysis (MCA)-based automatic segmentation of the mesh to calculate the distance between the yet-to-be-determined dot matrix and the dot matrix template. When the distance exceeded a specific threshold, the dot matrix was classified as a defective area. The layout inference performed on the fabric image was leveraged to differentiate between textural primitives, resulting in an overall detection rate of 0.975. However, the Lattice Segmentation assisted with the Gabor filter (LSG) algorithm exhibited optimal accuracy and false detection rate only for samples with geometric shapes. Combining the LSG with other methods may help compensate for its limitations. Table 4 provides a summary of the structural-based approaches for fabric defect detection.

The structural approach is computationally simple and reliable in identifying fabric defects with highly regular and simple textures. However, the effectiveness of the detection is determined by the size of the defects since it is difficult to maintain a stable underlying texture structure during industrial production. Detecting small and tiny defects using the structural approach poses difficulties.

## IV. THE LEARNING-BASED APPROACH TO FABRIC DEFECT DETECTION

### A. CLASSICAL MACHINE LEARNING METHODS

The classical machine learning methods automatically analyze data to obtain a model, which is then used to make predictions about unknown data [58]. This approach allows computers to learn from data and experience, and to discover an optimal "function" or "model" that fits the application scenario. By simulating the relationship between inputs and outputs, classical machine learning enables prediction, judgment, grouping, and problem solving. As the amount of data samples increases, the "function" or "model" can further self-improve. However, this improvement is heavily dependent on the available data. The basic process of classical machine learning method is depicted in Fig. 3. The most frequently used algorithms for fabric defect detection include Principal Component Analysis (PCA) [59], Dictionary Learning [60], Canny operator [61], K-Nearest Neighbor (KNN) [62], Support Vector Machine (SVM) [63], [64], Low-Rank Decomposition [65], and Plain Bayes [66]. Table 5 provides an overview of the traditional machine learning-based methods used for fabric defect detection.

The strengths of classical machine learning algorithms are as follows: 1) Theoretical and mathematical foundations of the algorithms are mature and easily explainable. 2) Computational speed is faster, yielding better performance for small datasets. 3) Unique advantage in exploring high-dimensional data and feature spaces. On the other hand, the weaknesses of classical machine learning algorithms include: 1) Limitations in processing large-scale data. 2) Limited ability to model complex relationships, leading to inadequate performance at times. 3) Difficulty in modeling nonlinear problems.

### B. DEEP LEARNING METHODS

Deep learning methods are popular in the textile industry for texture analysis and defect detection because they compensate for the limitations of traditional methods in handling

**TABLE 5. A summary of classical machine learning methods.**

| Reference | Dataset | Defect Types | Evaluation | Proposed Method | Method Category |
|---|---|---|---|---|---|
| K. Hanbay *et al.* [67] | FDDD Dataset | Needle breakages; Hole; Press-off; Gout | ROC curve; Sensitivity; Specificity; ACC; NPV; PPV | Fabric inspection system for circular knitting machine based on DST-PCA method | PCA |
| N. X. Zhang *et al.* [68] | DAGM 2007 Dataset; KolektorSDD Dataset | | P; R; F1 | Texture-defect detection method using principal components analysis (PCA) and histogram-based outlier score (HBOS) that requires | PCA |
| Y. Wu *et al.* [69] | Textile factory collection; Created dataset (Plain; Twill; Honeycomb; Warp satin; Weft satin; Basket weave; Diamond twill fabric samples) | | Gray-level histograms of the fabric samples; PSNR; RMSE | Dictionary learning method to represent fabric texture via a linear summation of dictionary atoms | Dictionary Learning |
| X. J. Kang *et al.* [70] | TILDA Dataset (Raw fabric; Yarn-dyed fabric; Patterned Fabric) | Holes; Oil spots; Thread errors; Objects on the surface | DACC; P; R; F-measure | Universal and adaptive defect detection algorithm based on dictionary learning | Dictionary Learning |
| Z. F. Liu *et al.* [71] | TILDA Dataset; FID Dataset | Broken end; Netting multiple; Hole; Thick bar; Thin bar; Dot-patterned; Star-patterned; etc. | Average precisions; R; F-measure; Mean absolute error (MAE) | Novel fabric defect detection algorithm based on a multiscale convolutional neural network and low-rank decomposition model | Low Rank Decomposition |
| A. D. Liu *et al.* [72] | Created dataset (Three types of irregular printed fabrics) | Small-size print; Medium-size print; Complex-distribution print | Visual effect; Detection Time; TPR; FPR; PPV; NPV | A double sparse low-rank decomposition method for defect detection in complex irregularly printed fabrics | Low Rank Decomposition |
| D. Z. Peng *et al.* [73] | Created dataset | Hook wire; Hole; Stain; Pilling; Crease; Broken weft; Other | False rate; MR; Recognition rate | Fast detection of raw fabrics based on speckle, Canny, and rotation integral algorithms | Canny operator |
| K. B. Zhang *et al.* [74] | Created dataset | Holes; Stains; Belt yarn; Cotton ball; and so on | $D_R$ | A novel fabric defect detection method, which is based on saliency metric for color dissimilarity and positional aggregation | KNN |
| Y. M. Huang *et al.* [75] | Created dataset | Screen turning | Average accuracy; Average detection time | Defect detection method based on support vector machine (SVM) for nonwoven fabric turning mesh defect detection | SVM |
| D. Yapi *et al.* [76] | TILDA Dataset (Uniform plain, twill, checkered, striped fabrics) | | $D_R$; False alarm rates ($F_R$); $D_{ACC}$; Local accuracy ($ACC_L$) | A method based on a statistical representation of fabric patterns using the redundant contourlet transform (RCT) | Plain Bayes |
| L. Liu *et al.* [77] | TILDA Dataset; Textile factory collection | Hole; Oil stain; Weft stripe; Crumple; Scratches; Pressed mark; Crease | P; Sensitivity; Specificity; ACC | A novel fabric defect classification method based on unsupervised segmentation and ELM | Plain Bayes |
| C. C. Ho *et al.* [78] | Fabric A; Fabric B; Knitting Dataset; Nano Fiber Dataset | Hooked yarn; Tufted yarn; Hooked yarn; Cross piece; Tearing; Broken warp; Hole; Broken weft; Thin film; Cross piece | ACC; P; R | Network pruning with the Bayesian optimization algorithm to automatically tune the network pruning parameters | Plain Bayes |

complex texture variations and small-sized defects [79]. Detecting fabric defects in the textile industry using deep learning methods usually starts with extracting the fabric defect region and then processing the defect image.

The deep learning methods can be categorized into three subgroups including supervised learning, unsupervised learning [80], [81], and a small number of semi-supervised learning [82], [83] approaches for fabric defect detection. The term ''supervised or not'' refers to the presence or absence of labeled data. If the input data is labeled, it falls under supervised learning; otherwise, it is classified as unsupervised learning. Supervised learning is used to tackle classification and regression problems, whereas unsupervised learning addresses clustering and dimensionality reduction problems. Semi-supervised learning combines supervised and unsupervised learning. Fig. 4 illustrates the different deep learning-based methods for fabric defect detection.

### 1) SUPERVISED LEARNING APPROACH

Supervised learning is the process of training an optimal model by having the network structure learn a large amount of sample data with labels. The model can generate a function that belongs to the set of functions through the correspondence between a portion of the input data and the output data that already exists, and then use this model to map all the inputs to the corresponding outputs and make simple judgments on the outputs to achieve the purpose of classification.

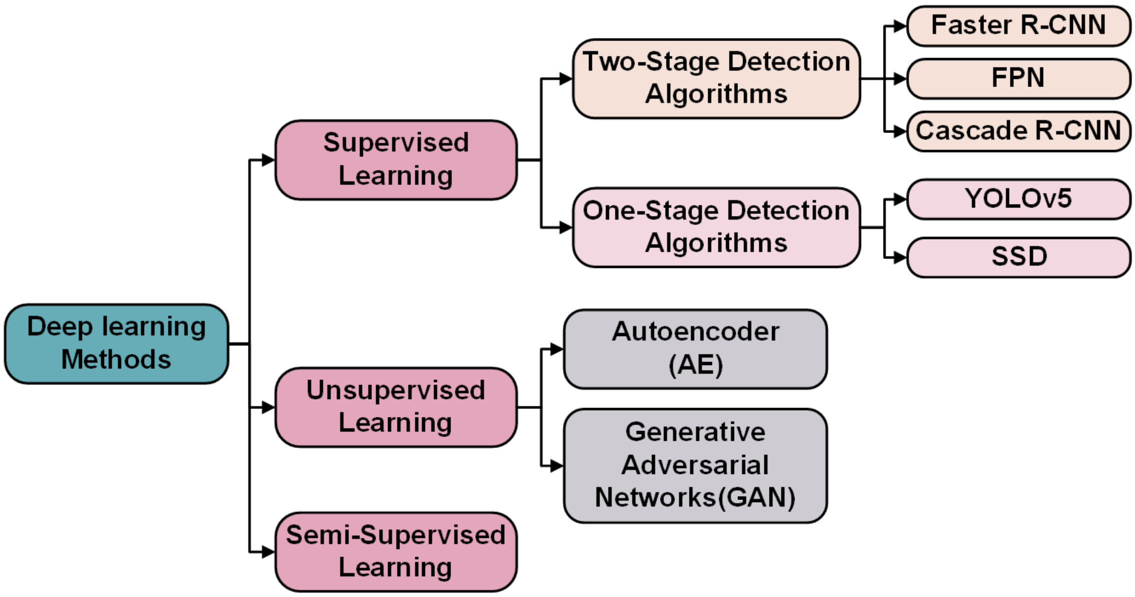



**FIGURE 4.** **Deep learning methods of fabric defect detection.**

Object detection is a typical application for this domain, it involves both object localization and image classification for multiple objects. The object detection algorithm falls into two categories: one-stage algorithm based on regression, and two-stage algorithm based on candidate frame generation and classification. The one-stage algorithm uses a single CNN to simultaneously classify and regress proposal frames, whereas the two-stage algorithm employs traditional image algorithms or trained CNNs to generate proposal frames, which are subsequently subject to classification operations and region adjustment. The one-stage algorithm generates one fewer proposal frame than the two-stage algorithm. The model frameworks for both algorithms are shown in Fig. 5.

*a: TWO-STAGE OBJECT DETECTION ALGORITHMS*

We present the process of proposing or improving the 6 basic models in the order in which the two-stage object detection models were proposed (R-CNN → Fast R-CNN → Faster R-CNN → R-FCN → R-CNN → FPN → Cascade R-CNN). Currently, the best and most widely used two-stage object detection models for fabric defect detection are Faster R-CNN [84], FPN [85], and Cascade R-CNN [86]. The Faster R-CNN model is a representative model that has inspired the development of numerous object detection and segmentation models. R-CNN [87] recognizes objects by labeling regions of interest in an image based on the basic structure of CNNs. However, since all candidate object regions in R-CNNs need to be extracted beforehand, this process is time-consuming and labor-intensive. In addition, the traditional CNNs require the input image to be normalized or resized to a fixed size, which can result in object stretching or information loss. To address these issues, a region of interest (RoI) pooling layer was introduced, leading to the development of Fast R-CNN [88]. In 2016, Ren et al. [84] proposed the Faster R-CNN model, which improved computational efficiency in region extraction by introducing a Region Proposal Network (RPN). Faster R-CNN utilizes shared convolutional layers to extract feature maps from the input image. These feature maps are then used as input to the RPN, which autonomously generates candidate regions. These candidate regions, along with the feature maps extracted from the convolutional neural network, are inputted into Fast R-CNN. The Fast R-CNN performs candidate region classification and boundary regression, resulting in a complete end-to-end CNN object detection model. The basic model framework of Faster R-CNN is depicted in Fig. 6.

To detect tiny fabric defects with extreme aspect ratios, Peng et al. [89] proposed the Priori Anchor Convolutional Neural Network (PRAN-Net). The PRAN-Net incorporated a Feature Pyramid Network (FPN) to maintain specific information about tiny defects. In addition, the authors devised a technique to generate sparse a priori anchors that effectively matched extreme aspect ratio defects, thereby reducing the number of redundant anchors and improving the accuracy and efficiency of detecting extreme defects. The defects were classified and refined using a classification network. When compared to one-stage algorithms, this method achieved a 7.2% and 7.4% improvement in detection accuracy on the denim dataset and plain fabric dataset, respectively, with a decrease in detection speed of less than 0.7 f/s. Compared to two-stage algorithms, the mean average precision (mAP) on both datasets was improved by at least 2.1% and 2.4%, leading to enhanced accuracy in detecting and localizing tiny and extreme fabric defects, while satisfying real-time detection requirements.

Fabric defect detection algorithms need to maintain a low computational cost while ensuring high detection accuracy, for which Wu et al. [90] proposed a wide-and-light network

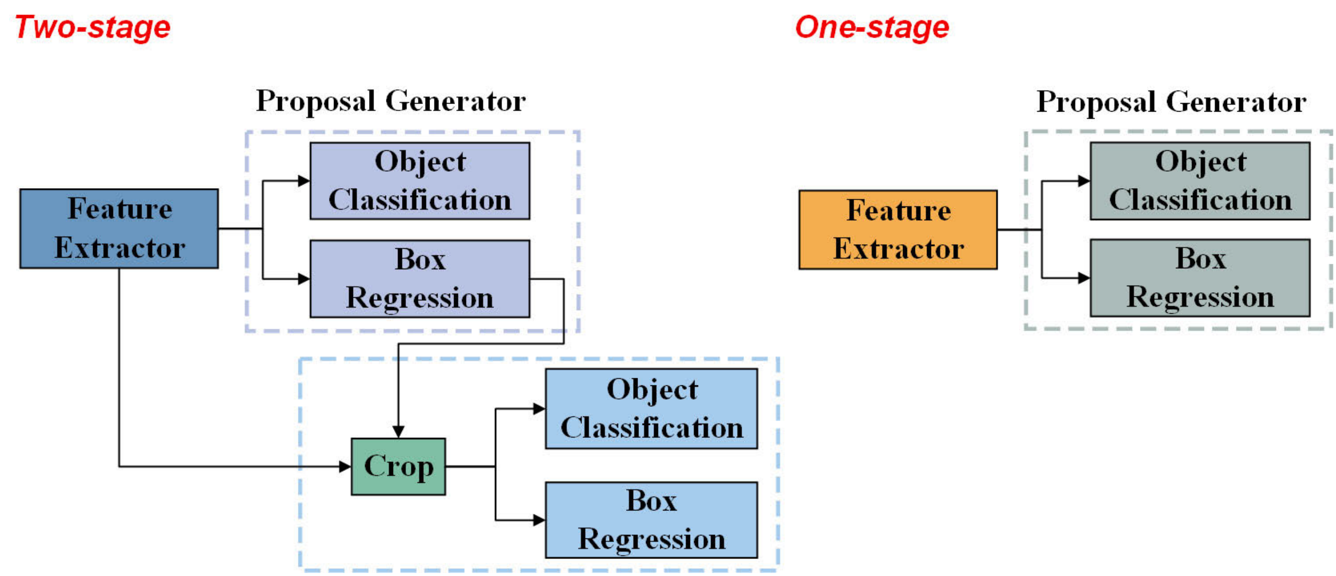



**FIGURE 5.** Modeling framework underlying two-stage and one-stage object detection algorithms.

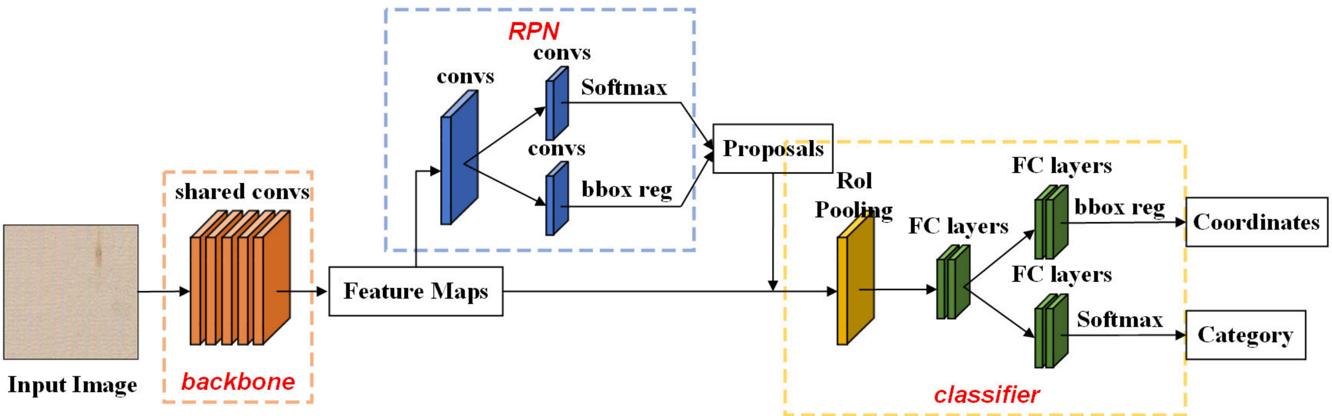



**FIGURE 6.** Basic modeling framework for Faster R-CNN.

(Walnet) structure based on Faster R-CNN. This structure incorporated multiscale convolutional kernels, dilatation convolution, and feature fusion to learn object features. Convolution, kernel decomposition, and bottleneck methods were employed to simplify feature extraction. Furthermore, a series of candidate frames with different sizes were designed to improve detection accuracy. Experimental results demonstrated that the proposed model achieved over 97% detection accuracy on white-gray fabrics, dark-red fabrics from the TILDA dataset, and mesh fabrics created in the laboratory. The model accurately detected common defects in fabrics while having a smaller network size compared to the Walnet model.

To address the interference problem caused by complex background textures in fabric defect detection, Chen et al. [91] proposed a genetic algorithm known as the Gabor Faster R-CNN (Faster GG R-CNN). This approach integrated the Gabor kernel into the Faster R-CNN for frequency analysis. They designed a two-phase training method based on the genetic algorithm (GA) and backpropagation to train the new Faster GG R-CNN model. The model had a strong detection ability for the four defects of the created complex texture dataset, with an average detection accuracy of 94.57%. The model effectively identified fabric defects of various backgrounds, locations, and sizes, including tiny defects or unevenly creased fabrics. However, for some fabric defects with larger sizes, the detection effect of Faster GG R-CNN was not as good as other methods. The model could be improved by multiscale feature extraction, however, the proposed method could not identify the color change region, which would be mistaken for stains.

Previous object detection algorithms, such as the Fast/Faster R-CNN models were divided into two parts: (1) a fully convolutional network consisting of shared parameters, and (2) a fully connected network with two branches after the RoI pooling layer. They did not share parameters, so each region needed to repeat the calculation, which would take a lot of time. To improve the detection speed, Dai et al. [92]

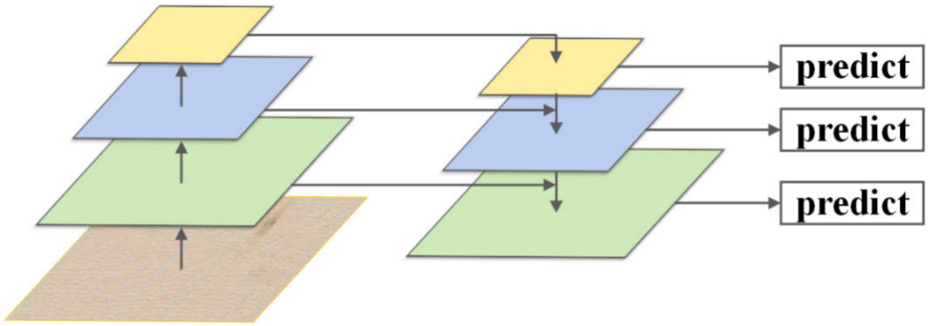



**FIGURE 7.** Basic modeling framework for FPN.

introduced the region-based fully convolutional neural network known as R-FCN, which adopts the latest ResNet neural architecture. They added a special convolutional layer at the end of the RPN network to construct a set of score maps sensitive to the location for each ROI, and at the same time, there was no further connection of other convolutional or fully connected layers after the pooling layer of the network, which shares the parameters. This further improved the accuracy and speed of the detection network. The basic model framework of R-FCN is shown in Fig. 7.

The high-level features have strong semantic information, and in the object detection problem, if the size of the object varies greatly, the receptive field of the highest feature layer is too large to recognize the small-sized object. To enhance the multiscale prediction performance of R-CNN, Lin et al. [85] first proposed the FPN structure as the neck. The FPN adds the multiscale feature fusion design to SSD, which utilizes the high-level feature mapping with rich semantic information. This gradually enhances the low-level feature mapping with rich geometrical details, facilitating the complementary nature of the multiscale features, also through the top-down process and the horizontal connection, to address the issue of low-level features lacking semantic information. This enhanced the detection of tiny objects and improved the detection accuracy of the model. The basic model framework of FPN is depicted in Fig. 8.

Zhou et al. [93] selected the lightweight framework of EfficientNets to enhance computational efficiency, and they proposed the L-FPN strategy to efficiently fuse multiscale features. In addition, they adopted the R-Compound Scaling to adjust the depth, width, and input resolution, to realize a range of detectors under various resource restrictions. By using the above strategies, the Efficient Defect detectors (EDDs) proposed in this article were experimented on the AliCloud Tianchi fabric defect dataset, and higher mAP was obtained with fewer parameters. Whereas the efficiency of the EDDs was high, it should be noted that EfficientNet was initially developed for natural images. As a result, there was room for further improvement in the design of the backbone. Furthermore, the accurate labeling of defect images was a labor-intensive and commercially costly task. The trend was to complete the training process with fewer labeled defect images.

Lu et al. [94] developed the channel-space adaptive augmented feature pyramid network CA-FPN, which performed an adaptive fusion of multiscale features by extracting intrinsic relationships between features at different scales. This approach enhanced the semantic information of defects while minimizing background interference. When combined with the anchorless detection strategy AutoAssign, the models achieved improved detection accuracy for nine types of defects on the AliCloud Tianchi fabric defect dataset, including small and large aspect ratio defects. These improvements were achieved without affecting detection time or increasing the model complexity. The model also exhibited strong generalization ability. Future research will focus on the structural optimization of the Swin transformer and the development of the semi-supervised learning approach.

In object detection, the definition of positivity and negativity relies on an intersection over union (IoU) threshold. When object detectors are trained with low IoU thresholds (e.g., 0.5), they often produce noisy detections, and their performance tends to degrade as the IoU thresholds increase. In 2018, Cai and Vasconcelos [86] introduced the Cascade R-CNN algorithm, which employs a multistage approach to train a series of detectors with gradually increasing IoU thresholds. Each detector utilizes the output of the previous detector to generate higher quality predictions. This architecture ensures a balanced distribution of positive and high-quality training samples for each network by defining high-quality intersection IoU thresholds. It also avoids false detections by reducing nonmaximum scores rather than suppressing the nonmaximum values directly, resulting in improved detection accuracy without the need for network modification or retraining. Refer to Fig. 9 for the basic model framework of Cascade R-CNN.

Li and Li [95] proposed three techniques to improve the accuracy of the Cascade R-CNN model. Firstly, they employed multiscale training to enable the input image to adapt to the box distribution of different scales. Secondly, a dimensional clustering method was used to cluster the widths and heights of defects dimensionally. Finally, soft nonmaximum suppression was implemented to prevent the

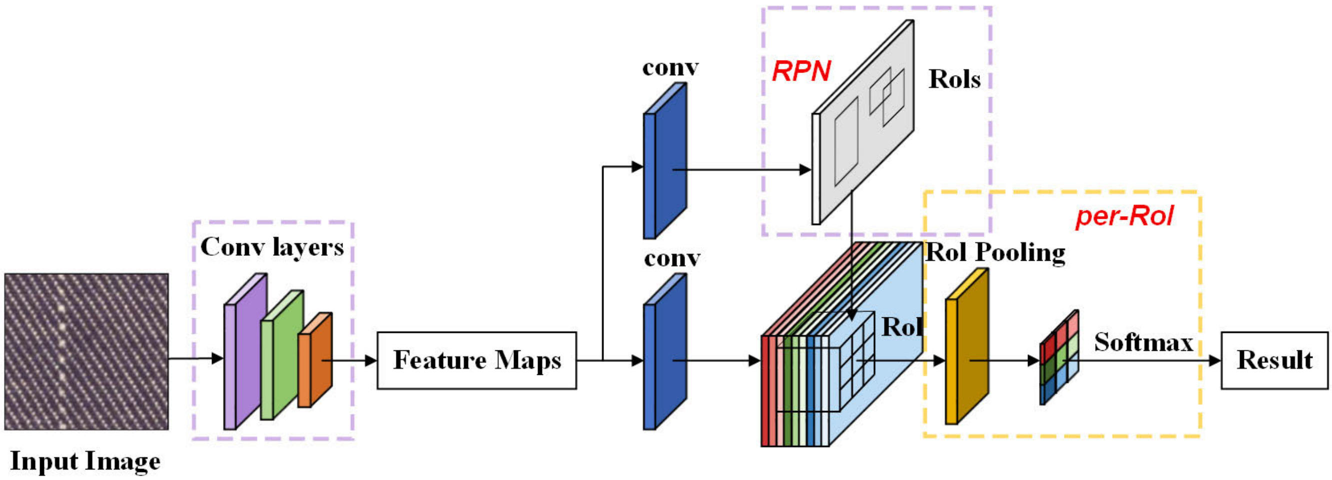



**FIGURE 8.** Basic modeling framework for R-FCN.

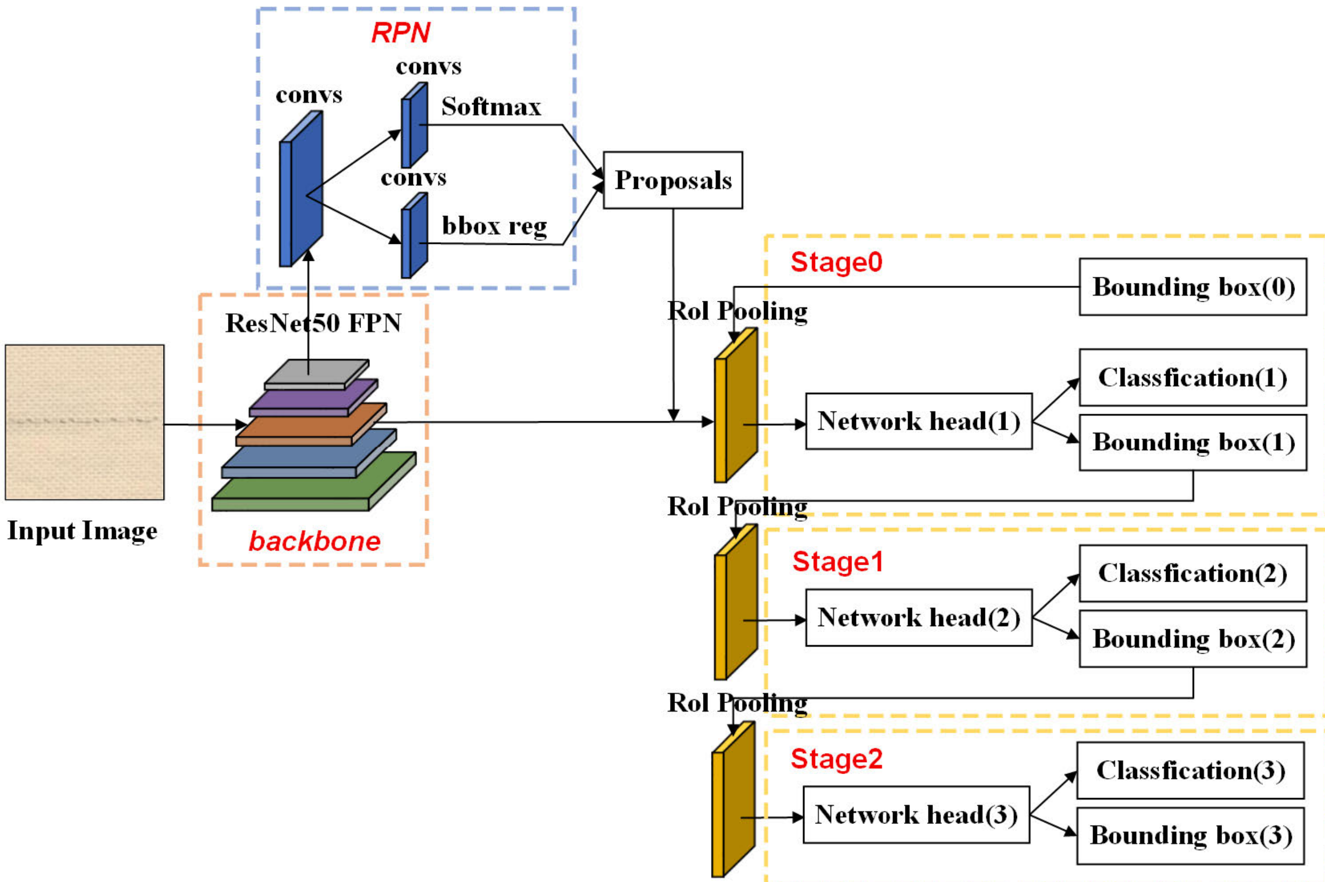



**FIGURE 9.** Basic modeling framework for Cascade R-CNN.

elimination of overlapping defect categories during repeated detection in the dataset. Experimental results demonstrated that these techniques effectively enhanced the accuracy of the detection algorithm on fabric datasets with highly unbalanced defect counts. Specifically, AP@.5 improved by 13.5%. Due to the limited availability of fabric defect datasets, the experiments were only conducted on defect datasets of unpatterned fabrics.

Despite some progress in deep learning-based fabric defect detection, most studies have focused on small-sized and simple fabric background images. Detecting fabric defects in complex backgrounds and large-sized images remains

**TABLE 6. A summary of two-stage detection algorithms.**

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| P. R. Peng *et al.* [89] | The Plain Fabric Dataset; The Denim Dataset | Oil stains; Coarse warp; Long coarse weft; Short coarse weft; Mispick; Knot; Three wire; Flower jump | ACC; mAP; Average Recall (AR); IoUs; FPS | A Priori Anchor Convolutional Neural Network (PRAN-Net) for Fabric Defect Detection |
| J. Wu *et al.* [90] | TILDA Dataset (White grey fabrics); Dark red fabrics; Grid fabrics | Broken yarns; Carryings; Holes; Fuzz balls; Scratches; Stains; Carryings; Broken yarns; Knots; | P; R; mAP | Wide-and-light network structure based on Faster R-CNN |
| M. Chen *et al.* [91] | Created dataset; Xuelang Manufacturing AI Challenge Contest Dataset | Stains; Holes; Floats; Broken weft; Missing weft; Double wefts; Broken end; Missing end | mAP; Run time; P; R | A Genetic Algorithm Gabor Faster R-CNN (Faster GG R-CNN) |
| J. Zhao *et al.* [97] | Textile factory collection (Untextured gray fabric; Checked gray fabric) | Ribbon yarn; Broken yarn; Cotton ball; Holes; Yarn shedding; Stains | P; R; mAP; F1; Loss value | Fabric defect detection system based on transfer learning and an improved Faster R-CNN |
| T. Zhou *et al.* [93] | Alibaba Cloud Tianchi Fabric Dataset | 20 common defects | mAP | Family of EDDs for fabric quality inspection |
| X. Y. Yu *et al.* [98] | Alibaba Cloud Tianchi Fabric Dataset | Sewing; Sewing print; Scrimp; Bug; Flaw; Color shade; Miss print; Hole; Fold | mAP; FPS; Model storage size (Param.) | An efficient scale-aware network (ES-Net) |
| J. Xiang *et al.* [99] | Smart Diagnosis of Cloth Flaw Dataset(SDCFD) | Warp defects; Weft defects; Regional defects | R; $D_R$ ; False detection rate($F_R$); Detection accuracy ($D_{ACC}$); mAP; FPS | Online inspection system for fabric defects based on deformed convolutional improved CenterNet |
| H. T. Lu *et al.* [94] | Alibaba Cloud Tianchi Fabric Dataset | Bug; Color shade; Flaw; Fold; Hole; Miss print; Scrimp; Sewing; Sewing print | mAP | A flexible anchor-free detector CA-AutoAssign is proposed by combining CA-FPN and an anchor-free detection strategy AutoAssign |
| F. Li and F. Li [95] | Textile factory collection | Knots; Three silk; Coarse picks; Broken spandex; Looped weft; Loose warp; etc. | mAP; AP@.5 | Improvement of Cascade R-CNN model using three techniques: multiscale training, dimension clusters method, and soft nonmaximum suppression |
| H. D. Li *et al.* [100] | Created dataset | | ACC; R; mAP | method of integrating deformable convolution and pyramid network in Cascade R-CNN (IDPNet) for fabric defect detection |
| L. Xue *et al.* [96] | Created dataset | Stains; Shade yarns; Sweing head; Broken figures; Mosquito ad; Stop marks; Wrinkles; Hole; Branch | mAP | Improvement of Cascade R-CNN model using three techniques: strategy of block detection, multimorphological Data Augmentation method, and improved the FPN module |
| S. Xin *et al.* [101] | Textile factory collection | Thin weave; Hole; 0il stains; Other | ACC; MR; FPS | Novel Multitask Cascade R-CNN model based on two-stage detection method |

a considerable challenge. In light of this, Xue et al. [96] selected the Cascade R-CNN as the baseline model, divided large fabric images into smaller chunks for training and detection, proposed a novel polymorphic data expansion method to augment the dataset size, enhanced the feature pyramid network module, and introduced the PAFPN model to improve defect detection accuracy. The proposed method achieved a detection accuracy of 78.93% on high-resolution fabric images, effectively addressing the detection of oversized defects, tiny defects, small defects, and dense defects. Future work can aim to further enhance the detection accuracy of small objects. Table 6 provides an overview of the methods utilized for two-stage object detection in fabric defect detection.

### *b: ONE-STAGE OBJECT DETECTION ALGORITHMS*

In recent years, the YOLOv5 algorithm [102] and the SSD algorithm [103] have emerged as popular one-stage object detection algorithms in the field of fabric defect detection. You Only Look Once (YOLO) [104] serves as the classical model for one-stage object detection, extracting global information from the feature map directly. In 2020, Glenn et al. [102] proposed the YOLOv5 model, an improved version of YOLO. The YOLOv5 model is available in four different versions: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5 × 4. The YOLOv5 model consists of four components: Input sides, Backbone, Neck, and Prediction. The Input side incorporates Mosaic data enhancement, adaptive anchor frame computation, and adaptive image scaling. The Backbone module includes the Focus, Conv structure, CSP layer, and SPP. The Neck part adopts the FPN+PAN structure. The detection side performs the final detection of three-scale feature maps based on the number of categories in the dataset. YOLOv5 strikes a balance between detection accuracy and speed. Fig. 10 illustrates the basic model framework of YOLOv5s.

Jin et al. [105] used a teacher-student framework to deal with the problem of insufficient images of fabric blemishes. The deep teacher network accurately identified fabric blemishes, while the shallow student network achieved real-time detection with minor performance degradation. In addition, multitask learning was implemented to detect prevalent and specific defects. The model was further improved by the

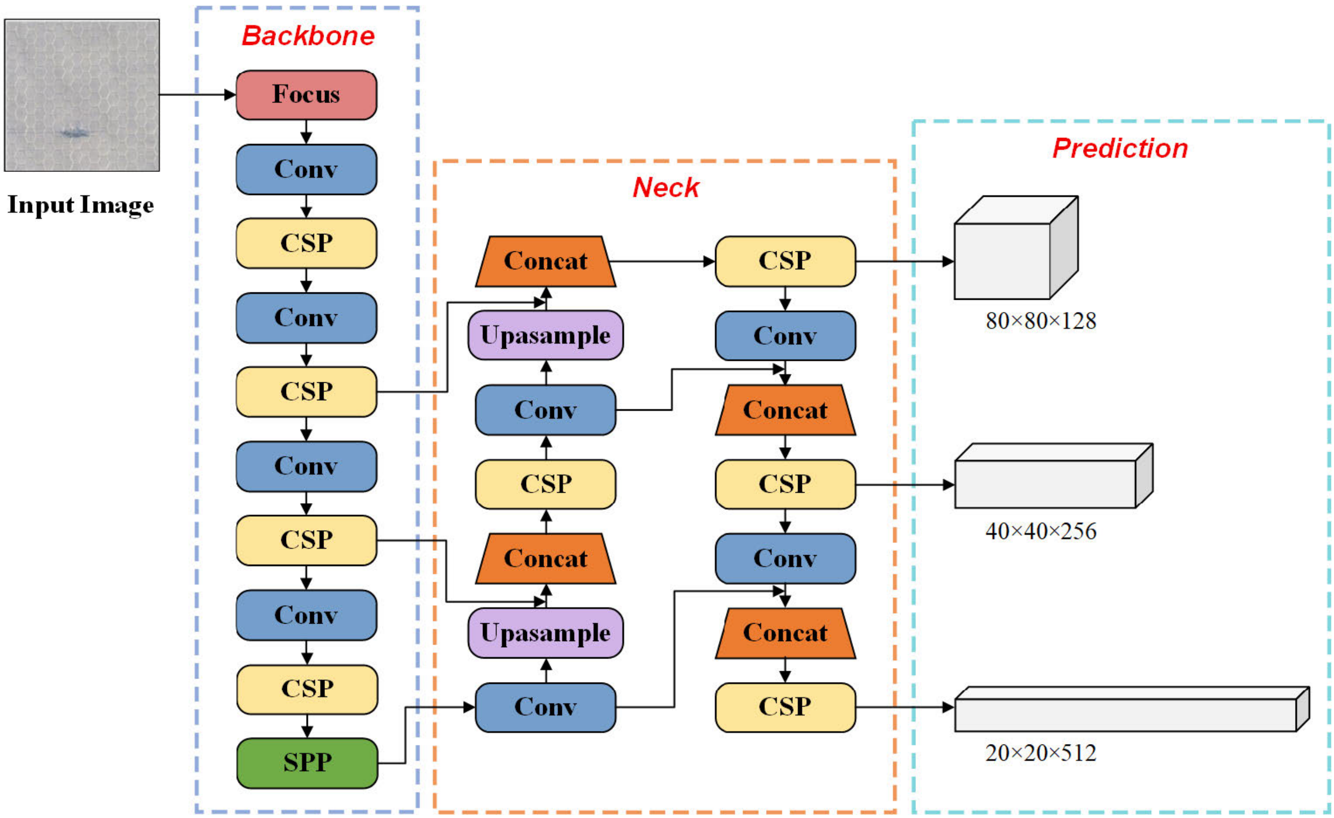



**FIGURE 10.** Basic modeling framework for YOLOv5s.

inclusion of a focal loss function and central constraints, enhancing recognition performance. They experimented with the proposed method on two publicly available datasets, Xuelang Tianchi AI and TILDA. The results demonstrated that although the student network was outperformed by other methods in detecting textile defects in collected images, the teacher network achieved the best detection performance. The student network provided an innovative approach for accurately detecting textile defects on embedded devices while minimizing time overhead.

To address the challenges posed by tiny flaws, defects with extreme length-to-width ratios, and long inspection times, Lin et al. [106] proposed a novel approach. They introduced a sliding window multihead self-attention regime, and replaced the original FPN with BiFPN to effectively detect small objects. They also integrated the Swin Transformer module into the original YOLOv5 algorithm. Furthermore, they introduced a generalized focal-loss function to enhance the learning of positive samples and reduce the false detection rate. Experimental results demonstrated that the improved algorithm achieved a detection accuracy of 85.6% on the fabric dataset, with a mAP value increased of 4.2% to reach 76.5%. These results satisfied the real-time detection request of embedded devices. However, it should be noted that the improved algorithm required a larger number of model computation parameters and longer training time.

Yu et al. [107] proposed CS-YOLO, a progressively refined redistribution pyramid network with supervised attention, based on the YOLOv5 model. This network was designed for defect detection in complex scenarios. CS-YOLO aligned a dense feature pyramid network (AD-FPN) to refine scale differences, introduced a phased feature redistribution module (PFRM) to enhance the interactions between cross-layer features, and utilized adaptive semantic self-redistribution of global information. In addition, the Adaptive Feature Purification Module (AFPM) enhanced the network's ability to discriminate flaws from complex contexts. Experimental results on the Tianchi fabric dataset show that CS-YOLO achieved a mAP value of 80.8%, surpassing other methods by 4.1% compared to the baseline YOLOv5. The network achieved a detection speed of 87 f/s and demonstrated strong model generalization capability.

Numerous model variations were introduced to enhance the candidate region selection method when Faster R-CNN was initially proposed. In 2016, Liu et al. [103] presented an alternative network called Single Shot MultiBox Detector (SSD), which selects the default box through the construction of a multiscale feature map. The base model for SSD is VGG16. To enhance the detection capability, an additional convolutional layer is added on top of VGG16 to obtain more feature maps. The architecture consists of a basic feature layer, an additional feature layer, a convolutional predictor for detection, and non-maximum suppression (NMS). The

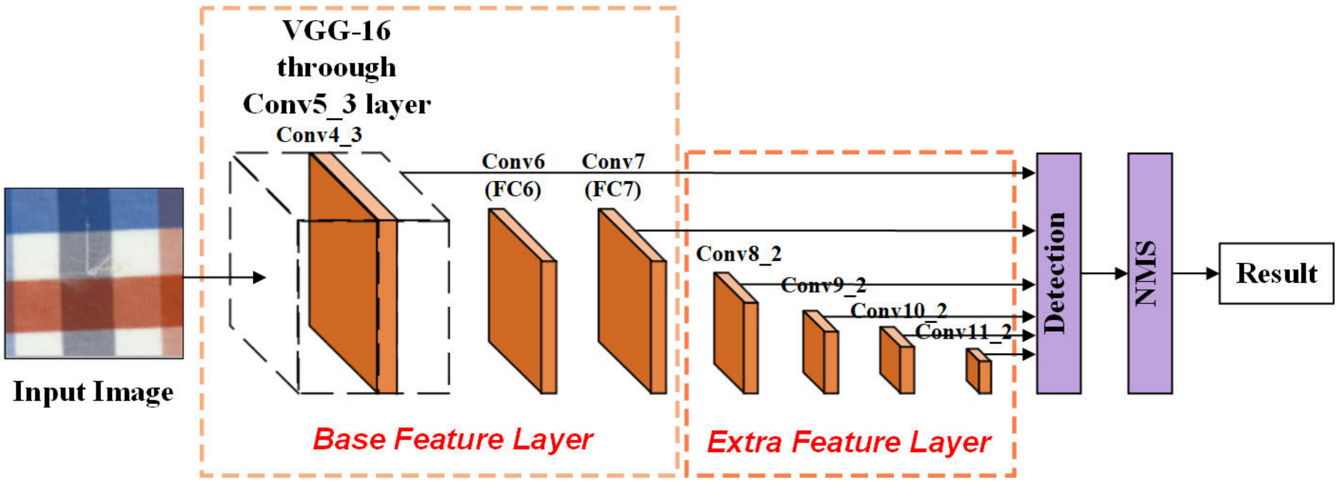



**FIGURE 11.** **Basic modeling framework for SSD.**

convolutional predictor is a subnetwork that consists of two parallel convolutional layers for regression and classification. Fig. 11 illustrates the framework of the base model of SSD.

Liu et al. [108] first used an object detection algorithm to detect fabric defects. They improved the existing SSD model by adding a third feature layer and utilizing the feature information from the underlying feature layer to enable small object detection. This enhancement made the improved SSD model more suitable for fabric defect detection. The improved model outperformed the classical SSD object detection model in terms of object retrieval capability and detection accuracy in the fabric domain. With the addition of training datasets and data types, the model could be further improved to enhance its sharing mechanism and real-time performance.

To address the challenges posed by complex and variable defect shapes, He et al. [109] proposed an adaptive fabric defect detection method based on the DenseNet-SSD algorithm. Instead of using the VGG16 backbone network in the SSD algorithm, they utilized the DenseNet network. This choice enhanced the transfer between feature mappings, mitigated the issue of vanishing gradients, and reduced the number of network parameters. Through experiments, they achieved an accuracy of 78.6% mAP and a detection speed of 61 f/s on a test set that included untextured fabrics, striped fabrics, and lattice fabrics.

Whereas the SSD-based model offers fast detection speed, it lacks sufficient detection accuracy. To strike a balance between speed and accuracy, Xie et al. [110] incorporated the full convolutional squeezing excitation block (FCSE) into the traditional SSD. This adjustment allowed for the adaptation of the number of default frames, enabling the detection of long defects on fabric surfaces. Experimental results on the TILDA and Xuelang datasets confirm that their SSD-based detection method improved detection accuracy by 3.6% and F1-measure (F1) by 5.3% compared to the original SSD algorithm. In addition, it could accurately and rapidly detect a wide range of defects on periodical and patterned fabric surfaces. However, the detection accuracy of the improved model was only 47.1% when it came to detecting defects in the solid-color texture background. Future work can focus on defect segmentation at the pixel level.

To effectively detect small defects and defects in colored fabrics, Zhao and Zhang [111] proposed an adaptive multi-scale fabric defect detection model called SE-SSDNet. The model combined the Squeeze-and-Excitation (SE) module with the SSD network to enhance its detection capability. The model improved the network's attention mechanism by incorporating SE modules into the SSD detection network. This enhancement improved detection efficiency and adaptability. It also utilized large-scale feature maps for detecting smaller defects and small-scale feature maps for detecting larger defects, effectively addressing the asymmetry. Test results demonstrated that the model could successfully detect flaws in textures of varying complexity. Compared with the three methods S_MobileNet, S_EfficientNet, and SSD, it achieved an average accuracy of 81.7%, significantly improving the accuracy and efficiency of fabric defect detection. The SE-SSDNet performed well in detecting monochromatic fabrics, however, it struggled to detect blemishes in brightly colored fabrics. Furthermore, the model's accuracy does not meet the requirements of practical detection, which can be improved by adjusting the fabric parameters. Table 7 provides a summary of the one-stage object detection algorithms used for fabric defect detection.

#### 2) UNSUPERVISED LEARNING APPROACH

Due to the difficulty in obtaining and labeling data, researchers have started to explore unsupervised learning approaches for solving fabric defect detection problems. Unsupervised learning involves training general-purpose networks with a small amount of unlabeled data, with the main objective of pre-training models (such as discriminators or encoders) that can be used for other tasks, achieving classification. In unsupervised learning, an algorithm is used to process a series of unlabeled training data, aiming to discover

**TABLE 7.** A summary of one-stage detection algorithms.

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| R. Jin *et al.* [105] | Xuelang Tianchi AI Challenge Dataset; TILDA Dataset | Puncture hole; Knots; Rubbing hole; Thin spinning; Jumps; Hanging warp; Lacking warp; Brushed hole; Stains; Scratch; Carrying; Others | area under the ROC curve (AUC) and mAP | Improved YOLOv5 Object Detection Algorithm for Handling Shortage of Fabric Defect Images Using Teacher-Student Architecture |
| S. Zhou *et al.* [112] | Created dataset (checkered gray fabric) | Ribbon yarn; Broken yarn; Cotton ball; Holes; Yarn shedding; Stains | P; R; F1; mAP | YOLOv 5s-4SCK algorithm by improving YOLOv 5s object detection algorithm |
| G. J. Lin *et al.* [106] | Alibaba Cloud Tianchi Fabric Dataset | Colorfly; Singeing; Knot; Warp loosening; Colorout; Warper's knot; Hole; Coarse | P; R; mAP; FPS; Parameter size of the model | A sliding window multihead self-attention mechanism is used to detect small objects, and the Swin Transformer module is introduced to replace the main module in the original YOLOv5 algorithm |
| X. Y. Yu *et al.* [107] | Alibaba Cloud Tianchi Fabric Dataset | Sewing; Sewing print; Scrimp; Bug; Flaw; Color shade; Miss print; Hole; Fold | mAP; Param.; FPS; GFLOPs | Three novel components (AD-FPN, PFRM, and AFPM) form a progressive redistribution pyramid network CS-YOLO that can be applied |
| Z. F. Liu *et al.* [108] | Created dataset | Holes; Oil; Surface debris; Longitude; Weft broken; Other | Test Result Chart; Object loss | A novel SSD model for fabric defect detection |
| X. Y. He *et al.* [109] | Created dataset (Untextured fabric, Striped fabric, Checkered fabric) | Broken holes; Stains; Warp breaks; Weft breaks; Felter; Thick knots | mAP; FPS | Adaptive fabric defect detection method based on DenseNet-SSD algorithm defect detection |
| H. S. Xie *et al.* [110] | TILDA Dataset; Xuelang Manufacturing AI Challenge Contest Dataset | Hole; Spot; Wire; Dark thread; Clip mark; Tight end; Crackiness | P; R; F1; mAP; FPS | Fabric defect detection algorithm by adding Fully Convolutional Squeeze-and-Excitation (FCSE) block to conventional SSDs |
| H. Q. Zhao and T. S. Zhang [111] | Textile defect detection dataset from Xi'an Polytechnic University；Created dataset | Podong; Maobian; Huangze; Duanjingwei; Dimo | ACC; Loss curve (Loss) | Method based on a combination of two networks, SE and SSD, namely the SE-SSD Net method |

underlying structures or distributions in order to gain more insights about the data.

Popular unsupervised learning approaches for fabric defect detection in this field are Autoencoder (AE) [113], [114] and Generative Adversarial Networks (GAN) [115]. An Autoencoder is a typical unsupervised learning algorithm that consists of three neural networks: an encoder, a decoder, and an implicit layer. It is designed to extract hierarchical features from high-dimensional complex input data and obtain a distributed feature representation of the original data using unlabeled data. The encoder compresses the image information into lower dimensions and then reproduces the image in a way that similar images will have similar encodings. On the other hand, the decoder reconstructs the original image from the encoded vector.

The Generative Adversarial Network is an unsupervised learning framework that includes both the generator and discriminator models. It aims to learn a generative model that accurately represents the distribution of training data through the competition between the discriminator and the generator. Taking noisy samples as input, the generator outputs new data, while the discriminator is trained to distinguish between real data samples and generated samples. The training process involves optimizing the discriminator to maximize the log-likelihood of correctly assigning labels to both true training samples and false generated samples, while the generator is trained to minimize the objective function to prevent the discriminator from incorrectly labeling the generated samples. This adversarial process allows the generator to synthesize more realistic samples.

To improve the discriminatory nature of fabric defect detection, Li et al. [116] conducted a study in which they trained a Fisher's criterion-based stacked denoising autoencoder (FCSDA) using fabric image patches of equal size. They classified the patches in the test set as either defective or nondefective, computed the residuals between the reconstructed image and defective patches, and used a thresholding method to localize the defects. The FCSDA method outperformed the image decomposition method (ID) and SDA in terms of localization accuracy and overall detection rate (ODR) on both periodic pattern fabrics and complex jacquard pattern warp knit fabrics. However, this method required both examples of defective patches and labeling of the data for model training.

Mei et al. [117] utilized a convolutional noise reduction self-encoder network to reconstruct image blocks at multiple levels of the Gaussian pyramid. They used the reconstructed residuals of each image block as a metric for direct pixel prediction. To generate final detection results, they segmented and synthesized the reconstructed residual maps, which highlighted the defective regions at each level of resolution using a CDAE network. The approach demonstrated the ability to train a model with a limited number of defect-free samples and achieve intelligent detection for multiple types of textile fabrics and defects on two public datasets and one created dataset. However, further improvements are needed to enhance the accuracy and stability of the model, particularly, for more complex patterned fabric textures.

Aiming to address the problem of defect detection in fabrics with periodic patterns and solid color textures,

**TABLE 8. A summary of unsupervised learning approaches.**

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| Y. D. Li, *et al.* [116] | Periodic pattern and jacquard pattern fabrics | Broken end; Hole; Netting multiple; Thin bar; Dot | ACC; TPR; FPR; FPV | Fisher criterion-based stacked noise reduction self-encoder (FCSDA) |
| S. Mei *et al.* [117] | Created dataset; KTH-TIPS Dataset; Kylberg Texture Dataset；Created ms-texture dataset | | $D_R$; $F_R$; $D_{ACC}$; R; P; F1 | An unsupervised and efficient fabric defect detection model, MSCDAE, based on multi-scale convolutional denoising autoencoder networks |
| H. S. Xie *et al.* [118] | FID Dataset(Star, box, and dot pattern fabrics); TILDA Dataset(Solid color textured fabrics) | 5 to 6 defect types | TPR; FPR; PPV; NPV; F-Measure index | An algorithm based on Direction Template and Image Pyramid |
| G. H. Hu *et al.* [120] | The dataset created by Ngan *et al.*; TILDA Dataset; Created dataset | Holes; Broken yarn; Broken end; Dirty yarn; Knots. | TPR; FNR; FPR; PPV; ACC | The method extends the standard DCGAN, which consists of a discriminator and a generator, by introducing a new encoder component |
| J. H. Liu *et al.* [121] | Simple and complex texture dataset | Color spot; Oil stain; Knot; Broken end; Broken yarn; White strip | IoU; P; R; F−measure | A multilevel GAN was used to synthesize plausible defects in a defect-free fabric texture and a semantic segmentation network was trained |
| J. Liu *et al.* [122] | 2019 Guangdong Industrial Intelligence Innovation Competition; Textile factory collection | Rough dimensions; Knots; Holes; Three wires; Yarn; Stain; Broken yarn | mAP | Use the neural network to learn the distribution of defects, the improved GAN to train the defect block data, and Faster R-CNN to detect defects. |

Xie et al. [118] proposed a defect detection algorithm based on directional templates and image pyramids to localize the candidate defective image blocks by using the trained SDCAE model for image reconstruction. The algorithm achieved an average F-Measure of 69.58% for localization accuracy on FID Dataset and an F-Measure of 80.65% on solid-color fabrics in the TILDA Dataset. However, the algorithm only achieved defect localization at the block-level and could be further improved to achieve pixel-level defect detection.

The concept of the GAN was originally introduced by Goodfellow et al. [119]. Hu et al. [120] proposed an approach based on the deep convolutional generative adversarial network (DCGAN), which incorporated a new encoder component to reconstruct images without defects. In addition, it highlighted potentially defective regions by creating residual mappings and then generated binarized segmentation results by thresholding the residual mappings and likelihood mappings. This algorithm demonstrated insensitivity to illumination variations and image blurring, along with high detection accuracy and efficiency for both simple uniform textured fabrics and complex patterned fabrics. However, the algorithm did not consider the spatial dependency between pixels during detection, which may result in noisy segmentation. Therefore, future improvements can include introducing a Conditional Random Field (CRF) model to enhance accuracy and to integrate the method into an automatic defect detection system.

To address the complex diversity of fabric textures and defects, Liu et al. [121] proposed a method to synthesize reasonable defects in a defect-free fabric texture through a multilevel GAN, which utilized adversarial loss to train a defect fusion network to fuse the generated defects into defect-free samples, and the trained multilevel GAN continuously updated the existing fabric defect dataset to fine-tune the pre-trained semantic segmentation network for better detection of defects under different conditions. The network could detect defects of different types and sizes in both simple and complex background textures, achieving an average F-measure value of 96.2%, a defect recall rate of more than 96.8%, and 98.5% detection accuracy for all defects except knots on the simple texture dataset, and an average detection accuracy of 97.0% on the complex texture dataset. Table 8 provides a summary of the unsupervised learning approaches for fabric defect detection. Table 9 compares the unsupervised learning approaches commonly used for fabric defect detection. It describes the strengths and weaknesses of each approach considered.

### 3) SEMI-SUPERVISED LEARNING APPROACH

Semi-supervised learning is the process of incorporating unlabeled samples into supervised classification algorithms to achieve semi-supervised classification and defect detection tasks with a minimum amount of labeled data and a large amount of unlabeled data. In this scenario, two sets of samples are involved: Labeled and Unlabeled, with a much smaller quantity of labeled samples (L) compared to unlabeled ones (U) (L $\ll$ U). Initially, a limited set of labeled samples is employed to train a network and produce a "partially trained" model. Subsequently, this partially trained model is utilized to label the unlabeled data, thereby generating "pseudo-labeled" data. A semi-supervised learning approach is created by combining the labeled data set with the pseudo-labeled data set, integrating the descriptive and predictive aspects of both supervised and unsupervised learning.

Zheng et al. [123] followed the MixMatch rule for complex data expansion. They introduced a new loss function computation method with a cropping technique for data expansion and proposed a convolutional neural network based on a residual structure for accurate defect detection. The algorithm was experimented on the DAGM texture dataset and achieved better performance with a small number of labeled samples.

To accurately construct the defective region boundary and locate the defects computationally, Zhou et al. [124] performed hybrid detection of fabric defects based on the

**TABLE 9.** Comparison Of fabric defect detection using unsupervised learning approaches.

| Method | Structure | Strengths | Weaknesses |
|---|---|---|---|
| Autoencoder(AE) | Encoder and decoder | ● Technical simplicity: reconstructing inputs<br>● Multilayer stackable<br>● intuitive<br>● Neuroscience-based research | ● Each layer is universally trained<br>● No global optimization<br>● Poor performance compared to supervised learning<br>● Multiple layers will fail |
| Generative Adversarial Networks(GAN) | Generator and discriminator | ● Global training for the entire network<br>● Easy to program and implement | ● Difficulty in training and conversion issues；<br>● Outperforms supervised learning only in specific situations<br>● Poor generalization capability |

**TABLE 10.** A summary about semi-supervised learning approaches.

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| X. Q. Zheng *et al.* [123] | DAGM 2007 Dataset | | TPR; True negative rate (TNR); Average accuracy | A generic semi-supervised deep learning-based approach for ASI |
| Q. H. Zhou *et al.* [124] | AITEX Datasets; DAGM 2007 Dataset | Broken yarn; Contamination; Broken pick | P; Sensitivity; F-Score; ROC; AUC | A hybrid semi-supervised method for fabric defect detection based on variational autoencoder(VAE) and Gaussian mixture model (GMM) |
| Y. Q. Huang *et al.* [125] | Dark Red Fabric(DRF); Light Blue Fabric(LBF); Patterned Texture Fabric(PTF); Fiberglass Fabric(FF) | Carrying; Thin bar; Knots; Fuzz balls; Warp; Weft; Stain; Line; Broken end; Hole; Netting multiple; Thick Bar | IoU; Location accuracy (P); the number of error detection and missing detection; FPS | A convolutional neural network consisting of two parts, a segmentation network, and a decision network, for defect segmentation and detection |
| L. H. Shao *et al.* [126] | FID Dataset; AITEX Datasets; TILDA Dataset | Multiple netting; Holes; Broken ends; Thin bars; Thick bars; Slender defects; Small defects | Balance error rate (BER); MioU; Mean pixel accuracy (MPA); Time | A pixel-wise semisupervised fabric defect detection method combined with multitask mean teacher (MT) |

variational autocoder (VAE) and the Gaussian mixture model (GMM). The VAE model was initially trained to extract features and reconstruct images of the positive samples. Subsequently, a GMM was integrated into the VAE to extract the encoder's feature vectors, and density estimation was conducted. The proposed algorithm was validated using the AITEX and DAGM 2007 public datasets, resulting in an AUC value of 0.982. The hybrid detection algorithm addressed the limitations of single detection methods and demonstrated strong performance in defect detection. Future research can focus on exploring approaches to handle variations in lighting conditions.

To solve the problem of data imbalance in actual production, Huang et al. [125] presented a two-part network model for defect segmentation and detection: a segmentation network and a decision network. Firstly, an untrained fabric dataset was fed into the segmentation network, and its output was used to train the decision network. Subsequently, the trained network was employed to localize defects. The method learned the potential features of defects using a small number of defect samples. Experimental evaluations were performed on three datasets encompassing various fabric textures and defect types. Remarkably, accurate segmentation results could be achieved with approximately 50 defect samples. This significantly reduced the need for extensive manual annotations and enabled real-time detection at a speed of up to 25 frames per second. Unsupervised learning can be explored further in the future research.

For the diversity of fabric defects and the low contrast between the defects and the background, Shao et al. [126] introduced a pixel-based semi-supervised fabric defect detection approach that incorporated a multitask mean trainer (MT). They proposed a multitask student and teacher network (ST-CNN) to incorporate defect contour and defect DM information as structural a priori into the fabric defect detection network. This enabled joint learning on labeled and unlabeled data. The ST-CNN utilized a multitask supervised loss for labeled data and a multitask consistency loss for unlabeled data. They conducted experiments on three publicly available fabric defect detection datasets and found that the approach was highly effective in detecting various defect types, including multiple defects, fine defects, and similarities between defects and background texture. It outperformed the current dominant MT-based pixel-by-pixel segmentation algorithms. However, the network's unit detection time was longer. Table 10 provides a summary of the semi-supervised approaches for fabric defect detection.

Additional deep learning approaches for fabric defect detection are presented in Table 11.

## V. APPLICATION

### A. PUBLIC DATASET OF FABRIC DEFECTS

Fabric defect detection remains challenging due to the scarcity of fabric defect samples. A limited number of samples can lead to low model accuracy and poor generative ability. Fig. 12 illustrates the percentage representation of defect datasets utilized in the references cited in this article. The widely used open dataset for fabric defects in the references is TILDA Dataset with a usage percentage of 18%. In addition, five other well-known fabric defect datasets, such as FID Dataset and Alibaba Cloud Tianchi Fabric Dataset

**TABLE 11.** Other deep learning algorithms used in fabric defect applications.

| Reference | Dataset | Defect Types | Evaluation | Proposed Method |
|---|---|---|---|---|
| G. D. Sun *et al.* [127] | TILDA Dataset(Plain weave fabric); Created dataset | Holes; Broken weft; Oil stain; Broken warp; Broken | Correct detection rate (CDR); Missing detection rate (MDR); $F_R$; Detection speed | A fast fabric defect detection framework (Fast-DDF) based on gray histogram back-projection |
| Q. Xiao *et al.* [128] | Created dataset(Ten kinds of fabric samples) | | ACC | Building a new objective evaluation method of fabric pilling by combining an integrated image analysis technology with a deep learning algorithm |
| J. Xiang *et al.* [129] | Created dataset; Alibaba Cloud Tianchi Fabric Dataset | Artificial folds; Double pick; Broken end; Broken warp | $D_R$; $F_R$; AUC; DACC | A deep learning-based defect detection framework for plain fabrics including two stages of local defect prediction and global defect recognition |
| Q. Liu *et al.* [130] | Created dataset (AliyunFD-10500; Kaggle; Actual photograph) | Line; Float; Hole; Stain | mAP; P; R; FPS | Improved YOLOv4 algorithm for a new SPP structure using SoftPool instead of MaxPool for fabric defect detection |
| A. Suryarasmi *et al.* [131] | Textile factory collection | Seam; Dirt; Fringe; Fold; Thread off; White spot; Uneven cloth; Selvage | F1; ACC; FNR | Lightweight CNN-based architecture for fabric defect detection |
| L. Cheng *et al.* [132] | AITEX datasets; DRIVE datasets | | ACC; R; Specificity; mIoU | Separation Convolution UNet (SCUNet) combined with convolutional downsampling, depth-separable convolution, and cross-parallel ratio loss function(IoU Loss) |

are referenced. While some datasets contain a substantial number of fabric images, creating exhaustive fabric datasets remains unfeasible due to the wide variety of fabric defects, morphological variations, and challenges in observation and recognition. Furthermore, collected fabric images often suffer from noise interference, such as external objects, flashes of light, fold marks, and blurring, among others. Consequently, the number of usable images is limited. There is currently no standardized dataset available encompassing all types of fabric defects. It is worth noting that 40% and 13% of the researchers opted to create their own datasets for their respective studies and went to textile mills to collect defect images for use in studying the effectiveness of the proposed algorithms. Recently, researchers have made efforts to create fabric image datasets, however, only a few of these datasets are publicly accessible. To support research in textile inspection automation, this article compiles a list of 12 commonly used open-source fabric image datasets as reference. The brief details and links of the datasets are shown in Table 12. Below are a few examples of some of the datasets.

#### 1) TILDA DATASET

The TILDA dataset is widely used in the references and is openly accessible in the public domain [133]. TILDA obtains 8 representative textiles such as solid color fabrics, periodic patterned fabrics, and patterned fabrics, among others. A total of 800 different images are generated, each of which has a size of 768×512 pixels. The dataset includes typical defects including hole, float, wire, and dark thread [134].

#### 2) FID DATASET

A fabric cycle pattern dataset provided by the Industrial Automation Research Laboratory of the Department of electrical and electronic engineering, University of Hong Kong, contains 156 fabric images of three types of fabrics: dot, star, and box. Each fabric contains 5-6 types of defects such as broken ends, holes, reticular multiple, thick rods, thin rods, and nodules. Specifically, the knot is a blemish unique to the dot pattern [93].

#### 3) ALIBABA CLOUD TIANCHI FABRIC DATASET

Alibaba Cloud Tianchi Fabric Dataset provides 9,576 (2446×1000) images for training, including 5,913 defect images and 3,663 normal images, each of which is labeled in detail. The annotated data are detailed with the specific location of the defects and the defect categories. The dataset consists of two types of fabrics, solid color fabrics and fancy fabrics, and covers 15 types of important defects such as flaws, color shade, and miss print in the textile industry, and each image contains one or more types of defects [56].

### *B. DEEP LEARNING FRAMEWORK*

Before applying deep learning algorithms to detect fabric defects, it is crucial to select a suitable framework for developing the algorithm. A deep learning framework encompasses tools, libraries, and resources necessary for deep learning development, including pre-trained models that facilitate automatic derivation, differentiation, and gradient mechanisms, thereby simplifying neural network implementation. In addition, these frameworks contain built-in components such as fully convolutional networks, convolutional networks, and other basic network components, which streamline coding tasks. Consequently, complex deep learning model development is greatly simplified using these frameworks.

In this article, we analyze the percentage of deep learning framework usage in fabric defect detection (Fig. 13). TensorFlow and PyTorch are the two most commonly used frameworks, with 57% employing TensorFlow and 43% utilizing PyTorch. These frameworks are highly popular in the field of deep learning due to their superior performance, coding convenience, visualization features, supportive communities,

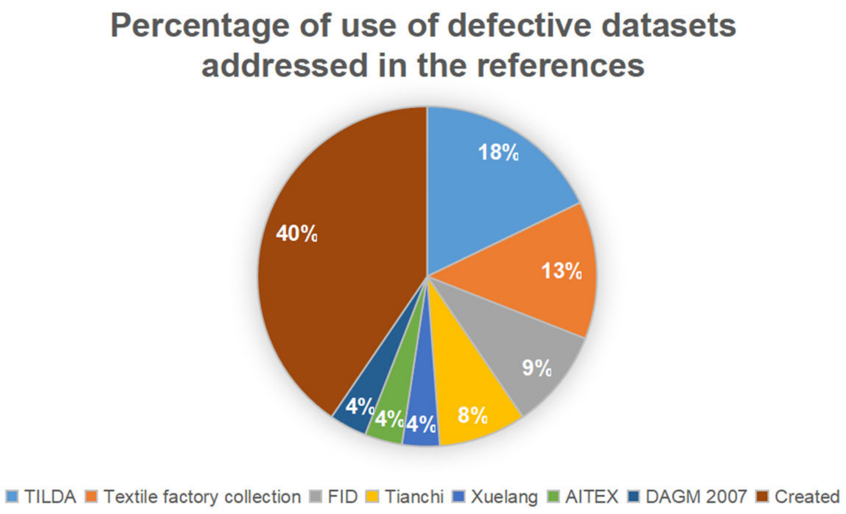



**FIGURE 12.** Percentage of use of defective datasets addressed in the references.

**TABLE 12.** Fabric defects public dataset.

| Name | Number of Images | Image Resolution | Source |
|---|---|---|---|
| TILDA Dataset | 8 Categories (700 TIFF images of 7 defective fabrics and 8 grayscale images; 100 images of defect-free fabrics) | 768×512 pixels | http://github.com/emfcamp/TiLDA |
| Alibaba Cloud Tianchi Fabric Dataset | 16 Categories (5913 images of 15 different defective fabrics; 3663 images of defect-free fabrics) | 4096×1696 pixels | https://tianchi.aliyun.com/competition/entrance/231666/information |
| FID Dataset | 3 Categories (Star Texture: 25 images of defective fabrics and 25 images of fabrics without defects; Box texture: 26 images of defective fabrics and 30 images of non-defective fabrics; Dot Texture: 30 images of defective fabrics and 30 images of non-defective fabrics) | 2560×1920 pixels | https://ytngan.wordpress.com/codes/ |
| Xuelang Manufacturing AI Challenge Contest Dataset | 10 Categories (1168 images of 9 different defective fabrics; 2163 images of defect-free fabrics) | 2560×1920 pixels | No data available |
| AITEX Fabric Image Dataset | 13 Categories (105 images of 12 different defective fabrics; 140 images of defect-free fabrics) | 4096×256 pixels | http://www.aitex.es/afifid/ |
| Fabric defect | 24 images and corresponding masked images | 512×512 pixels | https://github.com/msminhas93/FabricDefect |
| Fabric Stain Dataset | 2 Categories (398 images of color-stained defective fabrics; 68 images of defect-free fabrics) | 1920×1080 pixels 0r 1080×1920 pixels | https://www.kaggle.com/priemshpathirana/fabric-stain-dataset |
| Fabric defect Dataset | 3 Categories (281 images of fabrics with hole defects; 136 images of horizontally defective fabrics; 249 images of vertically defective fabrics) | 640×360 pixels | https://www.kaggle.com/rmshashi/fabric-defect-dataset |
| Smart Diagnosis of Cloth Flaw Dataset(SDCFD) | 2 Categories (Approximately 4,000 images of fabrics with color stains; Approximately 4,000 defect-free fabric images) | 4096×1696 pixels | No data available |
| DAGM 2007 Dataset | 6 Categories (150 images of fabrics with different defects; 1000 defect-free fabric images) | 512×512 pixels | https://hci.iwr.uni-heidelberg.de/node/3616 |
| Kylberg Texture Dataset | 28 texture images, each with 160 unique textures | 576×576 pixels | http://www.cb.uu.se/~gustaf/texture/ |
| KTH-TIPS Dataset | 11 texture images with 81 images per texture | 1280×960 pixels | http://www.nada.kth.se/cvap/datasets/kth-tips/download.html |

and language support. To better understand the differences between the two frameworks, Table 13 presents a summary of their unique features.

### C. FABRIC DEFECT DETECTION SYSTEM

Since the 1980s, computer vision technology has made significant advancements, enabling its application in various aspects of fabric quality control. Fabric defect detection systems can be categorized as online and offline detection systems. Online detection occurs during fabric production, allowing for timely adjustments based on defect detection; whereas offline detection in the fabric is completed after the finishing process. Currently, there are not many intelligent automatic fabric detection systems on the market, and there is no one solution for all types of fabrics and defects.

**TABLE 13.** Deep learning framework.

| Framework | Languages | Characterizations | GitHub Source |
|---|---|---|---|
| TensorFlow | Python/C++/Java/Go/R/Swift/C#/JavaScript | • Operating with Static Calculation Charts, Debugging requires tfdbg<br>• Code must be written manually and fine-tuned for distributed training<br>• Ability to display model diagrams, plot scalar variables, realize images, embedding visualization<br>• Deploying models in TensorFlow directly using TensorFlow Serving<br>• Programming is more difficult to get started<br>• Using dynamic diagrams, any debugging tool can be used<br>• Utilizing native support for asynchronous execution to asynchronous execution | https://github.com/tensorflow/tensorflow |
| PyTorch | Python/C++ | • Very simple and limited functionality, poor visualization<br>• No framework is provided for deploying models directly on the web<br>• The design is simple and easy to understand, so you can get started quickly | https://github.com/pytorch/pytorch |

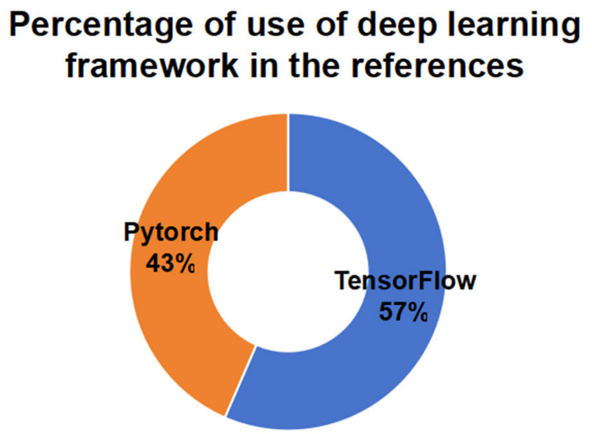



**FIGURE 13.** Percentage of use of deep learning framework in the references.

### 1) OFFLINE DETECTION SYSTEMS

A highly mature fabric inspection system available in the market is the Fabriscan defects automatic fabric inspection machine developed by the Swiss company Uster. This offline inspection system utilizes high-resolution cameras and neural network technology to detect a wide range of objects. The system operates in two main phases: first, the neural network is trained, and then the detection phase begins, during which the system categorizes identified abnormal areas and assesses the fabric's surface quality. The system is applicable to all kinds of complex fabrics, achieving a detection rate of approximately 90% and an inspection speed of 120 m/min, however, it is costly [135].

The FS220 photoelectric automatic fabric inspection machine developed by Shaanxi Changling Textile Electromechanical Technology Co. Ltd. in China is suitable for offline inspection of any visible defects. It utilizes machine vision and image processing technology and consists of a fabric hauling system, vision system, image processing system, control system, and marking system. With four CCD cameras, this machine captures fabric images and sends the image information to the industrial control machine. The fabric inspection speed is categorized into four grades: 15 m/min, 30 m/min, 60m/min, and 1200 m/min. The false judgment rate of this fabric inspection machine is under 15%, and it can inspect fabric with a width of 2200 mm, including the recognition of small defects [136].

The Uster Q-Bar 2 Fabric Inspector, also developed by Uster, is a fabric monitoring system that offers various algorithms for identifying specific defects and determining their causes. It is suitable for both online and offline inspection of visible defects. When a defect occurs in the fabric, the inspection system promptly responds to prevent widespread or recurring defects. This system can be applied from the loom to the entire roll, with a maximum width of work quality control reaching 2250 mm [137].

### 2) ONLINE DETECTION SYSTEMS

Belgium Barco has developed a loom online real-time monitoring system named Cyclops. By installing mobile cameras on the loom, the system can detect warp and fabric defects. Upon detecting defects, the system issues an alarm or shuts down the loom, while recording the defect location and characteristics. Additionally, the system categorizes the detected defects, stores them in a fabric quality dataset, and generates distribution maps and various quality reports. Cyclops has a simple hardware structure and is easy to maintain. However, it cannot detect weft defects and incurs high computational costs [138].

The IQ-TEX4 blank fabric automatic inspection system from Israel's EVS uses high-resolution color line scanning technology and an enhanced defect classification algorithm. It can simulate human vision to distinguish between defects and deformation, while offering real-time monitoring. For plain fabrics, this system achieves an online detection speed of 1000 m/min and can detect defects as small as 0.1 mm. One disadvantage is that the product's software update speed is sluggish and it lacks strong adaptability [139].

Germany's Opdix photoelectric technology company has developed an online textile inspection system that combines neural networks and sensors. This system is based on image processing and pattern recognition algorithms, with sensors placed on the surface of the fabric to detect defects such as oil, broken warp, holes, weft break, and jumping. It has high adaptability and can detect defects in fabric with a width of up to 2-3 meters, with a minimum resolution of 0.25 mm×0.25 mm.

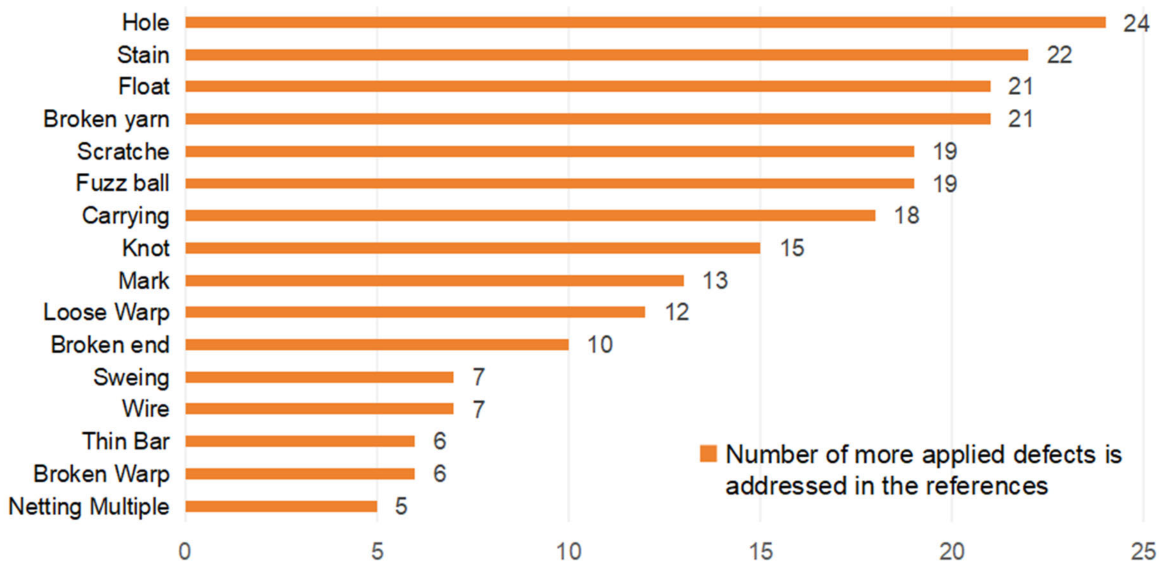



**FIGURE 14.** **The number of more applied defects is addressed in the references.**

The Web Ranger surface inspection system, produced by WINTRISS Engineering Technologies Inc. in the United States, utilizes hundreds of extracted images and unique image processing technology to accurately categorize different defects based on subtle differences in their characteristics. The system allows for modular settings that can be adjusted according to the width of the material being inspected, the production speed, and the size (resolution) of the defects. This comprehensive solution ensures fast and accurate detection of all defects during the online production process [140].

Although the above-mentioned automatic fabric inspection machines are mature and represent the most advanced products on the market, these systems are stable and their processing algorithms are more accurate and provide results in real-time, they have several drawbacks. These include high price and cost, and due to technical constraints, the effectiveness of problem solving is not enough, the system on the different fabric products of the general type.

## VI. DISCUSSION

Further to the above discussion, it is evident that computer vision inspection for textiles is a growing trend. The following results are derived by summarizing the references studied in this review:

### *A. NOMENCLATURE AND ANALYSIS OF FABRIC DEFECTS*

Fabric defects are defects presented on fabrics that may weaken their intended properties and affect the appearance of the finished product, these defects are manifested as color abnormalities, surface damage, irregular shapes, and texture changes. Most defects occur in or perpendicular to the direction of motion. Fabric defects can arise due to various reasons within each stage from spinning to the finished fabric. As spinning technologies evolve and fabric types become more diverse, fabric patterns also become increasingly intricate. Consequently, the types of fabric defects continue to expand, and the same defect may exhibit different characteristics in different fabrics. Furthermore, different people often use distinct terms to describe these defects, further complicating the categorization process. In this article, we categorize the defect types found in 93 related references on fabric defect detection, ultimately identifying 70 different types of fabric defects. Fig. 14 provides an overview of the defect types covered in these references, revealing that 16 types of defects appear in five or more references and the Holes, Stains, Floats, and Broken yarns are the most frequently encountered defects. Fig.15 illustrates the samples of the four types of defects. Hole (Fig. 15(a)) is a hole formed by the breakage of two or more adjacent yarns in a fabric, which can be caused by a variety of reasons, such as careless handling of the fabric, failure of machine parts, chemical corrosion, insect infestation, and control errors in the finishing process (burnishing, shearing, etc.) Stain (Fig. 15(b)) refers to discontinuous areas of off-color in the fabric, which is caused by contamination by foreign matter, such as dust, oil, or metal rust. Stain (Fig. 15(b)) refers to a discontinuous area in the fabric that is of a different color and is caused by contamination by foreign matter, such as dust, oil or rust, etc. Float (Fig. 15(c)) refers to a continuous section of yarn that spans two or more warps or wefts, and is caused by slackness in the warp yarns or faulty chaining of the yarns. Broken yarn (Fig. 15(d)) usually refers to the absence of a yarn in a section of the fabric. In addition, solid-color fabrics have smooth surfaces, no color changes, and fewer types of common defects, but the characteristic differences of each defect are small, making it difficult to perform accurate detection and classification. While multi-color fabrics have more color changes, complex patterns, and many types of defects, it is difficult to distinguish between the fabric

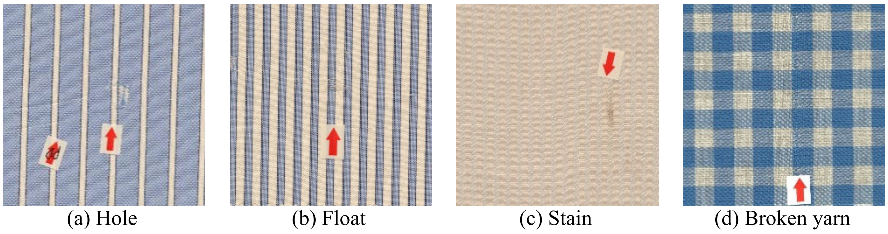



**FIGURE 15.** The samples of the four types of defects.

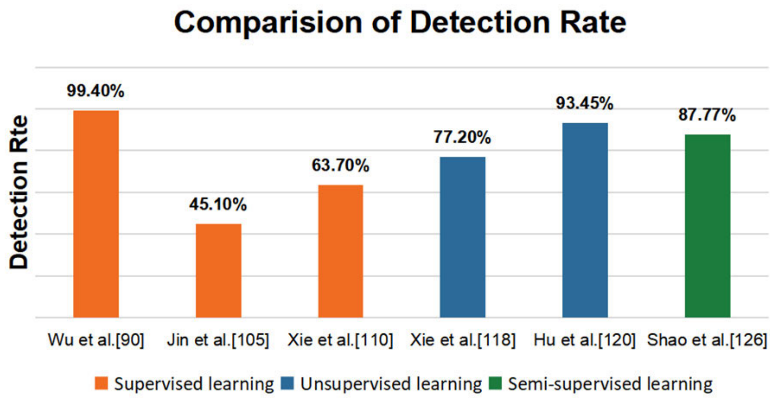



**FIGURE 16.** Comparison of detection rates of deep learning methods.

background and defects, and the detection is more difficult, requiring strong image processing capabilities.

### B. REVIEW OF METHODOLOGIES

Hanbay et al. [4] conducted a comprehensive analysis of various traditional methods, highlighting their respective strengths and weaknesses. Many of these approaches are limited in terms of effectiveness for specific defect categories, fabric types, or defect locations within the fabric. Meeradevi et al. [141] reviewed six different approaches for fabric defect detection using computer vision: structural, statistical, spectral, learning, hybrid, and others. Among these approaches, the deep learning model achieved the highest accuracy of 99.4%, demonstrating robustness against natural variations in raw data. The traditional defect detection methods rely heavily on external factors such as lighting conditions and background, leading to decreased accuracy when faced with environmental changes. Deep learning methods, on the other hand, can learn complex nonlinear input-output relationships, allowing for a wider range of applications. They also demonstrate strengths in robustness, adaptability to the environment, and accuracy, making them effective for industrial applications.

Deep learning methods have become the mainstream approach in fabric defect detection. Therefore, this article focuses solely on investigating deep learning methods. The retrieved references are categorized into three classifications: supervised learning, unsupervised learning, and semi-supervised learning. However, comparing the performance of these approaches based on deep learning is challenging due to the lack of fully harmonized evaluation metrics. To facilitate a fair comparison, this article selects several representative references from the widely used TILDA Dataset. Fig. 16 provides a general comparison of the detection results of supervised learning, unsupervised learning, and semi-supervised learning approaches on the TILDA Dataset. Although the evaluation metrics used are not exactly the same, they all measure the detection rate. Among the reviewed references, three papers are based on supervised learning, with reference [90] achieving the highest detection rate of 99.40%. There are two references and one reference based on unsupervised and semi-supervised learning approaches, respectively, with detection rates of 93.45% and 87.77%.

The supervised learning approach is widely adopted and characterized by high detection accuracy but necessitates an extensive amount of labeled sample data for model training. Obtaining fabric image samples is challenging in actual factory production, making this approach impractical. In comparison, the unsupervised learning approach does not rely on labeled samples or require laborious data labeling, making it suitable for more complex tasks. However, the convergence of detection models is difficult, and the accuracy does not match that of the supervised learning approach. In addition, evaluating the performance effectiveness of the unsupervised learning approach often mandates additional time for training and optimization. Semi-supervised learning offers an effective means of improving performance by utilizing unlabeled data but employs a more intricate approach, entails higher training costs, and results in reduced detection accuracy compared to using all labeled data.

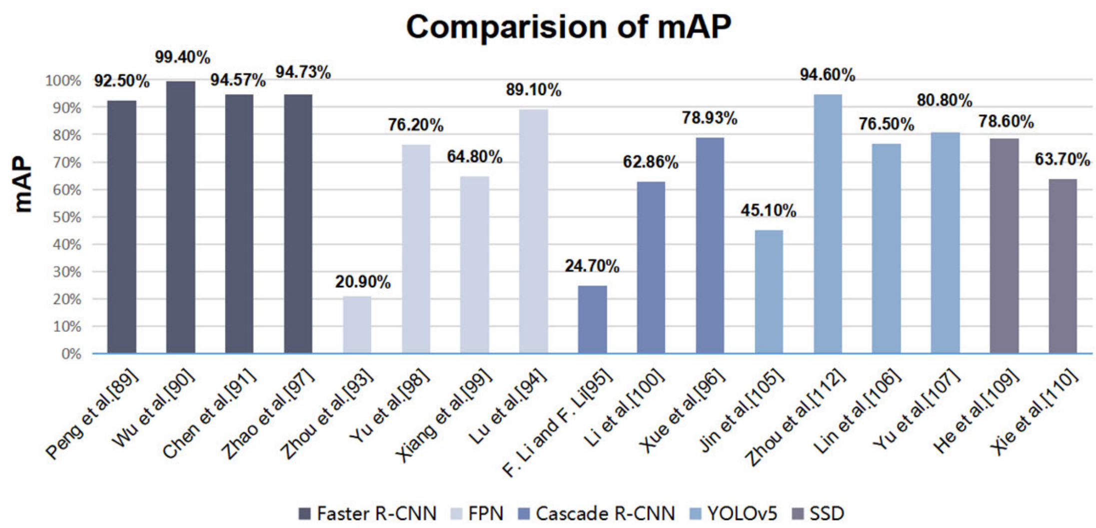



**FIGURE 17.** Comparison of mAP for supervised learning object detection algorithms.

The performances of object detection algorithms based on supervised learning are comparatively evaluated in the charts shown in Figures 15 and 16. These charts compare the best detection results of the algorithms proposed in the cited references using mAP and Frames Per Second (FPS) as evaluation metrics. mAP and FPS are the most commonly used indicators in object detection to assess algorithm effectiveness and guide algorithm adjustments. In Fig. 17, the Walnet model, based on Faster R-CNN and proposed in reference [90], achieved the highest mAP of 99.4% on white-grey fabrics from the TILDA Dataset, with over 97% mAP on the other two fabrics. In this article, we collate improved algorithms, building upon the Faster R-CNN model as the baseline, that achieved the best detection results with more than 92% mAP. On the other hand, Fig. 18 compares the FPS of the reference object detection algorithms. The considered references demonstrate one-stage object detection algorithms that excel in detection speed. Reference [107] proposed CS-YOLO, which exhibited the fastest detection speed of up to 87 f/s on the Alibaba Cloud Tianchi Fabric Dataset. In addition, reference [109] introduced the DenseNet-SSD model, and reference [106] presented the improved YOLOv5 model, achieving FPSs of 61 f/s and 58.8 f/s respectively, meeting the requirement for real-time detection.

Further analysis shows that the two-stage object detection algorithm provides deep semantic features of the object, resulting in higher accuracy and improved localization in fabric defect detection. It is particularly effective in detecting small defects and can further enhance detection accuracy through optimization techniques. However, this algorithm involves generating a large number of candidate regions, resulting in increased computation complexity. Consequently, it is slow, falling short of real-time detection requirements. In contrast, the one-stage object detection algorithm eliminates the need for candidate box generation, simplifying the detection process. It strikes a balance between speed and accuracy, exhibiting faster detection speed and meeting the demands of online detection. However, the detection accuracy of the one-stage object detection algorithm is relatively low, making it less suitable for detecting small-sized fabric defects and more susceptible to misdetection and missed detection. By improving the YOLOv5 model, as demonstrated in reference [112], the mAP of 94.6% was achieved on the fabric dataset. This significant improvement enhanced the detection accuracy of the one-stage object detection algorithm, bringing it closer to the performance of the two-stage object detection algorithm. Table 14 provides a comparison of supervised learning object detection algorithms, encompassing all commonly used deep learning methods for fabric defect detection. The table presents an overview of the strengths and weaknesses associated with each algorithm considered.

### *C. RESEARCH QUESTIONS*

Through the above discussion, we answer the research questions that guided the review and provide a concise summary of the main findings of the review as a means of obtaining conclusions and trends in the detection of fabric surface defects in recent years.

- **RQ1** What is the most frequently used defect type for fabric detection? Holes, Stains, Floats, and Broken yarns are the most frequently encountered defects.
- **RQ2** What are the most commonly used publicly available fabric defect datasets? The most widely used datasets in the literature are researcher-built datasets, which are usually constructed using images from publicly available datasets, and the most commonly used publicly available dataset is the TILDA database. Additionally, numerous researchers have opted to gather defect images directly from factories, demonstrating

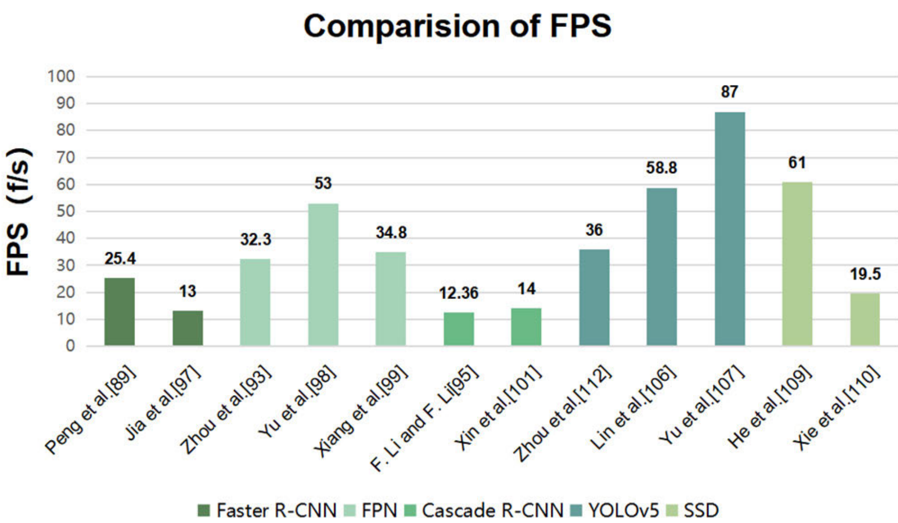



**FIGURE 18.** Comparison of FPS for supervised learning object detection algorithms.

**TABLE 14.** Comparison of fabric defect detection using object detecting algorithms.

| | Algorithm | Strengths | Weaknesses |
|---|---|---|---|
| One-stage object detection algorithms | YOLO Series | ● Fast detection, no need for complex frameworks<br>● Prediction based on whole picture information, better performance for global information<br>● Strong model generalization capability | ● Fixed number of objects that the network can detect<br>● Poor detection of small objects<br>● Lower accuracy and higher leakage rates |
| | SSD | ● Improved handling of multi-sized objects<br>● Can detect objects of different sizes<br>● Balancing the strengths and weaknesses of YOLO and Faster R-CNNs | ● Average recall for small objects<br>● Insufficient feature extraction for detection objects<br>● The model debugging process is very experience-dependent |
| Two-stage object detection algorithms | R-CNN Series | ● Better detection of small defects<br>● Training is simple, saves time and space<br>● Higher detection accuracy and lower recall rate for missed detections | ● Slower detection speed<br>● Complexity in calculating costs and inability to achieve real-time detection |
| | R-FCN | ● Further improve the accuracy of the test<br>● Simple network structure<br>● Reduces a large number of redundant calculations and dramatically increases the speed of detection | ● Alternate training patterns are not convenient and concise enough<br>● There is still some way to go before real-time object detection can be realized. |
| | FPN | ● Improved network handling of small objects<br>● Predictions can be made independently in different layers and high-level features can be fused with low-level features<br>● Can be combined with both single-phase and two-phase object detection algorithms | ● The cumbersome and inefficient detection process<br>● Large computational time costs<br>● Requires large amounts of memory |

their dedication to implementing intelligent fabric inspection in real-world settings.

**RQ3** In what ways are deep learning methods effective in detection compared to traditional methods? Deep learning methods can handle complex tasks with less interference from the background, leading to stable detection effects, high accuracy, flexible modeling, and elimination of the tedious parameter adjustment step, allowing for broader algorithm expansion.

**RQ4** What are the differences in detection performance between supervised, unsupervised, and semi-supervised learning methods? Current CNN-based supervised learning approaches for fabric defect detection can achieve high-precision detection when provided with abundant training data. The main drawback of these approaches is their heavy reliance on human labor for collecting and labeling training samples, which poses challenges in the context of large-scale industrial textile production. Unsupervised or semi-supervised learning approaches can help address the scarcity of labeled samples. However, unsupervised learning often lacks reliability and accuracy in detection compared to supervised learning. It makes them very useful for handling large amounts of unlabeled data, but they perform poorly in tasks such as classification. Semi-supervised learning offers a framework that combines supervised and unsupervised learning, enhancing the algorithm's generalization ability by utilizing unlabeled data and simultaneously ensuring the accuracy of learning using labeled data. Allowing for similar or even enhanced accuracy using a smaller number of labeled samples. Despite this potential, there is a scarcity of research and practical applications exploring automatic fabric defect detection approaches based on semi-supervised learning.

**RQ5** What are the strengths and weaknesses of two-stage and one-stage object detection algorithms, respectively? The two-stage algorithm exhibits higher accuracy, a lower false detection rate, and superior detection performance in large objects and complex scenes, albeit at a slower speed. Conversely, the one-stage object detection algorithm boasts a faster detection speed but is susceptible to higher false detection rates when localizing and detecting small objects.

## VII. CONCLUSION

This article categorizes the retrieved literature on fabric defect detection into two main categories: traditional methods and learning-based methods. It focuses primarily on deep learning methods and introduces the fundamental principles of supervised learning, unsupervised learning, and semi-supervised learning. The article also outlines the basic model framework of commonly used object detection algorithms for fabric defect detection, surveys and reviews recent deep learning methods, and analyzes their strengths, weaknesses, and scope of application. In addition, it organizes 12 commonly used public datasets for fabric defects, summarizes commonly used deep learning frameworks, and elaborates on the progress of fabric inspection systems worldwide.

The continuous development and application of computer vision technology results in improved detection accuracy, enabling the identification and categorization of even minute defects. Moreover, the use of high-speed image processing technology and parallel computing technology enhances the detection speed, facilitating real-time detection and classification of fabrics in high-speed production lines. the detection algorithms are being continuously optimized to improve accuracy and speed across various types of fabric and defects.

Future work in fabric defect detection encompasses the following areas:

1) For the defect detection task, the dataset is key. Establishing a larger and more public dataset of fabric defects to expand the dataset. Consider using existing publicly available datasets to build more generalized datasets.

2) Defect image capture is also an important part of the impact of fabric defect detection, image acquisition of equipment information, lighting conditions, and acquisition methods may have an impact on the detection results, how to capture high-resolution, low-noise, high-quality defective sample images can be used as one of the directions for future consideration.

3) Addressing the scarcity of publicly available data resources, the high cost of manual dataset labeling, variety of fabric defects, and sample imbalance by focusing on training networks without labeling, aiming for unsupervised or small sample learning.

4) Increasing research on hybrid methods, combining the strengths and weaknesses of different methods, the characteristics of different fabrics and their defect types, and the requirements of different industrial production, including both deep learning and traditional methods or classical machine learning methods, increase detection accuracy, and real-time performance by improving and optimizing models.

5) Enhancing the robustness of defect detection algorithms and then putting proven detection algorithms into practical production to meet the evolving needs of the textile industry, as most existing methods are only suitable for specific defect types or datasets.

6) There is a current trend of applying algorithms developed for detecting other surface defect types to fabric defect detection. Similarly, algorithms designed for detecting fabric defects could also be extended to detect other types of defects, thereby advancing the field of intelligent defect detection.

In conclusion, fabric defect detection technology has made significant progress. However, challenges remain, particularly regarding adaptability to different fabric types and the detection of complex defects. Moving forward, the continuous development and application of computer vision technology will contribute to further advancements and practical applications of fabric defect detection technology.

## REFERENCES

[1] A. Kumar, "Computer-vision-based fabric defect detection: A survey," *IEEE Trans. Ind. Electron.*, vol. 55, no. 1, pp. 348–363, Jan. 2008, doi: 10.1109/TIE.1930.896476.

[2] Z. Zhan, J. Zhou, and B. Xu, "Fabric defect classification using prototypical network of few-shot learning algorithm," *Comput. Ind.*, vol. 138, Jun. 2022, Art. no. 103628, doi: 10.1016/j.compind.2022.103628.

[3] E. Shady, Y. Gowayed, M. Abouiiana, S. Youssef, and C. Pastore, "Detection and classification of defects in knitted fabric structures," *Textile Res. J.*, vol. 76, no. 4, pp. 295–300, Apr. 2006, doi: 10.1177/0040517506053906.

[4] K. Hanbay, M. F. Talu, and Ö. F. Özgüven, "Fabric defect detection systems and methods—A systematic literature review," *Optik*, vol. 127, no. 24, pp. 11960–11973, Dec. 2016, doi: 10.1016/j.ijleo.2016.09.110.

[5] T. J. Kang, C. H. Kim, and K. W. Oh, "Automatic recognition of fabric weave patterns by digital image analysis," *Textile Res. J.*, vol. 69, no. 2, pp. 77–83, Feb. 1999, doi: 10.1177/004051759906900201.

[6] O. Alata and C. Ramananjarasoa, "Unsupervised textured image segmentation using 2-D quarter plane autoregressive model with four prediction supports," *Pattern Recognit. Lett.*, vol. 26, no. 8, pp. 1069–1081, Jun. 2005, doi: 10.1016/j.patrec.2004.10.002.

[7] S. Ozdemir and A. Ercil, "Markov random fields and Karhunen–Loeve transforms for defect inspection of textile products," in *Proc. IEEE Conf. Emerg. Technol. Factory Automat.*, Kauai, HI, USA, Nov. 1996, pp. 697–703, doi: 10.1109/ETFA.1996.573989.

[8] X. Yang, G. Pang, and N. Yung, "Robust fabric defect detection and classification using multiple adaptive wavelets," *IEE Proc.-Vis., Image, Signal Process.*, vol. 152, no. 6, p. 715, Dec. 2005, doi: 10.1049/ip-vis:20045131.

[9] J. Vaddin and S. Subbaraman, "Modelling of plain weave fabric structure and its use in fabric defect identification," in *Proc. Eur. Modeling Symp.*, Pisa, Italy, Oct. 2014, pp. 132–137.

[10] F. S. Cohen, Z. Fan, and S. Attali, "Automated inspection of textile fabrics using textural models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 13, no. 8, pp. 803–808, Aug. 1991, doi: 10.1109/34.85670.

[11] X. B. Yang, "Fabric defect detection of statistic aberration feature based on GMRF model," *J. Textile Res.*, vol. 34, no. 4, p. 26, Apr. 2013, doi: 10.13475/j.fzxb.2013.04.002.

[12] H.-G. Bu, X.-B. Huang, J. Wang, and X. Chen, "Detection of fabric defects by auto-regressive spectral analysis and support vector data description," *Textile Res. J.*, vol. 80, no. 7, pp. 579–589, Jul. 2009, doi: 10.1177/0040517509340599.

[13] J. Zhou, H. G. Bu, and J. Wang, "Feature extraction using auto-regression spectral analysis for fabric defect detection," *Adv. Mater. Res.*, vols. 175–176, pp. 366–370, Jan. 2011, doi: 10.4028/www.scientific.net/amr.175-176.366.

[14] Y. Zhang, G. Jiang, J. Yao, and Y. Tong, "Intelligent segmentation of jacquard warp-knitted fabric using a multiresolution Markov random field with adaptive weighting in the wavelet domain," *Textile Res. J.*, vol. 84, no. 1, pp. 28–39, May 2013, doi: 10.1177/0040517513485629.

[15] N. Ismail, W. M. Syahrir, J. M. Zain, and H. Tao, "Fabric authenticity method using fast Fourier transformation detection," in *Proc. Int. Conf. Electr., Control Comput. Eng. (InECCE)*, Kuantan, Malaysia, Jun. 2011, pp. 233–237.

[16] Y. Li and X. Di, "Fabric defect detection using wavelet decomposition," in *Proc. 3rd Int. Conf. Consum. Electron., Commun. Netw.*, Xianning, China, Nov. 2013, pp. 308–311.

[17] L. Chen, S. Zeng, Q. S. Gao, and B. Liu, "Adaptive Gabor filtering for fabric defect inspection," *J. Comput.*, vol. 31, no. 2, pp. 45–55, 2020, doi: 10.3966/199115992020043102006.

[18] C.-H. Chan and G. K. H. Pang, "Fabric defect detection by Fourier analysis," *IEEE Trans. Ind. Appl.*, vol. 36, no. 5, pp. 1267–1276, Oct. 2000, doi: 10.1109/28.871274.

[19] Z. Pan, N. He, and Z. Jiao, "FFT used for fabric defect detection based on CUDA," in *Proc. IEEE 2nd Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC)*, Chongqing, China, Mar. 2017, pp. 2104–2107.

[20] G. Lambert and F. Bock, "Wavelet methods for texture defect detection," in *Proc. Int. Conf. Image Process.*, Santa Barbara, CA, USA, 1997, pp. 201–204, doi: 10.1109/icip.1997.632054.

[21] P. Li, H. Zhang, J. Jing, R. Li, and J. Zhao, "Fabric defect detection based on multi-scale wavelet transform and Gaussian mixture model method," *J. Textile Inst.*, vol. 106, no. 6, pp. 587–592, Jul. 2014, doi: 10.1080/00405000.2014.929790.

[22] L. Yihong and Z. Xiaoyi, "Fabric defect detection with optimal Gabor wavelet based on radon," in *Proc. IEEE Int. Conf. Power, Intell. Comput. Syst. (ICPICS)*, Shenyang, China, Jul. 2020, pp. 788–793.

[23] A. Kumar and G. K. H. Pang, "Defect detection in textured materials using Gabor filters," *IEEE Trans. Ind. Appl.*, vol. 38, no. 2, pp. 425–440, Apr. 2002, doi: 10.1109/28.993164.

[24] B. Zhang and C. Tang, "A method for defect detection of yarn-dyed fabric based on frequency domain filtering and similarity measurement," *Autex Res. J.*, vol. 19, no. 3, pp. 257–262, Sep. 2019, doi: 10.1515/aut-2018-0040.

[25] J. Kim, H. Jo, J. Ri, and K. Han, "Automatic fabric defect detection using optimal Gabor filter based on hybrid beetle antennae search–gravitational search algorithm," *J. Opt.*, vol. 52, no. 4, pp. 1667–1675, Feb. 2023, doi: 10.1007/s12596-023-01126-9.

[26] S. Guan and X. Shi, "Fabric defect detection based on wavelet decomposition with one resolution level," in *Proc. Int. Symp. Inf. Sci. Eng.*, vol. 1. Shanghai, China, Dec. 2008, pp. 281–285.

[27] K. Sakhare, A. Kulkarni, M. Kumbhakarn, and N. Kare, "Spectral and spatial domain approach for fabric defect detection and classification," in *Proc. Int. Conf. Ind. Instrum. Control (ICIC)*, Pune, India, May 2015, pp. 640–644.

[28] L. Di, H. Long, and J. Liang, "Fabric defect detection based on illumination correction and visual salient features," *Sensors*, vol. 20, no. 18, p. 5147, Sep. 2020, doi: 10.3390/s20185147.

[29] Y. Xue Zhi, G. K. H. Pang, and N. H. C. Yung, "Fabric defect detection using adaptive wavelet," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Processing*, vol. 6. Salt Lake City, UT, USA, May 2001, pp. 3697–3700.

[30] M. Moezzi, A. Haji-Badali, and F. Barez, "Analysis of the wrinkle geometry of the woven fabrics during uniaxial bias extension test using Ricker wavelet algorithm," *Compos. A, Appl. Sci. Manuf.*, vol. 141, Feb. 2021, Art. no. 106230, doi: 10.1016/j.compositesa.2020.106230.

[31] V. Agilandeswari, J. Anuja, E. D. George, and R. Prasath, "Fabric quality testing using image processing," in *Proc. Int. Conf. Inf. Commun. Embedded Syst. (ICICES)*, Chennai, India, Feb. 2014, pp. 1–4.

[32] Y. Li, H. Luo, M. Yu, G. Jiang, and H. Cong, "Fabric defect detection algorithm using RDPSO-based optimal Gabor filter," *J. Textile Inst.*, vol. 110, no. 4, pp. 487–495, Oct. 18, 2018, doi: 10.1080/00405000.2018.1489951.

[33] S. Ma, W. Liu, C. You, S. Jia, and Y. Wua, "An improved defect detection algorithm of Jean fabric based on optimized Gabor filter," *J. Inf. Process. Syst.*, vol. 16, no. 5, pp. 1008–1014, 2020, doi: 10.3745/JIPS.02.0140.

[34] M. Boluki and F. Mohanna, "Inspection of textile fabrics based on the optimal Gabor filter," *Signal, Image Video Process.*, vol. 15, no. 7, pp. 1617–1625, Apr. 2021, doi: 10.1007/s11760-021-01897-3.

[35] Z. Wen, J. Cao, X. Liu, and S. Ying, "Fabric defects detection using adaptive wavelets," *Int. J. Clothing Sci. Technol.*, vol. 26, no. 3, pp. 202–211, May 2014, doi: 10.1108/ijcst-03-2013-0031.

[36] X. D. Gao, C. L. Wang, H. Zuo, and J. C. Liang, "Fabric blemish detection based on attributed relational histogram," *J. Textile Res.*, vol. 26, no. 2, pp. 121–123, Apr. 2005, doi: 10.13475/j.fzxb.2005.02.041.

[37] C. Li, G. Gao, Z. Liu, D. Huang, and J. Xi, "Defect detection for patterned fabric images based on GHOG and low-rank decomposition," *IEEE Access*, vol. 7, pp. 83962–83973, 2019, doi: 10.1109/ACCESS.2019.2925196.

[38] A. A. Hamdi, M. S. Sayed, M. M. Fouad, and M. M. Hadhoud, "Fully automated approach for patterned fabric defect detection," in *Proc. 4th Int. Japan-Egypt Conf. Electron., Commun. Comput. (JEC-ECC)*, May 2016, pp. 48–51.

[39] J. L. Raheja, S. Kumar, and A. Chaudhary, "Fabric defect detection based on GLCM and Gabor filter: A comparison," *Optik*, vol. 124, no. 23, pp. 6469–6474, Dec. 2013, doi: 10.1016/j.ijleo.2013.05.004.

[40] F. Arnia and K. Munadi, "Real time textile defect detection using GLCM in DCT-based compressed images," in *Proc. 6th Int. Conf. Modeling, Simulation, Appl. Optim. (ICMSAO)*, Istanbul, Turkey, May 2015, pp. 1–6.

[41] D. A. Gustian, N. L. Rohmah, G. F. Shidik, A. Z. Fanani, and R. A. Pramunendar, "Classification of troso fabric using SVM-RBF multi-class method with GLCM and PCA feature extraction," in *Proc. Int. Seminar Appl. Technol. Inf. Commun. (iSemantic)*, Semarang, Indonesia, Sep. 2019, pp. 7–11.

[42] Y. F. Zhang and R. R. Bresee, "Fabric defect detection and classification using image analysis," *Textile Res. J.*, vol. 65, no. 1, pp. 1–9, Jan. 1995, doi: 10.1177/004051759506500101.

[43] L. Song, R. Li, and S. Chen, "Fabric defect detection based on membership degree of regions," *IEEE Access*, vol. 8, pp. 48752–48760, 2020, doi: 10.1109/ACCESS.2020.2978900.

[44] D. Shumin, L. Zhoufeng, and L. Chunlei, "AdaBoost learning for fabric defect detection based on HOG and SVM," in *Proc. Int. Conf. Multimedia Technol.*, Hangzhou, China, Jul. 2011, pp. 2903–2906.

[45] G. Gao, D. Zhang, C. Li, Z. Liu, and Q. Liu, "A novel patterned fabric defect detection algorithm based on GHOG and low-rank recovery," in *Proc. IEEE 13th Int. Conf. Signal Process. (ICSP)*, Chengdu, China, Nov. 2016, pp. 1118–1123.

[46] P. Banumathi and G. M. Nasira, "Artificial neural network techniques in identifying plain woven fabric defects," *Res. J. Appl. Sci., Eng. Technol.*, vol. 9, no. 4, pp. 272–276, Feb. 2015, doi: 10.19026/rjaset.9.1404.

[47] D. Zhu, R. Pan, W. Gao, and J. Zhang, "Yarn-dyed fabric defect detection based on autocorrelation function and GLCM," *Autex Res. J.*, vol. 15, no. 3, pp. 226–232, Sep. 2015, doi: 10.1515/aut-2015-0001.

[48] R. S. Sabeenian, "Fabric defect detection using discrete curvelet transform," *Proc. Comput. Sci.*, vol. 133, pp. 1056–1065, Jul. 2018, doi: 10.1016/j.procs.2018.07.058.

[49] K. L. Mak, P. Peng, and K. F. C. Yiu, "Fabric defect detection using morphological filters," *Image Vis. Comput.*, vol. 27, no. 10, pp. 1585–1592, Sep. 2009, doi: 10.1016/j.imavis.2009.03.007.

[50] J. L. Raheja, B. Ajay, and A. Chaudhary, "Real time fabric defect detection system on an embedded DSP platform," *Optik*, vol. 124, no. 21, pp. 5280–5284, Nov. 2013, doi: 10.1016/j.ijleo.2013.03.038.

[51] P. Bandara, T. Bandara, T. Ranatunga, V. Vimarshana, S. Sooriyaarachchi, and C. D. Silva, "Automated fabric defect detection," in *Proc. 18th Int. Conf. Adv. ICT Emerg. Regions (ICTer)*, Colombo, Sri Lanka, Sep. 2018, pp. 119–125.

[52] R. Divyadevi and B. V. Kumar, "Survey of automated fabric inspection in textile industries," in *Proc. Int. Conf. Comput. Commun. Informat. (ICCCI)*, Coimbatore, India, Jan. 2019, pp. 1–4.

[53] A. Abouelela, H. M. Abbas, H. Eldeeb, A. A. Wahdan, and S. M. Nassar, "Automated vision system for localizing structural defects in textile fabrics," *Pattern Recognit. Lett.*, vol. 26, no. 10, pp. 1435–1443, Jul. 2005, doi: 10.1016/j.patrec.2004.11.016.

[54] L. Jia, C. Chen, J. Liang, and Z. Hou, "Fabric defect inspection based on lattice segmentation and Gabor filtering," *Neurocomputing*, vol. 238, pp. 84–102, May 2017, doi: 10.1016/j.neucom.2017.01.039.

[55] H. Y. T. Ngan, G. K. H. Pang, S. P. Yung, and M. K. Ng, "Wavelet based methods on patterned fabric defect detection," *Pattern Recognit.*, vol. 38, no. 4, pp. 559–576, Apr. 2005, doi: 10.1016/j.patcog.2004.07.009.

[56] X. Chang, C. Gu, J. Liang, and X. Xu, "Fabric defect detection based on pattern template correction," *Math. Problems Eng.*, vol. 2018, pp. 1–17, Mar. 22, 2018, doi: 10.1155/2018/3709821.

[57] B. Shi, J. Liang, L. Di, C. Chen, and Z. Hou, "Fabric defect detection via low-rank decomposition with gradient information and structured graph algorithm," *Inf. Sci.*, vol. 546, pp. 608–626, Feb. 2021, doi: 10.1016/j.ins.2020.08.100.

[58] Y.-R. Wang, W.-H. Lin, and S.-J. Horng, "A sliding window technique for efficient license plate localization based on discrete wavelet transform," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 3142–3146, Apr. 2011, doi: 10.1016/j.eswa.2010.08.106.

[59] J. Wang, G. Xu, C. Li, Z. Wang, and F. Yan, "Surface defects detection using non-convex total variation regularized RPCA with kernelization," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–13, 2021, doi: 10.1109/TIM.2021.3056738.

[60] D. Siegmund, B. Fu, A. José-García, A. Salahuddin, and A. Kuijper, "Detection of fiber defects using keypoints and deep learning," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 35, no. 5, Apr. 2021, Art. no. 2150016, doi: 10.1142/s0218001421500166.

[61] D. Subrata, W. Amitabh, S. Keerthika, and N. Thulasiram, "Defect analysis of textiles using artificial neural network," *Current Trends Fashion Technol. Textile Eng.*, vol. 6, no. 1, pp. 1–5, Jan. 2020.

[62] Y. Wang, N. Deng, and B. Xin, "Investigation of 3D surface profile reconstruction technology for automatic evaluation of fabric smoothness appearance," *Measurement*, vol. 166, Dec. 15, 2020, Art. no. 108264, doi: 10.1016/j.measurement.2020.108264.

[63] M. Azzeh, Y. Elsheikh, A. B. Nassif, and L. Angelis, "Examining the performance of kernel methods for software defect prediction based on support vector machine," *Sci. Comput. Program.*, vol. 226, Mar. 2023, Art. no. 102916, doi: 10.1016/j.scico.2022.102916.

[64] D. A. Karras, "Improved defect detection using support vector machines and wavelet feature extraction based on vector quantization and SVD techniques," in *Proc. Int. Joint Conf. Neural Netw.*, Portland, OR, USA, 2003, pp. 2322–2327.

[65] C. Li, G. Gao, Z. Liu, M. Yu, and D. Huang, "Fabric defect detection based on biological vision modeling," *IEEE Access*, vol. 6, pp. 27659–27670, 2018, doi: 10.1109/ACCESS.2018.2841055.

[66] D. Yapi, M. Mejri, M. S. Allili, and N. Baaziz, "A learning-based approach for automatic defect detection in textile images," *IFAC-PapersOnLine*, vol. 48, no. 3, pp. 2423–2428, Aug. 31, 2015, doi: 10.1016/j.ifacol.2015.06.451.

[67] K. Hanbay, M. F. Talu, Ö. F. Özgüven, and D. Öztürk, "Real-time detection of knitting fabric defects using shearlet transform," *TekstiL Konfeksİyon*, vol. 29, no. 1, pp. 3–10, Mar. 2019, doi: 10.32710/tekstilvekonfeksiyon.448737.

[68] N. Zhang, Y. Zhong, and S. Dian, "Rethinking unsupervised texture defect detection using PCA," *Opt. Lasers Eng.*, vol. 163, Apr. 2023, Art. no. 107470, doi: 10.1016/j.optlaseng.2022.107470.

[69] Y. Wu, J. Zhou, N. T. Akankwasa, K. Wang, and J. Wang, "Fabric texture representation using the stable learned discrete cosine transform dictionary," *Textile Res. J.*, vol. 89, no. 3, pp. 294–310, Nov. 28, 2017, doi: 10.1177/0040517517743688.

[70] X. Kang and E. Zhang, "A universal and adaptive fabric defect detection algorithm based on sparse dictionary learning," *IEEE Access*, vol. 8, pp. 221808–221830, 2020, doi: 10.1109/ACCESS.2020.3041849.

[71] Z. Liu, B. Wang, C. Li, M. Yu, and S. Ding, "Fabric defect detection based on deep-feature and low-rank decomposition," *J. Engineered Fibers Fabrics*, vol. 15, Mar. 4, 2020, Art. no. 155892502090302, doi: 10.1177/1558925020903026.

[72] A. Liu, E. Yang, J. Wu, Y. Teng, and L. Yu, "Double sparse low rank decomposition for irregular printed fabric defect detection," *Neurocomputing*, vol. 482, pp. 287–297, Apr. 2022, doi: 10.1016/j.neucom.2021.11.078.

[73] D. Peng, G. Zhong, Z. Rao, T. Shen, Y. Chang, and M. Wang, "A fast detection scheme for original fabric based on blob, Canny and rotating integral algorithm," in *Proc. IEEE 3rd Int. Conf. Image, Vis. Comput. (ICIVC)*, Chongqing, China, Jun. 2018, pp. 113–118.

[74] K. Zhang, Y. Yan, P. Li, J. Jing, X. Liu, and Z. Wang, "Fabric defect detection using salience metric for color dissimilarity and positional aggregation," *IEEE Access*, vol. 6, pp. 49170–49181, 2018, doi: 10.1109/ACCESS.2018.2868059.

[75] Y. Huang, M. Yi, W. Yang, and M. Yang, "Research on surface defect intelligent detection technology of non-woven fabric based on support vector machine," in *Proc. IEEE Int. Conf. Electr. Eng., Big Data Algorithms (EEBDA)*, Changchun, China, Feb. 2022, pp. 895–898.

[76] D. Yapi, M. S. Allili, and N. Baaziz, "Automatic fabric defect detection using learning-based local textural distributions in the contourlet domain," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 3, pp. 1014–1026, Jul. 2018, doi: 10.1109/TASE.2017.2696748.

[77] L. Liu, J. Zhang, X. Fu, L. Liu, and Q. Huang, "Unsupervised segmentation and elm for fabric defect image classification," *Multimedia Tools Appl.*, vol. 78, no. 9, pp. 12421–12449, Oct. 2018, doi: 10.1007/s11042-018-6786-7.

[78] C.-C. Ho, W.-C. Chou, and E. Su, "Deep convolutional neural network optimization for defect detection in fabric inspection," *Sensors*, vol. 21, no. 21, p. 7074, Oct. 25, 2021, doi: 10.3390/s21217074.

[79] W. T. Lv, Q. Q. Lin, J. Y. Zhong, C. Q. Wang, and W. Q. Xu, "Research progress of image processing technology for fabric defect detection," *J. Textile Res.*, vol. 42, no. 11, pp. 197–206, Nov. 2021, doi: 10.13475/j.fzxb.20200702710.

[80] J. Hou, Y. Zhang, Q. Zhong, D. Xie, S. Pu, and H. Zhou, "Divide-and-assemble: Learning block-wise memory for unsupervised anomaly detection," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2021, pp. 8771–8780.

[81] X. Tao, D. Zhang, W. Ma, Z. Hou, Z. Lu, and C. Adak, "Unsupervised anomaly detection for surface defects with dual-Siamese network," *IEEE Trans. Ind. Informat.*, vol. 18, no. 11, pp. 7707–7717, Nov. 2022, doi: 10.1109/TII.2022.3142326.

[82] D. Lee, S. Yu, H. Ju, and H. Yu, "Weakly supervised temporal anomaly segmentation with dynamic time warping," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2021, pp. 7335–7344.

[83] S. Sheynin, S. Benaim, and L. Wolf, "A hierarchical transformation-discriminating generative model for few shot anomaly detection," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2021, pp. 8475–8484.

[84] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137–1149, Jun. 2017, doi: 10.1109/TPAMI.2016.2577031.

[85] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature pyramid networks for object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 936–944.

[86] Z. Cai and N. Vasconcelos, "Cascade R-CNN: Delving into high quality object detection," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 6154–6162.

[87] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2014, pp. 580–587.

[88] R. Girshick, "Fast R-CNN," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2015, pp. 1440–1448.

[89] P. Peng, Y. Wang, C. Hao, Z. Zhu, T. Liu, and W. Zhou, "Automatic fabric defect detection method using PRAN-Net," *Appl. Sci.*, vol. 10, no. 23, p. 8434, Nov. 23, 2020, doi: 10.3390/app10238434.

[90] J. Wu, J. Le, Z. Xiao, F. Zhang, L. Geng, Y. Liu, and W. Wang, "Automatic fabric defect detection using a wide-and-light network," *Appl. Intell.*, vol. 51, no. 7, pp. 4945–4961, Jan. 2021, doi: 10.1007/s10489-020-02084-6.

[91] M. Chen, L. Yu, C. Zhi, R. Sun, S. Zhu, Z. Gao, Z. Ke, M. Zhu, and Y. Zhang, "Improved faster R-CNN for fabric defect detection based on Gabor filter with genetic algorithm optimization," *Comput. Ind.*, vol. 134, Jan. 2022, Art. no. 103551, doi: 10.1016/j.compind.2021.103551.

[92] J. F. Dai, Y. Li, K. M. He, and J. Sun, "R-FCN: Object detection via region-based fully convolutional networks," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 29, Barcelona, Spain, 2016, pp. 1–9.

[93] T. Zhou, J. Zhang, H. Su, W. Zou, and B. Zhang, "EDDs: A series of efficient defect detectors for fabric quality inspection," *Measurement*, vol. 172, Feb. 2021, Art. no. 108885, doi: 10.1016/j.measurement.2020.108885.

[94] H. Lu, M. Fang, Y. Qiu, and W. Xu, "An anchor-free defect detector for complex background based on pixelwise adaptive multiscale feature fusion," *IEEE Trans. Instrum. Meas.*, vol. 72, pp. 1–12, 2023, doi: 10.1109/TIM.2022.3229728.

[95] F. Li and F. Li, "Bag of tricks for fabric defect detection based on cascade R-CNN," *Textile Res. J.*, vol. 91, nos. 5–6, pp. 599–612, Sep. 9, 2020, doi: 10.1177/0040517520955229.

[96] L. Xue, Q. Li, Y. Lu, D. J. Zhang, Q. He, and H. Wang, "Fabric defect detection based on the improved cascade R-CNN," *Acad. J. Comput. Inf. Sci.*, vol. 4, no. 7, pp. 81–87, 2021, doi: 10.25236/ajcis.2021.040712.

[97] Z. Jia, Z. Shi, Z. Quan, and M. Shunqi, "Fabric defect detection based on transfer learning and improved faster R-CNN," *J. Engineered Fibers Fabrics*, vol. 17, Jun. 28, 2022, Art. no. 155892502210866, doi: 10.1177/15589250221086647.

[98] X. Yu, W. Lyu, D. Zhou, C. Wang, and W. Xu, "ES-Net: Efficient scale-aware network for tiny defect detection," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–14, 2022, doi: 10.1109/TIM.2022.3168897.

[99] J. Xiang, R. Pan, and W. Gao, "Online detection of fabric defects based on improved CenterNet with deformable convolution," *Sensors*, vol. 22, no. 13, p. 4718, Jun. 22, 2022, doi: 10.3390/s22134718.

[100] H. Li, H. Zhang, L. Liu, H. Zhong, Y. Wang, and Q. M. J. Wu, "Integrating deformable convolution and pyramid network in cascade R-CNN for fabric defect detection," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Toronto, ON, Canada, Oct. 2020, pp. 3029–3036.

[101] S. Xin, C. Zhao, and Y. Sun, "A machine vision-based fabric defect detection solution for textile production industry using object detection," in *Proc. 33rd Chin. Control Decis. Conf. (CCDC)*, Kunming, China, May 2021, pp. 3656–3661.

[102] J. Glenn. *YOLOv5*. Accessed: Jul. 24, 2020. [Online]. Available: https://github.com/ultralytics/yolov5/tree/v2.0

[103] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, "SSD: Single shot MultiBox detector," in *Proc. ECCV*, 2016, pp. 21–37, doi: 10.1007/978-3-319-46448-0_2.

[104] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 779–788.

[105] R. Jin and Q. Niu, "Automatic fabric defect detection based on an improved YOLOv5," *Math. Problems Eng.*, vol. 2021, pp. 1–13, Sep. 30, 2021, doi: 10.1155/2021/7321394.

[106] G. Lin, K. Liu, X. Xia, and R. Yan, "An efficient and intelligent detection method for fabric defects based on improved YOLOv5," *Sensors*, vol. 23, no. 1, p. 97, Dec. 22, 2022, doi: 10.3390/s23010097.

[107] X. Yu, W. Lyu, C. Wang, Q. Guo, D. Zhou, and W. Xu, "Progressive refined redistribution pyramid network for defect detection in complex scenarios," *Knowl.-Based Syst.*, vol. 260, Jan. 25, 2023, Art. no. 110176, doi: 10.1016/j.knosys.2022.110176.

[108] Z. Liu, S. Liu, C. Li, S. Ding, and Y. Dong, "Fabric defects detection based on SSD," in *Proc. 2nd Int. Conf. Graph. Signal Process.*, New York, NY, USA, Oct. 2018, pp. 74–78.

[109] X. He, L. Wu, F. Song, D. Jiang, and G. Zheng, "Research on fabric defect detection based on deep fusion DenseNet-SSD network," in *Proc. Int. Conf. Wireless Commun. Sensor Netw.*, New York, NY, USA, May 2020, pp. 60–64.

[110] H. Xie, Y. Zhang, and Z. Wu, "An improved fabric defect detection method based on SSD," *AATCC J. Res.*, vol. 8, no. 1, pp. 181–190, Mar. 28, 2022, doi: 10.14504/ajr.8.s1.22.

[111] H. Zhao and T. Zhang, "Fabric surface defect detection using SE-SSDNet," *Symmetry*, vol. 14, no. 11, p. 2373, Nov. 10, 2022, doi: 10.3390/sym14112373.

[112] S. Zhou, J. Zhao, Y. S. Shi, Y. F. Wang, and S. Q. Mei, "Research on improving YOLOv5s algorithm for fabric defect detection," *Int. J. Clothing Sci. Technol.*, vol. 35, no. 1, pp. 88–106, Oct. 2022, doi: 10.1108/ijcst-11-2021-0165.

[113] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P.-A. Manzagol, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion," *J. Mach. Learn. Res.*, vol. 11, pp. 3371–3408, Mar. 2010.

[114] S. Rifai, P. Vincent, X. Müller, X. Glorot, and Y. Bengio, "Contractive auto-encoders: Explicit invariance during feature extraction," in *Proc. 28th Int. Conf. Int. Conf. Mach. Learn.*, Bellevue, WAS, USA, 2011, pp. 833–840.

[115] X. Mao, Q. Li, H. Xie, R. Y. K. Lau, Z. Wang, and S. P. Smolley, "Least squares generative adversarial networks," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Oct. 2017, pp. 2813–2821.

[116] Y. Li, W. Zhao, and J. Pan, "Deformable patterned fabric defect detection with Fisher criterion-based deep learning," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 1256–1264, Apr. 2017, doi: 10.1109/TASE.2016.2520955.

[117] S. Mei, Y. Wang, and G. Wen, "Automatic fabric defect detection with a multi-scale convolutional denoising autoencoder network model," *Sensors*, vol. 18, no. 4, p. 1064, Apr. 2018, doi: 10.3390/s18041064.

[118] H. Xie, Y. Zhang, and Z. Wu, "Fabric defect detection method combing image pyramid and direction template," *IEEE Access*, vol. 7, pp. 182320–182334, 2019, doi: 10.1109/ACCESS.2019.2959880.

[119] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 27, 2021, pp. 1–9.

[120] G. Hu, J. Huang, Q. Wang, J. Li, Z. Xu, and X. Huang, "Unsupervised fabric defect detection based on a deep convolutional generative adversarial network," *Textile Res. J.*, vol. 90, nos. 3–4, pp. 247–270, Jul. 17, 2019, doi: 10.1177/0040517519862880.

[121] J. Liu, C. Wang, H. Su, B. Du, and D. Tao, "Multistage GAN for fabric defect detection," *IEEE Trans. Image Process.*, vol. 29, pp. 3388–3400, 2020, doi: 10.1109/TIP.2019.2959741.

[122] J. Liu, B. G. Zhang, and L. Li, "Defect detection of fabrics with generative adversarial network based flaws modeling," in *Proc. Chin. Autom. Congr. (CAC)*, Shanghai, China, Nov. 2020, pp. 3334–3338.

[123] X. Zheng, H. Wang, J. Chen, Y. Kong, and S. Zheng, "A generic semi-supervised deep learning-based approach for automated surface inspection," *IEEE Access*, vol. 8, pp. 114088–114099, 2020, doi: 10.1109/ACCESS.2020.3003588.

[124] Q. Zhou, J. Mei, Q. Zhang, S. Wang, and G. Chen, "Semi-supervised fabric defect detection based on image reconstruction and density estimation," *Textile Res. J.*, vol. 91, nos. 9–10, pp. 962–972, Oct. 22, 2020, doi: 10.1177/0040517520966733.

[125] Y. Huang, J. Jing, and Z. Wang, "Fabric defect segmentation method based on deep learning," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–15, 2021, doi: 10.1109/TIM.2020.3047190.

[126] L. Shao, E. Zhang, Q. Ma, and M. Li, "Pixel-wise semisupervised fabric defect detection method combined with multitask mean teacher," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–11, 2022, doi: 10.1109/TIM.2022.3162286.

[127] G. Sun, Z. Zhou, Y. Gao, Y. Xu, L. Xu, and S. Lin, "A fast fabric defect detection framework for multi-layer convolutional neural network based on histogram back-projection," *IEICE Trans. Inf. Syst.*, vol. E102.D, no. 12, pp. 2504–2514, Dec. 2019, doi: 10.1587/transinf.2019edp7092.

[128] Q. Xiao, R. Wang, H. Sun, and L. Wang, "Objective evaluation of fabric pilling based on image analysis and deep learning algorithm," *Int. J. Clothing Sci. Technol.*, vol. 33, no. 4, pp. 495–512, Nov. 2020, doi: 10.1108/ijcst-02-2020-0024.

[129] X. Jun, J. Wang, J. Zhou, S. Meng, R. Pan, and W. Gao, "Fabric defect detection based on a deep convolutional neural network using a two-stage strategy," *Textile Res. J.*, vol. 91, nos. 1–2, pp. 130–142, Jun. 28, 2020, doi: 10.1177/0040517520935984.

[130] Q. Liu, C. Wang, Y. Li, M. Gao, and J. Li, "A fabric defect detection method based on deep learning," *IEEE Access*, vol. 10, pp. 4284–4296, 2022, doi: 10.1109/ACCESS.2021.3140118.

[131] A. Suryarasmi, C.-C. Chang, R. Akhmalia, M. Marshallia, W.-J. Wang, and D. Liang, "FN-Net: A lightweight CNN-based architecture for fabric defect detection with adaptive threshold-based class determination," *Displays*, vol. 73, Jul. 2022, Art. no. 102241, doi: 10.1016/j.displa.2022.102241.

[132] L. Cheng, J. Yi, A. Chen, and Y. Zhang, "Fabric defect detection based on separate convolutional UNet," *Multimedia Tools Appl.*, vol. 82, no. 2, pp. 3101–3122, Jul. 2022, doi: 10.1007/s11042-022-13568-7.

[133] K. L. Mak and P. Peng, "An automated inspection system for textile fabrics based on Gabor filters," *Robot. Comput.-Integr. Manuf.*, vol. 24, no. 3, pp. 359–369, Jun. 2008, doi: 10.1016/j.rcim.2007.02.019.

[134] R. Thakur, D. Panghal, P. Jana, and A. Prasad, "Automated fabric inspection through convolutional neural network: An approach," *Neural Comput. Appl.*, vol. 35, no. 5, pp. 3805–3823, Oct. 15, 2022, doi: 10.1007/s00521-022-07891-1.

[135] R. Meier, J. Uhlmann, and L. M. Guo, "Uster Fabriscan automatic quality inspection system for fabrics," *Melliand China*, vol. 80, no. 3, pp. 48–51, 1999.

[136] B. Li, Y. H. Li, and Z. H. Lyu, "Performance and application of FS220 photoelectric auto cloth inspecting machine," *Cotton Textile Technol.*, vol. 45, no. 7, pp. 33–36, Jul. 2017.

[137] *USTER Q-BAR 2: The Formation Monitoring System*. Accessed: Apr. 16, 2021. [Online]. Available: https://www.uster.com/products/fabric-inspection/uster-q-bar/

[138] *Cyclops: Camera Based Automatic On-Loom Fabric Inspection*. Accessed: Apr. 16, 2021. [Online]. Available: https://bmsvision.com/products/cyclops

[139] *Israel's EVS Promotes Automatic Visual Inspection System*, Nonwovens, Hefa, Israel, 2013, p. 68.

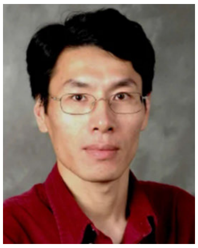
[140] M. Behravan, R. Boostani, F. Tajeripour, and Z. Azimifar, "A hybrid scheme for online detection and classification of textural fabric defects," in *Proc. 2nd Int. Conf. Mach. Vis.*, Dubai, United Arab Emirates, Dec. 2009, pp. 118–122.

[141] T. Meeradevi, S. Sasikala, S. Gomathi, and K. Prabakaran, "An analytical survey of textile fabric defect and shade variation detection system using image processing," *Multimedia Tools Appl.*, vol. 82, no. 4, pp. 6167–6196, Aug. 2022, doi: 10.1007/s11042-022-13575-8.


**PEIYAO GUO** received the bachelor's degree in engineering from the Inner Mongolia University of Technology, Huhhot, China, in 2021. She is currently pursuing the master's degree in textile engineering with Zhejiang Sci-Tech University. Her research interests include computer vision, fabric defect detection, and image processing.

**YANPING LIU** received the bachelor's degree in engineering from Quanzhou Normal University, Quanzhou, China, in 2022. She is currently pursuing the master's degree in textile engineering with Zhejiang Sci-Tech University. Her research interests include deep learning, fabric blemish generation, and object detection.

**YING WU** received the master's degree in engineering from Wuyi University, Jiangmen, China, in 2013, and the Ph.D. degree in engineering from Donghua University, Shanghai, China, in 2018. Since 2021, she has been a Postdoctoral Fellow with Tianjin University, Tianjin, China. She is currently a Master's Supervisor and a special Associate Professor with Zhejiang Sci-Tech University. Her research interests include fabric image processing technology, defect detection technology based on machine learning, and embroidery digitizing technology.



**R. HUGH GONG** received the bachelor's degree in mechanical engineering from Donghua University, Shanghai, China, in 1984, and the Ph.D. degree in philosophy from The University of Manchester, Manchester, U.K., in 1989. He then spent three years managing the Coats Viyella-Marks and Spencer Fabric Centre before taking up a lectureship with the Department of Textiles, UMIST, in 1992. He was the Director of Postgraduate Studies with the School and the Chair of the Postgraduate Degrees Panel, Faculty of EPS. His research interests include fibrous structures, such as yarns, nonwovens, nanofibers, and textile composites, and in the performance measurement, modeling, and recycling of flexible materials.

**YI LI** received the master's degree in population, resources and environmental economics from Northwest Normal University, Lanzhou, China, in 2008, and the Ph.D. degree in textile industry economics and management from Zhejiang Sci-Tech University, Hangzhou, China, in 2018. From July 2008 to September 2019, he was an Assistant Professor and a Lecturer with Zhejiang Sci-Tech University. Since September 2019, he has been a Distinguished Researcher, an Associate Professor, and a Master's Tutor with Ningbo University. His research interests include ecological economics and sustainable fashion studies.