Article

Towards Automated Fabric Defect Detection: A Survey of Recent Computer Vision Approaches

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Abstract: Defect detection is a crucial part of the pipeline in many industries. In the textile industry, it is especially important, as it will affect the quality and price of the final product. However, it is mostly performed by human agents, who have been reported to have poor performance, along with a costly and time-consuming training process. As such, methods to automate the process have been increasingly explored throughout the last 20 years. While there are many traditional approaches to this problem, with the advent of deep learning, machine learning-based approaches now constitute the majority of all possible approaches. Other articles have explored traditional approaches and machine learning approaches in a more general way, detailing their evolution throughout time. In this review, we will summarize the most important advancements of the last 5 years, and focus mostly on machine learning-based approaches. We also outline the most promising avenues of research in the future.

Keywords: Fabric Defect Detection; Deep Learning Based Textile Inspection; Computer Vision Quality Control; Defect Classification.

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1. Introduction

Clothing is a basic requirement for human life, and the textile industry is as old as civilization. Fabric is the most important component of this industry, and nowadays, its production has been mostly mechanized and automated. Defects occur during this process, and there are several inspection stages at many points to find them and fix them if possible, such as the one represented in Figure 1. This inspection is often done physically and visually, which ends up having many drawbacks [1]. The cost, monetary and time-wise of training inspectors for this role is steep, and it is estimated that these human operators have an accuracy of 60-75%, with this accuracy decreasing with longer work time. As such, it becomes desirable to automate this process, to both increase defect detection rates and decrease labor cost [2].

Fabric defect detection is not a trivial computer vision task. For starters, there is quite a large amount of defects to detect, with up to 235 different types of defects [3]. Some of the categories of these defects vary significantly according to their characteristics, while others vary slightly, which makes it difficult to apply general algorithms to this problem. A brief categorization can be seen in Figure 2. Furthermore, not all defects occur at the same rates, with some rare defects barely occurring at all, resulting in unbalanced datasets, which increases the difficulty in using supervised methods. Additionally, not all types of fabric have the same texture, with the same types of defects occasionally looking different in different types of fabrics, further compounding the problem [4].

Several surveys have been previously conducted in this area. We have collected the most relevant ones and summarized them in Table 1. We will briefly analyze them, and

Figure 1. Typical final inspection stage, from a textile factory in Portugal. Factories in many countries have a workflow and equipment similar to this one.

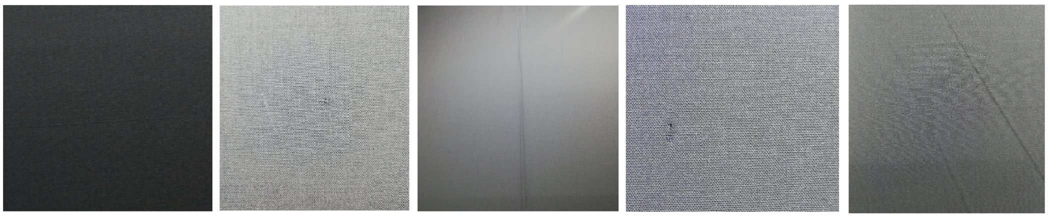

Figure 2. Some examples of fabric defects, in different fabric types. While some defects are easily spottable, others are of smaller size and harder to discern. Images acquired on site at textile factory in Portugal.

then explain in which ways our work differs. We collect data regarding the year the study was published, the authors, how many references each work has, the range in time from which they obtain their articles, whether they include traditional approaches, machine learning-based approaches and/or deep learning-based approaches.

Song *et al* [5] did the first work on the topic of textile defect detection. [5] presents a very introductory glance at the topic. Sixteen years later, Kumar *et al* presented an overview of more recent methods, dividing these between statistical approaches, spectral approaches, and model-based approaches [6]. Mahajan *et al* presented more approaches following the same taxonomy one year later in their work [7].

Ngan *et al* created the most cited review in this area two years after. This work built upon the previously established taxonomy, and introduced structural approaches and learning-based approaches. The advent of deep learning had not yet arrived, so the learning-based approaches section was somewhat sparse, but nonetheless, this approach taxonomy has not changed much since this work was published. The authors also introduce other approaches, such as hybrid approaches, or motiff approaches, which are sparsely found in the literature and mostly not covered by other reviews [8].

Table 1. Summary of analyzed survey articles.

Year	Authors	References	Article Range	Traditional	ML	DL
1992	Song et al [5]	27	1992	Y	Y	N
2008	Kumar et al [6]	162	1956-2007	Y	Y	N
2009	Mahajan et al [7]	122	1966-2009	Y	Y	N
2011	Ngan et al [8]	139	1980-2011	Y	Y	N
2014	Habib et al [9]	31	1988-2012	N	Y	N
2016	Hanbay et al [4]	99	1973-2016	Y	Y	Y
2017	Patil et al [10]	56	1979-2011	Y	N	N
2018	Oni et al [11]	35	2003-2016	Y	Y	N
2020	Czimmermann et al [12]	221	1973-2020	Y	Y	Y
2020	Rasheed et al [1]	89	1996-2020	Y	N	Y
2021	Li et al [13]	125	1999-2021	Y	Y	Y
2023	Kahraman et al [14]	107	1986-2022	N	N	Y

Habib *et al* presented a survey focused entirely on classifiers such as Support Vecotr Machines (SVMs) or Artificial Neural Networks (ANNs), without focus on traditional techniques [9]. Hanbay *et al* covered the entire previously defined taxonomy in detail, with focus on how to collect data from a hardware perspective, anmd with a brief look at deep neural networks, as they were starting to surface in the literature around that time [4]. Patil and Oni *et al* follow the footsteps of the previous authors, but do not cover deep learning-based approaches either, as these were still nascent at the time [10] [11].

In 2020 and onwards, more surveys start to be created in this area, and all of the ones created in this date range cover deep learning-based approaches. Czimmerman *et al* provide a comprehensive review of many of the recent developments across all approaches [12]. Rasheed *et al* use a different taxonomy, yet nonetheless cover all of he previously defined approaches [1].

Li *et al* use the previously defined taxonomy, and, as deep learning approaches become more stardardized, has a section on one-stage and two-stage detectors, as they have become more widespread throughout the literature at this point [13]. Finally, Kahraman *et al* focuses exclusively on deep learning methods, to the detriment of traditional methods, arguing that the former have now become the dominant approach and are thus worthier of exclusive attention [14].

Due to the rapid pace of the area, and the vast volume of articles released across all areas of deep learning, we believe that our survey is well timed to follow up on the work of the previously described authors. While Kahraman *et al* provided a comprehensive review of deep learning-based approaches, more approaches still have been devised thorughout these last two years, and in addition to the approaches, we mean to cover traditional approaches as well, to ascertain whether they still pose a promising avenue of research, or whether these approaches should be relegated to the background in favor of deep learning-based approaches, as recent trends suggest.

Our main contributions are:

- Summarizing the most important advancements in fabric defect detection over the last 5 years, with a focus on machine learning-based approaches.
- Addressing the limitations and challenges in fabric defect detection research, such as the lack of standardized datasets, the dominance of deep learning-based approaches, and issues with reproducibility.
- Proposing future trends and research directions to address these challenges and advance the field of fabric defect detection, including exploring traditional approaches, improving dataset quality, and considering edge device applications for defect detection in factory settings.

2. Taxonomy of fabric defect detection

There are multiple ways of grouping different types of approaches. One such way consists of motif-based approaches and non-motif-based approaches. Motif-based methods compare recurring motifs to detect defects, and as such require a defect-free ground truth of the motifs in a fabric. That ground truth is very hard to acquire in industry conditions, and as such, these approaches are much less widely used than non-motif-based approaches [15]. Therefore, in this survey, we focus on non-motif-based approaches, which have undergone far more significant research.

Non-motif-based approaches, due to their very general nature, can be further subdivided into other categories. These categories vary according to the researchers, but generally, are divided as follows:

- Statistical approaches;
- Spectral approaches;
- Model-based approaches;
- Structural-based approaches;
- Learning-based approaches.

However, due to the recent dramatic interest in artificial intelligence (AI) and deep learning (DL), some authors [16] have started categorizing the former 4 approaches as traditional approaches, and the later one as a separate approach, which is subdivided into:

- Classical machine learning methods;
- Deep learning methods;

We adopt this categorization, and will cover each of these types in the following subsections. However, our main focus will be on learning-based approaches, as these are the main focus of research in recent years, with the rising interest in deep learning.

3. Traditional methods

Here we outline the methods commonly referred to as traditional methods. These methods often consist of simple mathematical operations performed on the fabric images, and these techniques are often commonly used across many areas of image processing. These methods are now known as traditional as they do not involve the use of machine learning or deep learning.

3.1. Statistical approaches

Statistical approaches analyze the spatial distribution of gray pixel values in an image. These approaches generally comprise histogram statistics, auto-correlation functions, co-occurrence matrices, local binary patterns (LBP), and mathematical morphological features. While there are more approaches, we believe these are representative of the area [17].

3.1.1. Histogram statistics

A histogram displays statistical information of gray-level pixel distribution in an image. Some commonly used histogram statistics are range, mean, standard deviation, variance, and median. There are also histogram comparison statistics, such as L1/L2 norm, Mallows or EMD distance, Bhattacharyya distance, Matusita distance, Divergence, Chi-square, and Normalised correlation coefficient, which can be used as texture features [18]. Anomalous variations in these statistics can then be tracked, and usually correspond to defect in the fabric. A schematic representation of this is seen in Figure **??**, from [4].

This type of approach is considered to be simple, and not very taxing computationally, but has shown weak performance in detecting small defects [19] [20].

3.1.2. Co-occurrence matrices

Co-occurrence matrices, by which we mean spatial grey level co-occurrence matrices (GLCMs) are statistical methods that measure spatial relationships of grey-scale pixels into co-occurrence matrices. These functions calculate how often specific pairs of pixels, with certain values and spatial relationships occur in an image, given a displacement vector, and extract texture features from these matrices [21].

This method has been used multiple times across a wide variety of tasks [22] [23]. However, this method shows lower performance compared to other alternatives, and overall is quite computationally demanding [12].

3.1.3. Auto-correlation functions

Auto-correlation functions measure spatial frequency and depict maxima at multiple locations corresponding to the length (or width) of the repetitive primitive of an image [24]. This method is used primarily in textures with a repetitive nature, such as textiles, and are unsuited to more erratic textures [25].

While there are other works that use this method as a foundation, this method does not appear to be popular in the literature in isolation, as Hoseini *et al* are the only authors who used this method directly, to the best of our knowledge [26].

3.1.4. Local binary patterns

An LBP is a texture operator, introduced by Ojala *et al* [27] as a shift invariant complementary measure for local image contrast. It uses the gray level of a sliding window's central pixel as a threshold against surrounding pixels, and outputs a weighted sum of thresholding neighbouring pixels. It has been applied in defect detection with different types of surfaces, such as ceramic [28], wood [29], and OLED panels [30].

Some authors have achieved success with this approach in the area of fabric defect detection. Zhang *et al* used an approach combining GLCM and LBP methods to extract defect features to train a BP Neural Network, which achieved a 97.6% classification accuracy on the TILDA dataset [31]. This texture operator is relatively insensitive to changes in illumination and image rotation, and it has a low computational cost, but reportedly has lower performance than other alternatives [32].

As of the last 5 years, Makaremi *et al* used an approach with a modified LBP, using a clustering and thresholding step, and achieving a detection rate of 91.86% [33]. Lizarraga-Morales *et al* used this method, along with a rule-based classification system with higher than state of the art results [34]. Khwakhali *et al* combines this method and gray-level co-occurence, achieving accuracy rates up to 83.9% [35]. Li *et al* created a new operator based on the LBP, the multidirectional binary pattern (MDBP), which compares gray-level differences between neighboring pixels and extracts the detailed distribution of textures in local regions [36]. Talab *et al* proposed a new rotation-invariant mapping method, which extends nonuniform patterns to remove more discriminative features, and achieved better classification accuracies than baseline LBPs [37].

3.1.5. Mathematical morphological features

Mathematical morphology performs geometric description and representation of a shape by extracting useful components from an image. This is done through basic operations such as expansion, erosion, opening and closing [38]. It is used across a wide variety of fields, such as medicine [39], or civil engineering [40].

There are many different approaches using this method to detect defects in fabric, with defect detection rates ranging from 80.3% to 98% [41] [42] [43] [44] [45]. This method is quite sensitive to defect sizes and shapes, and effective for segmentation tasks, but it is at its most effective when performed on patterned fabric, and quite ineffective otherwise [46].

In the last 5 years, few authors have used this method. Song *et al* used a method based on the membership degree of each fabric region, and used a thresholding method and morphological processing to discover the location of defects [47]. Jiang *et al* proposed a method using a Roberts cross operator with a mathematical morphology approach [44]. Liu *et al* use Canny and morphological processing to segment defects [48]. Beyond these, few of these types of methods were discovered in the literature.

3.2. Spectral approaches

Spectral approaches employ spatial and frequency domain features, with spatial features being used to discover a defect's location, while frequency features help determine whether a defect is present. These approaches work by firstly extracting texture primitives, and then generalizing the obtained texture with spatial layout rules. These approaches are widely used in the literature, but are only effective when used on textures with a high degree of periodicity, and are ineffective otherwise [49].

We will cover the most common approaches of this type, namely: Fourier transform, wavelet transform, Gabor transform and filtering methods.

3.2.1. Fourier transform

The Fourier transform, derived from the Fourier series, involves converting signals from a spatial domain to a frequency domain [50]. As the spatial domain is often noise-sensitive, the frequency domain is often a better alternative towards finding defects [51].

There are many works that use this technique across many types of defects, in different materials, such as ceramics [52], electronic surfaces [53], solar cells [54], and other industrial images [55].

Regarding fabric defect detection, multiple studies used this approach, for many different types of fabric, such as plain cotton fabric [56], cotton and wool [57] [58], or woven denim [59].

As of the last 5 years, however, no approach was found to exclusively use this approach. Works such as [60] and [61] use the Fourier transform as a complement to other methods, but beyond that, this technique appears to have fallen out of use.

3.2.2. Wavelet transform

The wavelet transform technique was developed as an alternative to the Fourier transform, to achieve multi-resolution signal decomposition. This transform converts an image into a series of wavelets, small waves of varying frequency, which provide information on horizontal, vertical and diagonal directions in that given image [62] [63].

There are many different variations of this technique in the literature for fabric defect detection, including Fuzzy Wavelet Analysis [64], multiscale wavelets [65], wavelet reconstruction [66] [67], and adaptive level-selection wavelet transforms [68], with detection rates varying from 85% to 97.5%.

Contemporarily, wavelet transform is mostly used as an intermediate image pre-processing step or as a feature extractor for neural networks [69] [70] [71]. There are still works which mainly use this technique, such as Saleh *et al*, which uses à troux wavelets to extract approximate sub-images [72]. Hu *et al* devised an unsupervised approach using un-decimated wavelet decomposition and statistical models to build feature maps, which are then analyzed for defects with the log-likelihood function [73]. Beyond that, other works, such as [74], [75] use this method as a complement or comparison to other methods.

3.2.3. Gabor transform

Gabor filters are a well-known method for analyzing textured images, using a joint or spatial-frequency representation. These filters are a Gaussian distribution function, and can be customized with different scale and angle values according to the analyzed texture [4]. This approach attempts the optimal joint localization in spatial and spatial frequency domains [76].

This approach has been used in many different ways throughout the past decades. These can be grouped in 2 main categories. In the first, several filters, stored in certain frequencies and orientations cover all occurring frequencies in an image, computing their correlation. This is computationally intensive, but achieves high recognition quality [77]. The second approach, which is far more popular, revolves around implementing filters optimally designed to recognize defects in a desired area. It is less computationally demanding, but requires excellent parameter setting, which is quite hard to achieve [78].

In regards to fabric defect detection, this approach has been used many times over the last decades. Kumar *et al* first used this approach to detect most common types of defects, partially or fully, using horizontal or vertical projection signals [79]. Jing *et al* uses genetic algorithms to adjust Gabor filters to detect defects in patterned fabric, achieving high defect detection accuracy with lower computational costs [80]. Bissi *et al* use a complex symmetric Gabor filter bank and Principal Component Analysis (PCA), achieving defect detection rates of 98.8% and false rates between 0.2-0.37% [81]. Hu uses an elliptical Gabor filter, tuned with genetic algorithms, followed by a gray-level thresholding process, to identify defects, with accuracies of 95% [82].

In recent years, most of the research in this area employing Gabor filters follows the second-mentioned approach and optimizes Gabor filters with new algorithms, such as the Cuckoo optimization algorithm [83] or the Random Drift Particle Swarm Optimization (RDPSO) algorithm [20]. New approaches, however, are using Gabor filters less as a primary means of defect detection, and more as a feature extractor for machine learning methods, like Random Decision Forests [74], or neural networks, such as multipath CNNs [84] or Faster R-CNNs [85].

3.3. Model-based approaches

Model-based approaches revolve around the construction of an image model that can both describe and synthesize texture. These approaches are most effective with fabric images with stochastic surface variations, or for randomly textured fabrics for which statistical or spectral approaches are ineffective [7].

While there are many different types of approaches, the literature is mostly focused on autoregressive models and Markov Random Fields (MRFs). We now briefly cover each of these in their own subsections.

3.3.1. Autoregressive models

These models characterizes the linear dependence of pixels in any given textured image. As such, to compute it, one is required only to solve a system of linear equations, which requires much less computational time, making this a widely used technique for many areas [86].

However, this technique does not seem to be highly used for fabric defect detection. Bu *et al* used a Burg-algorithm-based Auto-Regressive spectral estimation model, with a Support Vector Data Description as a detector, with low false alarm rates [87]. Zhang *et al* use autoregressive models along with a variational autoencoder, with competitive results [88]. Few other such works are seen in the literature, suggesting this might not be a promising avenue of research.

3.3.2. Markov Random Fields

Markov Random Fields (MRFs) approaches model context dependent entities, such as pixels, which depend on their neighboring pixels, by combining statistical and structural information. They are often used in segmentation [89] or classification problems [90].

Cohen *et al.* used Gaussian MRFs to model defect-free fabric texture, using statistics derived from the GMRF model as a hypothesis testing problem. They achieved a high detection success rate, but with questionable reliability, due to a limited dataset of samples [91]. Zhang *et al* used an adaptive weighting function to intelligently segment jacquard warp-knitted fabric images [92].

In recent years, very few works were found exploring this approach recently, which casts doubt regarding its applicability in this area. Xu *et al* used a similar approach recently, but the results were not conclusive regarding the obtained accuracy values [93]. Chang *et al* proposed a bilayer MRF approach, which reduces original fabric image samples to obtain a constraint layer, which can be used to locate the defects, with state of the art results [94].

3.4. Structural-based approaches

Structural approaches consider the fabric texture as a composition of texture elements, referred to as texture primitives, with a certain spatial arrangement, according to arrangement rules. The goal for these approaches then is to extract the texture primitives, which can consist of individual pixels, uniform gray-level regions, or line segments, and from there infer their spatial arrangement rules, by learning their statistical properties or modelling geometric relationships. This approach is considered more effective in regular textures [95].

Due to its more general character, it is somewhat harder to seek approaches such as this in the literature. Older approaches such as Chen *et al* use a skeleton structure to describe a model [96], or Bennamoun *et al* use a texture blob model [97].

More recent methods include Tolba *et al*, who developed a Multiscale Structural Similarity Index (MS-SSIM)-based method, with a 99.1% detection rate [98]. Cao *et al*, who develop a new Prior-Knowledge Guided Least Squares Regression (PG-LSR) method, but the results were unclear [99]. Jia *et al* proposed a method based on lattice segmentation, dividing the image into non-overlapping lattices, which are then compared to defect-free benchmarks, named template statistics, with lattice similarity scores, to determine the presence of defects [100].

Overall, this method does not appear to be very popular, or it is so general in nature that many methods from other categories could ostensibly be grouped in this one.

4. Deep Learning-based Methods

These approaches are based on machine learning algorithms, as well as neural networks. Recently, due to the immense growth achieved by AI across all areas of research, these have become the most common method across the literature in the area, and this growth is likely to continue [14].

There are many different approaches in this area, given the wide selection of neural network architectures available. Due to the immense volume of literature available on this very topic, which would allow us to create a whole other state-of-the art review solely focused on it, and the already dense nature of this work, we were unable to fully review every article, and relied on previous surveys in the area to determine the major trends in this area of the literature.

Overall, as mentioned previously, the wide variety of deep learning neural network architectures makes it very hard to summarize the entire area. However, we can clearly identify two trends, which seem to hold for the last decade.

The first is the use of Convolutional Neural Networks (CNNs), which are composed of multiple convolutional layers, mixed in with subsampling or pooling, performing increasingly more complex feature extraction between the input and output layers, until reaching a final classification layer [13]. This appears to be the most commonly used approach in the reviewed articles.

The second is the use of generative models, which are neural networks trained to approximate high-dimensional probability distributions using a large number of samples. Their architectures involve numerous hidden layers. These models are usually used for generative tasks, such as finishing a word at the end of a sentence, or generating images based on several instances. There are several variants of this approach, such as Generative Adversarial Models (GANs), or autoencoders [101] [102]. These are the second most popular approach.

While there are more deep learning architectures, these two are by far the most explored areas of the literature, which makes them the most potentially viable path towards solving our current problem. As such, this state-of-the-art will focus more on these methods. As datasets are crucial in any supervised deep learning methods, we will cover the datasets we encountered for this area as well. Each of these topics will be approached in their own subsection ahead.

4.1. CNN-based approaches

The inner workings of CNNs have been discussed before, and have been covered in detail in other sources, such as [103]. As such, we will mostly focus on converting the most important latest articles, and summarizing their main contributions.

Jing *et al* used a LeNet architecture, achieving between 95.9-98.01% detection rate on the TILDA, Hong Kong, and a private dataset, compared to other architectures, such as AlexNet, VGG16, and others [104].

Jeyaraj *et al* used a multi-scaling CNN, by averaging the results of 3 CNN architectures, achieving 96.5% accuracy, and 96.4% sensitivity on the TILDA dataset [105]. The same authors later tried using a ResNet512 architecture, achieving an average accuracy of 96.5% and a precision of 98.5%, outperforming Support Vector Machines (SVMs) and Bayesian classifiers [106].

Sun *et al* used an end-to-end multi-convoluted model, based on gray histogram back-propagation, achieving an average detection accuracy of 96.12% on the TILDA dataset [107].

Almeida *et al* used a custom CNN with false negative (FN) reduction methods, achieving an accuracy of 95% against a self-made dataset [108].

Zhao *et al* used a visual long-short-term memory-based model, which involved a shallow CNN, achieving accuracy values ranging from 95.73-99.47% [109].

Durmusoglu and Kahraman used a VGG19 CNN model, and achieved 94.62% accuracy against the TILDA dataset [110]. The same authors later switched to capsule networks instead, a new alternative to CNNs that have become popular for other task types recently, and achieved 98.7% accuracy [111].

Jing *et al* used a Mobile-Unet model, using MobileNetV2 as an encoder and five deconvolutional layers as a decoder. It achieved accuracy values between 92-99% on the Hong Kong dataset, and a self-made one [112].

4.1.1. Object detection

Many approaches to this problem are based on object detection approaches across other domains. These approaches are often based on one-stage detectors and two-stage detectors. One-stage detectors such as Single Shot MultiBox Detector (SSD) [113] or You Only Look Once (YOLO) [114] treat object detection as a regression problem, and learn class probabilities and bounding box coordinates directly. Two-stage detectors such as R-CNN, Fast R-CNN [115], Faster R-CNN [116] or Mask R-CNN [117] approach the problem in two stages, using a Region Proposal Network (RPN) in the first stage to generate regions of interest, which are sent to the next stage for classification and bounding box regression. One-stage detectors are often much faster than two-stage detectors, but have lower accuracy rates [118].

Many of the approaches covered in the literature in this area consist of taking one the former types of approaches and performing changes to their architecture. As such, to better compartmentalize each approach, we found it best to consider one-stage and two-stage-based approaches separately, in each of the following subsections.

One-stage detectors Many works consist of making alterations to YOLO models.

Liu *et al* used a lightweight CNN model, named YOLO-LFD, achieving a detection accuracy of 97.2%, competitive over other YOLO models, with a much lighter computational load [119]. The same authors later used a new weakly-supervised learning framework, named DLSE-Net, to classify fabric defects with 91% accuracy, which, while worse than the previously mentioned approaches, outperformed other weakly-supervised approaches [120].

Liu *et al* implement a new Spatial Pyramid Pooling (SPP) module, with Maxpool operations replaced with Softpool, into the YOLOv4 backbone, along with image pre-processing with contrast-limited adaptive histogram equalization (CLAHE), improving over baseline results [121].

Guo *et al* introduced an Atrous Spatial Pyramid Pooling (ASPP) module, along with a convolution squeeze-and-excitation (CSE) attention channel module into the YOLOv5 backbone [122].

Li *et al* also improved on the YOLOv5 network, by replacing the bottleneck structure with a coordinate attention module, switching the SiLU activation function with Mish, the CIoU loss function with SIoU, and combining focal loss and GHM loss functions as the target confidence loss function [123].

Wang *et al* use a modified YOLOv3, with a coordinate attention module, a new tiny defect detection layer, culminating in a new anchor-free detector, YOLOX-CATD, which does not require anchor-related hyperparameter tuning [124].

Two-stage detectors We overall found fewer works with approaches based on two-stage detectors. We will briefly describe some of the most representative ones in this section.

Chen *et al* improved a faster R-CNN backbone with Gabor filters, optimized with genetic algorithms, achieving better accuracy in [85].

Li *et al* used a Cascade R-CNN, with a Switchable Atrous Convolution layer, and an upgraded Feature Pyramid Network [125].

Wu *et al* used a network structure based on Faster R-CNN, WALNet, with a dilated convolution module, which employs a multi-scale convolution kernel to adapt to defects of different sizes [126].

4.2. Generative model-based approaches

As previously mentioned, a lot of the research in this area revolves around autoencoders or GANs. We will first mention relevant autoencoder approaches in the literature, followed by GAN-based approaches.

Tian *et al* proposed an MXNet-based autoencoder, using cross-patch similarity to detect and reconstruct similarities between different patches of the selected image. Tested on the Hong Kong dataset, this method yielded accuracy values between 94.98-99.30% [127].

Han *et al* used stacked convolutional autoencoders on synthetic datasets, created with a new method, using expert knowledge to extract defect characteristics. It achieved accuracy values between 78.8-87.1%, but the new method it introduced would allow for the creation of new datasets without needing much defect data, it at all [128].

Zhang *et al* used a deep denoising convolutional autoencoder (DDCAE), performing image reconstruction with a depth denoising convolution self-encoder, followed by a mathematical morphology analysis of the resulting image. It achieved performance rates between 91-100% on a self-made dataset [129].

Regarding GAN-based methods, Hu *et al* used an unsupervised method, with a deep convolutional generative adversarial network that reconstructs a given defect image without the aforementioned defect, and compares it to the original image to discover the presence of defects. It achieved accuracy levels between 82.92-93.45% [130].

Liu *et al* devised a GAN-based framework, capable of automatically adapting to different fabric textures, with a customized deep semantic segmentation network. They achieved accuracy levels between 90.5-99.3% [131]. The same author later used proposed another approach wherein a GAN model to build fault blocks from an acquired distribution of fabric defect features, applying a Faster R-CNN for further defect detection. The system achieved an accuracy of 95.3% on a supposedly publicly available dataset which we were unable to procure [132].

4.3. Method comparison

To summarize the information presented in the previous sections, we present Table **??**, which condenses the main points of the previously described approaches.

5. SOTA Datasets

In this area, until recently, there were relatively few good datasets available. In recent years, the ZJU-Leaper dataset [133] was created, addressing many of the problems thus far encountered, but its adoption in recent works seems rather slow. Table 2 summarizes all the widely available datasets discovered regarding fabric defect detection.

Table 2. Comparison of datasets for fabric defect detection.

Dataset	Samples	Multi-Class Defects	Defect Types	Synthetic Images	Public Availability
ine TILDA [134]	3200	Yes	8	No	Yes (https://universe.roboflow.com/irvin-andersen/tilda-fabric/dataset/2), accessed on 4 April 2024
HKU Fabric [135]	162	Yes	6	Yes	Yes (https://ytngan.wordpress.com/codes/ accessed on 4 April 2024)
Fabric Stain Dataset [136]	466	No	-	No	Yes (https://www.kaggle.com/datasets/priemshpathirana/fabric-stain-dataset accessed on 4 April 2024)
DHU FD [109]	1500	Yes	10	No	No
Aliyun Tianchi Fabric [137]	15,436	Yes	15	No	No
YDFID-1 [138]	3501	No	-	No	No (https://github.com/ZHW-AI/YDFID-1/blob/main/README_ENG.md accessed on 13 November 2022)
ZJU-Leaper [133]	98,777	No	-	No	Yes (http://www.qaas.zju.edu.cn/zju-leaper/accessed on 4 April 2024)
Lusitano	36,000	No	35	No	Yes (https://kailashhambarde.github.io/Lusitano/accessed on 4 April 2024)

The most used dataset for this type of work across the literature seems to be the TILDA dataset [134], which has a relatively low amount of samples, and poor labels, but is the most established, as it was the first such dataset made publicly available. The HKU Fabric

Method type	Method	Advantages	Disadvantages
Statistical approaches	Histogram statistics	Simple Computationally easy	Weak performance
	Co-occurence matrices	Good for many task types	Computationally demanding
	Auto-correlation function	Good for repetitive textures	Unsuited for erratic textures
	Local Binary Patterns	Insensitive to lighting/rotation changes Low computational cost	Lower performance
	Mathematical Morphological features	Sensitive to defect sizes/shapes Effective for segmentation tasks	Ineffective on irregular fabric
Spectral approaches	Fourier transform	Used extensively in literature Good complement to other methods	Outdated in isolation
	Wavelet transform	Good for image pre-processing/feature extraction	Outdated in isolation
	Gabor transform	High accuracy Low computational cost	Outdated in isolation Some approaches require extensive parameter tuning
Model-based approaches	Auto-regressive models	Low computational demand	Underused in fabric defect detection/hard to assess performance
	Markov Random Fields	Often used for segmentation/classification problems	Underused in this area
Structural-based approaches	Texture primitive extraction	Effective in regular textures	Unpopular method/hard to assess performance
Deep learning-based approaches	CNN-based	Most commonly used approach High performance Many possible implementations	Immense training data required Need for extensive manual labor/annotation Inference can be computationally demanding
	Generative model-based	Requires less training data Competitive performance	Computationally demanding Longer training time

dataset is also used across many of the works, but it has an even smaller amount of samples, which are of varying quality, and not very similar to defects observed in factory conditions.

The other datasets are occasionally used in other publications. Often, they are used as a complement or comparison to the aforementioned TILDA and HKU datasets, and rarely does an article focus exclusively on them. The Aliyun Tianchi Fabric dataset in particular seems to be used more frequently in more recent publications. Regardless, they all have several problems, such as a lack in greater numbers of samples, or of defect types. ZJU-Leaper was introduced to correct many of these problems. However, given its relative recency, it has not been used in many works.

Many of the articles we later analyzed, however, used private datasets, either assembled from self-collected data, or provided to them by third parties in the industry, and these datasets were then not released. Furthermore, while some of the previously mentioned public datasets, such as ZJU-Leaper and DAGM, boast a good level of quality, they are not as standardized nor hold a benchmark status in this area, compared to datasets such as MVTec, widely considered the benchmark to use in more generalized unsupervised anomlay detection problems [139].

This poses another problem in this area, as the lack of a standardized dataset and the use of self-collected data makes it harder to reproduce many of the methods described in such works.

6. Challenges and limitations

This area shows several limitations, which have been mentioned throughout our work. We will review the main ones in this section.

As mentioned, the different types of approaches are often categorized as traditional or deep learning-based, with the latter now being the predominantly investigated one by a wide margin. [14] While this in itself is not problematic, some issues need to be addressed.

Firstly, as pointed out in many subsections of the traditional approaches section, the traditional approaches are now mostly unused, or used mostly as complements or pre-processing steps to the deep learning approaches. While deep learning shows great results and much promise across almost all areas where it is applied, it is not necessarily the simplest or most convenient approach for most use cases. Considering fabric defect detection operations are to be mostly conducted in factories, where computational resources may not be readily available, it is possible that deep learning methods would either be impractical, or require a large investment in computational resources, which might not be economically feasible to factory personnel. [140] Traditional approaches are mostly less computationally demanding, which would justify more research to improve upon such methods, but as research on them has greatly diminished, and most of the more important works in the approaches are now somewhat outdated, it becomes hard to ascertain how well they compare to deep learning approaches, and whether the performance gains achieved by deep learning methods justify their continued investment over the traditional methods.

Secondly, the border between the two different approaches is getting harder and harder to establish. As previously established, many contemporary deep learning approaches utilize some form of the previously defined traditional methods (e.g - using using a Faster R-CNN with Gabor filters optimized by genetic algorithms [80]), either as feature extraction, for classification purposes, or other ends.

Thirdly, the new deep learning methods show more promising results, and as such, further research in this area appears to be conducted almost exclusively in this manner. As such, further investigation of traditional approaches without the use of deep learning is being largely abandoned. [14]

As deep learning becomes the dominant approach to this problem, other problems present themselves. Many of the proposed deep learning approaches can be split into CNN-based approaches and generative model-based approaches. While the latter requires little in training data, the former is essentially dependent on such data, which raises the previously assessed problem of the availability of standardized datasets for this problem.

As mentioned, many of the datasets used are now outdated, contain few samples, few variety in defect types, or have some other problem, or a combination of the previous ones. While new datasets such as ZJU-Leaper are a promising direction, their adoption remains slow, and the old datasets remain the dominant ones. [133] This area requires more datasets, which can be adopted as standards, to conduct further research on supervised approaches going forward.

Regarding the data used, there is still a lack of consensus on what taxonomy of defects should be considered, with different authors considering different types of defects. While some defects such as holes are universally considered, the terminology and types of defects are left unclear. Recent advances in single-class anomaly detection could potentially trivialize this problem, with such taxonomies becoming immaterial to the task of detecting defects regardless of taxonomy. However, the lack of standards in this area means that research will continue with differing understandings of what is considered a defect until these standards are addressed. [133]

While generative model-based approaches show promise in their low requirements of training data, which offsets this problem, research into these methods is clearly progressing more slowly than into CNN-based approaches. The reasons for this are unclear, yet the trend is observable, which cements the need for better, more standardized datasets.

Still on the matter of datasets, it is noted that many authors either used their own self-collected datasets, or used paid third-party datasets. This poses a problem of reproducibility, with the current authors being unable to replicate the obtained results, due to the lack of access to those datasets. Without reproducibility, it becomes harder to ascertain which of the analyzed works truly pose new and promising areas of research.

Finally, on the matter of reproducibility, there is another observed problem that was unmentioned throughout the previous analysis. Of nearly all the articles analyzed, nearly none of the authors released the code they used to run their experiments. This further raises reproducibility problems, which compounds the previously mentioned difficulties in assessing the most promising future avenues of research.

7. Future trends and research directions

In the previous section, we highlighted many problems and challenges we identified in this area. We believe the most promising trends and research directions to follow in the future will consist then in addressing those challenges, and also highlight the current trends spotted in the literature, and in what directions those may follow in the future.

Regarding trends spotted in the literature, as previously stated, the current trends clearly point towards deep learning-based approaches. Current approaches focus more on CNN-based approaches, and as further refinements to the architectures of these networks surface in the literature, we predict they may be applied to this area as well. Further refinements to one and two-stage detectors are consistently observed in the literature, across more areas than even fabric defect detection, so it stands to reason that there will continue to be innovations in this area as well. Generative model-based approaches are rarer, but given the increased interest in generative AI in recent years, it is possible that these approaches will gain more popularity in the future. Golden template-based approaches were observed in the literature, and we believe they may pose a possible avenue of research in the near future, as they would assist in solving the problem caused by the lack of standardized datasets, as we previously observed.

Another way of approaching the lack of standardized datasets would be through the use of synthetic data, to augment and balance currently existing datasets. While this approach is explored and used in other areas [141], we found very few articles exploring such an apporach in this area.

Other possible architectures, such as capsule networks [142], and transformers [143], have barely been studied in this context, or not at all. As such, we believe this could pose another possible research direction, with the possibility of studying how these architectures can be improved towards this specific area.

The ZJU-Leaper dataset, as pointed out previously, is unconcerned as to the possible classification of defects, and is designed to facilitate the task of defect detection without any classification. As such, we believe this may pose a possible research direction by which to tackle this problem, avoiding the defect taxonomy problem identified in the previous section.

As previously stated, deep learning-based approaches are far more taxing on computational resources than traditional approaches. A new trend that seems to be emerging to tackle this problem consists of using edge devices to perform defect detection in factory settings. While such works are more practical than theoretical in nature, they are very suited to the problem at hand, and research into them is likely to continue, which is a desirable outcome.

We also highlight that while these works are valid and worthwhile contributions to the area of fabric defect detection and anomaly detection as a whole, the ultimate purpose of these works is to improve task performance in industrial settings. In taht regard, we point out that few of these studies try to ascertain whether the proposed solutions are valid in factory conditions. When these considerations occur, it is usually in the context of edge devices, as previously mentioned. As such, we believe future works should be more mindful of their potential future industrial applications, and tests should be done considering factory environment constraints.

Finally, we again point out that traditional approaches have mostly fallen out of use in recent years, but given the time gap between their use and the advent of deep learning-based approaches, it is possible these methods have not been given the attention they deserve, and may be able to achieve competitive SOTA results with a fraction of the computational resources demanded by deep learning-based approaches. As such, we believe more resources and research should be devoted to these methods, to ascertain whether or not any performance decreases achieved by using them would outweigh the decreased computational resource need.

8. Conclusions

Fabric defect detection is a very important area of research, as it may lead to the automation of intensive and defective human labor, with significant economic consequences. We have conducted a literature review to discern the most relevant trends and approaches observed, mostly throughout the last 5 years.

We conclude that most approaches in this area can be divided into traditional approaches, which consist of a vast family of methods using statistical, spectral, morphological or structural information of fabric images, or into deep learning-based approaches, which leverage the recent growth of deep learning and apply it to this area. Most of the latter approaches consist of CNN-based approaches, with variations in basic CNN architectures tailored to this task type, or in generative model-based approaches. While deep learning-based approaches appear to boast greater performance than traditional methods, we believe the former are now greatly lacking in research efforts, and believe they pose a promising area of research.

We also outline and summarize the most relevant works identified in this area, and provide an analysis of the current major challenges and limitations observed in the literature, and identify the most promising future areas of research.

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Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
CNN	Convolutional Neural Networks
GAN	Generative Adversarial Model
ML	Machine Learning
DL	Deep Learning
AI	Artificial Intelligence
GLCM	Grey Level Co-occurrence Matrix
LBP	Local Binary Pattern
MDBP	Multi Directional Binary Pattern
PCA	Principal Component Analysis
RDPSO	Random Drift Particle Swarm Optimization
MRF	Markov Random Field
MS-SSIM	Multiscale Structural Similarity Index
PG-LSR	Prior-Knowledge Guided Least Squares Regression
SVM	Support Vector Machine
FN	False Negative
SSD	Single Shot MultiBox Detector
YOLO	You Only Look Once
RPN	Region Proposal Network
SPP	Spatial Pyramid Pooling
ASPP	Atrous Spatial Pyramid Pooling
CSE	Convolution Squeeze-and-Excitation
DDCAE	Deep Denoising Convolutional Autoencoder

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