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A Novel Dataset for Fabric Defect Detection: Bridging Gaps in Anomaly Detection

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Abstract: Detecting anomalies in texture has become a significant concern across various industrial processes. One prevalent application of this is in inspecting patterned textures, especially in the domain of fabric defect detection, which is a commonly encountered scenario. This task entails dealing with a wide array of colours and textile varieties, spanning a broad spectrum of fabrics. Due to the extensive diversity in colours, textures, and defect characteristics, fabric defect detection presents a complex and formidable challenge within the realm of patterned texture inspection. While recent trends have seen a rise in the utilization of deep learning methods for anomaly detection, there still exist notable gaps in this field. In this paper, we introduce a novel dataset comprising a diverse selection of fabrics and defects from a textile company based in Portugal. Our contributions encompass the provision of this unique dataset and the evaluation of state-of-the-art (SOTA) methods' performance on our dataset.

Keywords: anomaly detection; texture inspection; fabric defect detection

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1. Introduction

Clothing is a basic necessity, and the textile industry is one of the oldest industries in human civilization. As such, ensuring high product quality by detecting fabric defects has posed a persistent challenge for the textile industry. Currently, human inspection remains the primary method due to the lack of superior alternatives. However, this approach is labour-intensive and prone to errors due to visual fatigue and distractions. Human accuracy in defect detection hovers around 60–75%, diminishing further as work time increases, or for visually intricate fabrics like stripes.

Several constraints compound this issue: industrial processes must remain seamless without any disruption, and the array of fabric defects is vast, and constantly evolving with new collections. Furthermore, each manufacturer holds different standards for what constitutes a defect, with up to 235 different types of defects [1]. Traditionally, computer vision-based solutions to the problem involved performing mathematical operations on the images, such as analysing grey-pixel-value distribution in an image, histogram statistics, and other such methods, but these methods boasted questionable performance, and few if any were actually applied in the previously described factory conditions.

Recently, there has been a notable increase in the adoption of deep learning-based approaches for anomaly and defect detection. In this area, these approaches boast considerable increases in performance over traditional approaches, but as in other areas where deep learning is applied, massive quantities of data are necessary to train the deep learning models. Furthermore, as mentioned before, the lack of a universal standardized taxonomy of what is to be considered a defect makes it difficult to create universally applicable datasets for this area.

The defects themselves are also sometimes difficult even for humans to spot. Some defects vary significantly according to their characteristics, while others vary slightly, making applying general algorithms to this problem difficult. 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 fabric types have the same texture, with the same types of defects occasionally looking different in different types of fabrics, further compounding the problem [2].

Due to these difficulties, vast quantities of data are necessary to train models that can accurately detect such defects. Despite that, there are few good datasets in this area, with most of them suffering from either a severe deficit in available samples, annotation, or all of the former, although the situation has improved in recent years with datasets such as ZJU-Leaper [3]. One of the innovations of these new datasets consists in, instead of labelling each defect individually, addressing all defects as a single class, following the idea of one-class classification. This approach has been used across many different areas to solve the issue of unbalanced datasets, with promising results. In Table 1, we summarize the most important aspects of each dataset we encountered in our search. For each dataset, we collected how many samples it has, whether it classifies defects as multiple classes, and if so, how many, as well as whether it uses synthetic images or not.

Table 1. Comparison of datasets for fabric defect detection.

Dataset	Samples	Multi-Class Defects	Defect Types	Synthetic Images	Public Availability
ine TILDA [4]	3200	Yes	8	No	Yes (https://universe.roboflow.com/irvin-andersen/tilda-fabric/dataset/2), accessed on 4 April 2024
HKU Fabric [5]	162	Yes	6	Yes	Yes (https://ytngan.wordpress.com/codes/ accessed on 4 April 2024)
Fabric Stain Dataset [6]	466	No	-	No	Yes (https://www.kaggle.com/datasets/priemshpathirana/fabric-stain-dataset accessed on 4 April 2024)
DHU FD [7]	1500	Yes	10	No	No
Aliyun Tianchi Fabric [8]	15,436	Yes	15	No	No
YDFID-1 [9]	3501	No	-	No	No (https://github.com/ZHW-AI/YDFID-1/blob/main/README_ENG.md accessed on 13 November 2022)
ZJU-Leaper [3]	98,777	No	-	No	Yes (http://www.qaas.zju.edu.cn/zju-leaper/accessed on 4 April 2024)
Lusitano (our dataset)	36,000	No	35	No	Yes (https://kailashhambarde.github.io/Lusitano/accessed on 4 April 2024)

In our study, we conducted a comparative analysis between our proposed dataset and existing datasets, as illustrated in Figure 1. To perform this comparison, we randomly selected images representing both defective and non-defective fabric samples. Subsequently, we analysed the pixel intensity and cumulative density function (CDF) of these chosen images. Our observations revealed that our proposed dataset exhibited significantly higher levels of complexity in terms of pixel intensity and CDF disparities between defect and non-defect images.

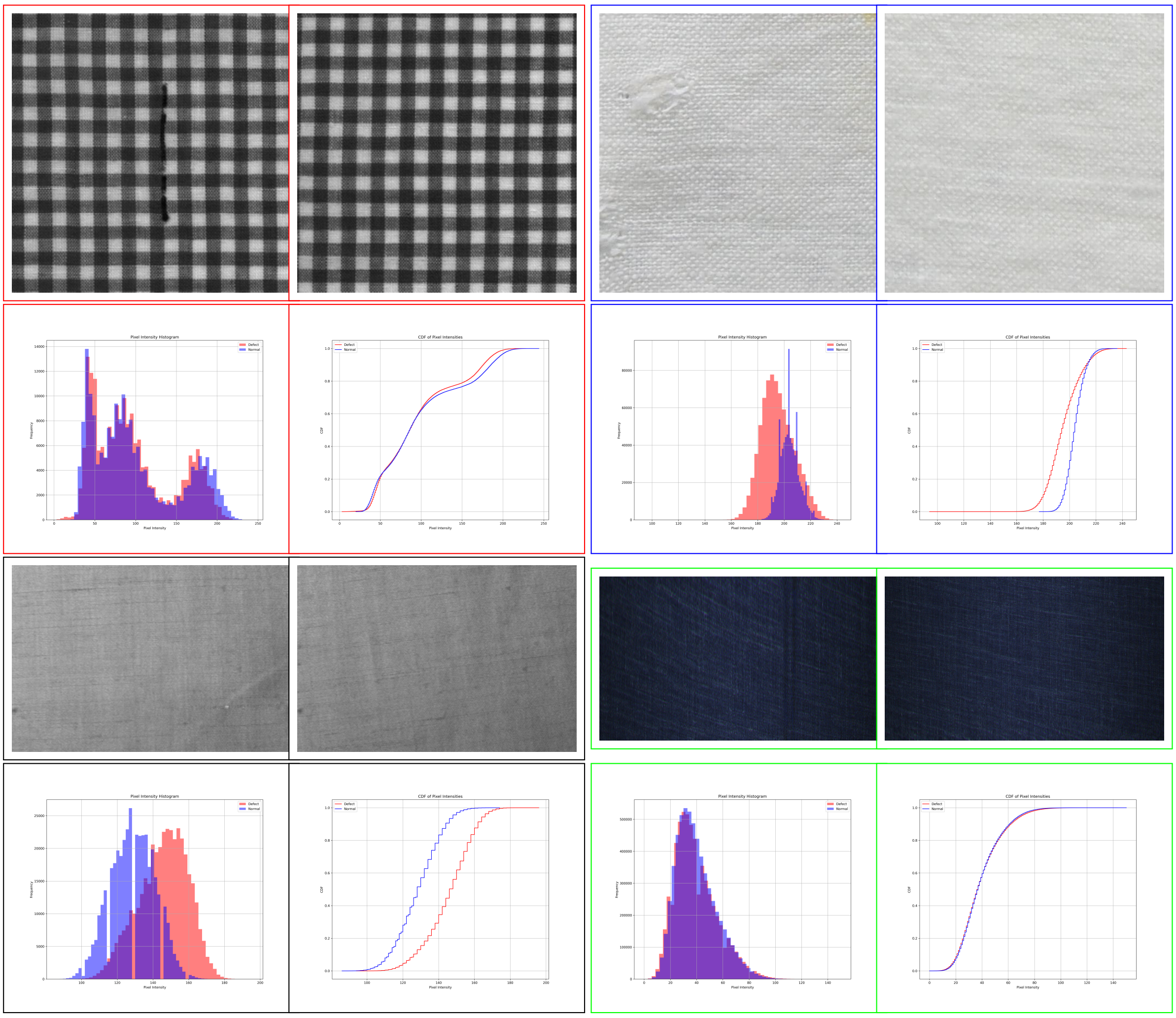

Figure 1. The red frame shows images from the HKU fabric dataset. In the first row, the first image exhibits a defect, while the second image does not. Both images are from the same fabric type. In the second row, the first image shows the pixel intensity of the defect and normal images, while the second image displays the cumulative distribution function (CDF) of both images. The blue frame represents images from the zipper dataset, while the green frame depicts images from the Lusitano dataset.

To further improve efforts in this area, we propose our new dataset. Its main innovation consists in applying the one-class classification paradigm, which means our dataset contains only fabric images without defects, so that neural networks can be trained to detect any anomaly encountered as a defect. We collected 32,000 fabric images without defects, which can be used for training purposes, and created a test set with 1100 normal and 1300 defect images. All of these images were obtained directly from the factory, in industry conditions, and no data augmentation or post-processing was performed. While the total number of pictures does not match that of the ZJU-Leaper dataset, it surpasses that of other datasets. Furthermore, the absence of augmented or synthetic data entails that this dataset can be used for real use cases, or that any future users may apply data augmentation/synthesis pipelines as necessary for their particular use cases.

We also tested several baseline anomaly detection methods on this dataset and present the results. We believe our new dataset thus poses a valuable contribution to the area of fabric defect detection.

2. Related Work

2.1. One-Class Classification

A one-class classification is an approach that involves labelling only a single class in a dataset so that any mild deviation from these data is classified as an anomaly. This method is widely applied in financial fraud detection, cybersecurity, healthcare, and automated visual inspection [10]. The primary advantage of this approach is its ability to detect anomalies without needing labelled data for every possible class of anomalies, which is especially useful in rare or diverse scenarios.

Various techniques exist to handle the problem of texture defect detection, including statistical, transform-based, model-based, and graph-based approaches. Each of these methods offers distinct advantages and drawbacks. More recently, deep learning-based feature extraction has produced outstanding results in identifying important patterns. For instance, supervised training methods [11] are often used in industrial settings for defect detection. However, gathering data for every possible defect is laborious and may lead to poor performance if some defect types are not considered.

Unsupervised approaches, such as autoencoders [12], suffer from high generalization capabilities, making them less effective for specific defect types. To improve performance, knowledge distillation [13] has been adapted for unsupervised anomaly detection [14,15]. This involves training a student network on normal samples using the output of a pre-trained teacher network. During testing, the student network replicates the features of the teacher network for normal samples but fails to do so for anomalous samples, allowing for the computation of a relevant anomaly score.

Several one-class classification methods have been developed, including but not limited to PatchCore [16], FastFlow [17], PaDiM (Patch Distribution Modeling) [18], Cut-Paste [19], Uninformed Student [20], and Patch SVDD [21]. Zhou et al. used one-class classification for fabric defect detection with mixed results [22]. In our study, we evaluated two methods, DBFAD [23] and RD4AD [24], chosen based on their availability as open-source code and their suitability for one-class classification.

The advantages of the selected methods are that they are effective in scenarios where anomalies are rare or diverse, as they do not require labelled data for every possible anomaly.

2.2. Fabric Defect Detection

There are multiple ways of grouping different types of fabric defect detection approaches. One 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. This ground truth is hard to acquire in industry conditions, so these approaches are less used than non-motif-based approaches [25].

Non-motif-based approaches, which have undergone far more research, can be further subdivided into other categories, generally classified as:

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

However, due to the recent interest in artificial intelligence (AI) and deep learning (DL), some authors [26] have started categorizing the former four approaches as traditional approaches, and the latter one as a separate approach, further subdivided into:

- Classical machine learning methods;
- Deep learning methods.

We adopted this categorization and cover each of these types in the following subsections.

2.2.1. Traditional Methods

We briefly cover each traditional method, along with their respective submethods, in the following sections.

Statistical Approaches

Statistical approaches analyse the spatial distribution of grey pixel values in an image. These approaches comprise histogram statistics, auto-correlation functions, co-occurrence matrices, local binary patterns (LBP), and mathematical morphological features [27].

Histogram statistics. A histogram displays statistical information on the grey-level pixel distribution in an image. Some commonly used histogram statistics are the 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 [28]. Anomalous variations in these statistics can then be tracked and usually correspond to defects in the fabric.

This type of approach is simple and not taxing computationally but has shown weak performance in detecting small defects [29,30].

Co-occurrence matrices. Spatial grey-level co-occurrence matrices (GLCMs) are statistical methods that measure the 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 [31]. This method has been used multiple times across a wide variety of tasks [32,33] but shows lower performance than alternative methods and is computationally demanding [34].

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 [35]. This method is used primarily in textures with a repetitive nature, such as textiles, and are unsuited to erratic textures [36].

Local binary patterns An LBP is a shift-invariant complementary measure for local image contrast. It uses the grey 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 [37], wood [38], and OLED panels [39]. It is insensitive to changes in illumination and image rotation and has a low computational cost but low performance [40].

Mathematical morphological features. Mathematical morphology performs a geometric description and representation of a shape by extracting useful components from an image. This is accomplished through basic operations such as expansion, erosion, opening, and closing [41]. It is used across fields such as medicine [42] or civil engineering [43]. This method is sensitive to defect sizes and shapes and effective for segmentation tasks but is at its most effective when performed on patterned fabric and ineffective otherwise [44].

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 extracting texture primitives and then generalizing the obtained texture with spatial layout rules. These approaches are widely used but only effective when used on textures with a high degree of periodicity and are ineffective otherwise [45].

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

Fourier transform. The Fourier transform, derived from the Fourier series, involves converting signals from a spatial domain to a frequency domain [46]. As the spatial domain is often noise-sensitive, the frequency domain is a better alternative towards finding defects [47]. There are many works that use this technique across many types of defects, in different materials such as ceramics [48], electronic surfaces [49], solar cells [50], and other industrial images [51].

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 [52,53]. Contemporarily, the wavelet transform is mostly used as an intermediate image preprocessing step or as a feature extractor for neural networks [54–56].

Gabor transform. Gabor filters are a well-known method for analysing textured images, using a joint or spatial-frequency representation. These filters use a Gaussian distribution function and can be customized with different scale and angle values according to the analysed texture [2]. This approach attempts the optimal joint localization in spatial and spatial frequency domains [57]. In regards to fabric defect detection, this approach has been used many times over the last decades [58–60] but more recently has been mostly used as a feature extractor for machine learning methods [61–63].

Model-Based Approaches

These revolve around the construction of an image model that can both describe and synthesize texture. They are most effective with fabric images with stochastic surface variations, or for randomly textured fabrics for which statistical or spectral approaches are ineffective [64].

While there are many different types of approaches, the literature is mostly focused on autoregressive models and Markov Random Fields (MRFs).

Autoregressive models. These models characterize the linear dependence of pixels in any given textured image. As such, to compute it, one is only required to solve a system of linear equations, which requires much less computational time, making this a widely used technique for many areas [65]. However, this technique does not seem to be used much for fabric defect detection.

Markov Random Fields. Markov Random Fields (MRFs) model context-dependent entities, such as pixels, which depend on their neighbouring pixels, by combining statistical and structural information. They are often used in segmentation [66] or classification problems [67]. In recent years, very few works were found exploring this approach, which casts doubt regarding its applicability in this area [68,69].

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 grey-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 [70].

2.2.2. 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 [71].

There are many different approaches in this area, given the wide selection of neural network architectures available. However, we can clearly identify three main approaches which have been prominent 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 [72]. This appears to be the most commonly used approach in the reviewed articles.

The second is based on object detection approaches across other domains. These revolve around the use of one-stage or two-stage detectors. One-stage detectors such as Single-Shot MultiBox Detector (SSD) [73] or You Only Look Once (YOLO) [74] 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 [75], Faster R-CNN [76], or Mask R-CNN [77] 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 much faster than two-stage detectors but have lower accuracy [78].

The third 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 [79,80].

Each of these topics is approached in their own subsection ahead.

CNN-Based Approaches

Jing et al. used a LeNet architecture, achieving good detection rates on TILDA, HKU, and a private dataset, compared to other architectures such as AlexNet, VGG16, and others [81]. Jeyaraj et al. used a multi-scaling CNN, averaging the results of three CNN architectures [82]. The same authors later tried using a ResNet512 architecture, outperforming Support Vector Machines (SVMs) and Bayesian classifiers [83]. Sun et al. used an end-to-end multi-convoluted model, based on grey histogram back-propagation [84].

Almeida et al. used a custom CNN with false negative (FN) reduction methods [85]. Zhao et al. used a visual long short-term memory-based model, which involved a shallow CNN [7]. Durmusoglu and Kahraman used a VGG19 CNN model [86]. The same authors later switched to capsule networks instead, a new alternative to CNNs that have recently become popular for other task types [87].

Jing et al. used a Mobile-Unet model, using MobileNetV2 as an encoder and five deconvolutional layers as a decoder. It achieved good accuracy on the HKU dataset, and a self-made one [88].

Object Detection

These approaches are often based on one-stage detectors and two-stage detectors, as mentioned. We summarize relevant examples of each in the following subsections.

One-stage detectors. Many works consist in making alterations to YOLO models. Liu et al. used a lightweight CNN model named YOLO-LFD, competitive over other YOLO models, with a much lighter computational load [89]. 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 supervised approaches, outperformed other weakly supervised approaches [90].

Liu et al. implemented a new Spatial Pyramid Pooling (SPP) module, with Maxpool operations replaced with Softpool, into the YOLOv4 backbone, along with image preprocessing with contrast-limited adaptive histogram equalization (CLAHE), improving over baseline results [91].

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 [92]. 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 [93].

Wang et al. used a modified YOLOv3, with a coordinate attention module and a new tiny defect detection layer, culminating in a new anchor-free detector, YOLOX-CATD, which did not require anchor-related hyperparameter tuning [94].

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

Chen et al. improved a faster R-CNN backbone with Gabor filters optimized with genetic algorithms, achieving better accuracy in [63]. Li et al. used a cascade R-CNN with a switchable atrous convolution layer and an upgraded feature pyramid network [95]. Wu et al. used a network structure based on Faster R-CNN, WALNet, with a dilated convolution module, which employed a multi-scale convolution kernel to adapt to defects of different sizes [96].

Generative Model-Based Approaches

Regarding autoencoders, Tian et al. proposed an MXNet-based autoencoder, using cross-patch similarity to detect and reconstruct similarities between different patches of the selected image [97]. Han et al. used stacked convolutional autoencoders on synthetic datasets, created with a new method, using expert knowledge to extract defect characteristics, with a method that would allow for the creation of new datasets without needing many defect data at all [98]. 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 [99].

Regarding GAN-based methods, Hu et al. used an unsupervised method with a deep convolutional GAN that reconstructed a given defect image without the aforementioned defect and compared it to the original image to discover the presence of defects [100]. Liu et al. devised a GAN-based framework capable of automatically adapting to different fabric textures with a customized deep semantic segmentation network [101]. The same author later proposed another approach wherein a GAN model was used to build fault blocks from an acquired distribution of fabric defect features, applying a faster R-CNN for further defect detection.

3. Lusitano Dataset Description

The Lusitano dataset was collected over a 3-month period, spanning from January to March, from Paulo de Oliveira, S.A., based in Covilhã, Portugal (https://www.paulo-oliveira.pt/), accessed on 2 April 2024 , a prominent textile company in Portugal renowned for its innovative contributions to the textile industry.

To constitute the dataset, we placed 1 camera (shown in Figure 2) in front of a fabric inspection machine with a strong and nearly uniform light source.

This dataset comprises images with dimensions of 4096 × 1024, meticulously captured by an industrial-grade Teledyne Dalsa Linea camera (https://www.teledynedalsa.com/en/products/imaging/cameras/linea/, accessed on 27 March 2024)The camera's high resolution and precision ensured the accurate depiction of textile samples, capturing intricate details crucial for defect analysis.

It is noteworthy that the defects depicted in this dataset were not artificially generated; rather, they stemmed from genuine occurrences observed during this collection period. These defects represented real-world challenges encountered in textile production processes.

The dataset provides an encompassing view of various fabric examples. Figure 3 showcases normal images.

We provide two folders, training and test, in the same folder architecture, an MVTEC AD dataset [102], containing images normal in training and normal in testing, and both defect and normal images. Details of the number of samples per split are shown in Table 2, where the training set contains 32k normal images for model training, and the testing set contains 1038 normal and 1646 defect images.

Figure 2. Camera setup at the textile factory.

Table 2. Details of the dataset split for fabric defect detection/classification.

Split	Normal	Defects
ine Training	32k	0.0
Test	1038	1646

Figure 3. Normal fabric images: A collection of high-resolution images showing various examples of normal fabric textures. Different fabric types have different colors and textures. These images serve as reference samples for fabric quality assessment.

The dataset under consideration shows minimal differential changes between pixels in normal and defect images, as visually depicted in Figure 4. In the provided illustration, the top row showcases original images, with the first image depicting a defect image characterized by a linear defect. In contrast, the second image portrays a normal image featuring the same fabric sample. In the subsequent row, pixel density histograms are presented, revealing slight discrepancies in density between normal and defective fabric images. Finally, the third row displays cumulative histograms, further illustrating the marginal variations observed between the two normal and defective images. These results highlight the difficulties in identifying defects in fabric samples because of the slight variations in pixel properties between normal and defective examples.

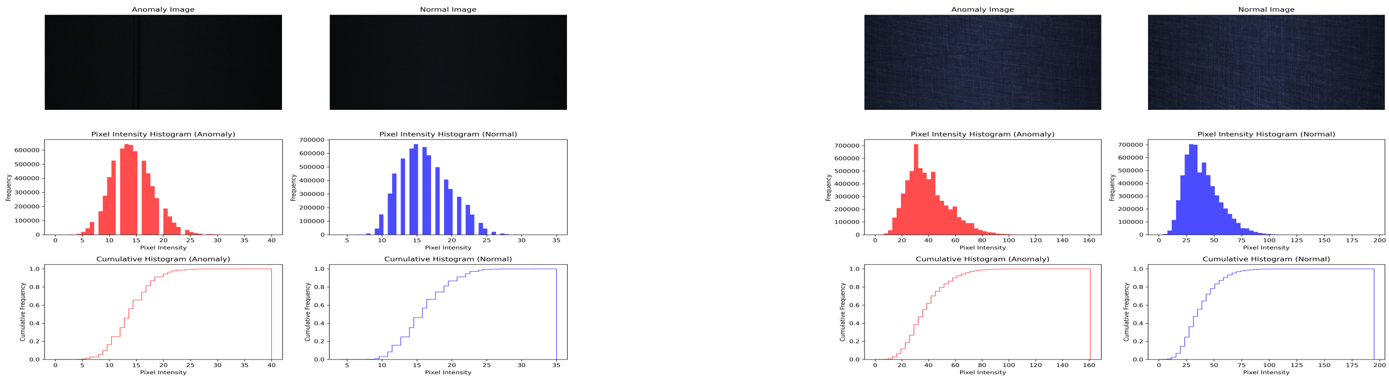

Figure 4. Comparison of defect and normal images along with their pixel-wise and cumulative histograms.

4. Experiments and Discussion

In this section, we evaluate SOTA methods on our novel fabric dataset. Our objective here is to report baseline quantitative and qualitative results, assessing the performance of these methods in real fabric defect detection. By conducting this evaluation, we aim to gain insights into the effectiveness of the SOTA techniques in handling the unique characteristics and challenges posed by our fabric dataset.

4.1. SOTA Methods

To evaluate the SOTA method on our proposed fabric dataset, we considered two methods purely based on the following factors, open-source code and a one-class classification approach, hence DBFAD [23] and RD4AD [24]; the following sections explain these methods in detail.

4.1.1. Reverse Distillation from One-Class Embedding for Anomaly Detection (RD4AD)

The Reverse Distillation from One-Class Embedding for Anomaly Detection (RD4AD) [24] method comprises a pre-trained teacher encoder, a trainable one-class bottleneck embedding module, and a student decoder. This methodology leverages a multi-scale feature fusion block to amalgamate low- and high-level features extracted by the encoder and subsequently map them onto a compact code using the one-class embedding block.

During the training phase, the RD4AD method employs reverse distillation, wherein the student decoder endeavours to replicate the teacher encoder's behaviour by minimizing the similarity loss function. In the inference stage, the reverse distillation encoder extracts features, while the decoder generates anomaly-free representations. The detection of anomalies is predicated upon discerning low similarity between feature vectors from the encoder and decoder. The RD4AD method computes the final prediction by aggregating multi-scale similarity maps.

4.1.2. Distillation-Based Fabric Anomaly Detection (DBFAD)

Distillation-based fabric anomaly detection [23] is a method utilizing residue reverse distillation for detecting defects within textures.

The method introduces a novel approach, termed reverse distillation, for unsupervised anomaly detection in fabric textures, specifically targeting the challenge of fabric defect detection in industrial processes. This method emphasizes the absence of defective samples during training, enabling generalization and fast inference. It utilizes a teacher–student architecture to enhance the student model's reconstruction capabilities for anomaly detection.

4.2. Experiment Setup

We evaluated two methods, DBFAD [23] and RD4AD [24], chosen based on their availability as open-source code (https://github.com/SimonThomine/DBFAD accessed on 2 April 2024) and their suitability for a one-class classification approach (https://github.com/hq-deng/RD4AD.git accessed on 2 April 2024) for the proposed fabric dataset.

To evaluate the efficiency of the selected methods, we adopted a systematic approach. Initially, we divided the entire training dataset into six distinct parts, with data volumes of 1k, 2k, 4k, 8k, 16k, and 32k normal images. We enhanced the quality of our input data by cropping the images to a standard dimension of 2000 × 1000 pixels (width × height) from the centre, addressing the noise present around the image corners, a common issue in our dataset. This resizing process was applied to the testing images as well, ensuring consistency throughout our evaluation process.

Following this preprocessing phase, we trained each chosen method on each dataset partition and tested each iteration on the testing dataset to measure performance.

For the RD4AD [24] method, we configured the parameters as follows: 200 epochs, a learning rate of 0.005, a batch size of 16, an image size of 256 × 256 pixels, a patience of 5. For the DBFAD [23] method, the configuration was as follows: 100 epochs, a learning rate of 0.005, a batch size of 16. an image size of 256 × 256 pixels, a patience of 10.

We utilized the Nvidia RTX A6000, Santa Clara, CA, USA for both training and testing purposes. These implementation details were consistent across all dataset splits, ensuring a fair and comprehensive evaluation of our methods. This systematic approach allowed us to rigorously compare the performance of DBFAD and RD4AD under varying data volumes, ensuring robust and reliable results for fabric defect detection.

4.3. Results and Discussion

The Lusitano dataset offers a comprehensive look into the fabric inspection domain, capturing real-world textile samples with meticulous detail. This dataset, sourced from Paulo de Oliveira, S.A., showcases normal and defective fabric examples crucial for anomaly detection and defect classification tasks. The high-resolution images, acquired using an industrial-grade camera, ensure the faithful representation of fabric textures, enabling a precise analysis of defects. The dataset's composition, detailed in Table 2, delineates the distribution of normal and defective samples across training and testing sets.

With 32k normal images for training and 1100 normal along with 1300 defect images for testing, the dataset provides a balanced representation of fabric variations and defects, facilitating robust model evaluation. Visual inspection of the dataset, as depicted in Figures 3 and 4, highlights the subtle differences between normal and defective fabric samples. These images serve as reference points for fabric quality assessment, emphasizing the need for accurate anomaly detection techniques to identify defects reliably.

Figure 4 presents a comparative analysis of defect and normal fabric images, showcasing their pixel-wise and cumulative histograms. The first row exhibits a defect image on the left and a normal image on the right, both representing the same fabric type. Despite the visual differences between the defect and normal images, the pixel histograms in the second row appear remarkably similar, indicating comparable distributions of pixel values across both image types. Similarly, the cumulative histograms in the third row display a limited discriminative power between defect and normal fabrics based solely on pixel intensity distributions. This observation underscores the challenge of distinguishing between defective and normal fabrics with fabrics of the same type.

In our experimental evaluation, we scrutinized two state-of-the-art anomaly detection methods for fabric defect detection: DBFAD and RD4AD. Both methods leverage innovative approaches to detect anomalies within fabric textures, employing reverse distillation techniques to enhance anomaly detection capabilities. Results from RD4AD are illustrated in Figure 5, and those of DBFAD are depicted in Figure 6.

Our experimental setup, detailed in the experiment setup section, encompassed a systematic evaluation of DBFAD and RD4AD across different dataset sizes. By dividing the training dataset into six partitions and conducting evaluations with varying data volumes, we aimed to evaluate the scalability and performance of the selected methods.

The results, summarized in Table 3, explore evaluation metrics for fabric defect anomaly detection, comparing DBFAD and RD4AD across dataset sizes using AUC and mAP. Both methods showed an increasing AUC with larger datasets, but improvements were modest. RD4AD consistently outperformed DBFAD in AUC and mAP. AUC and mAP improved notably with dataset size, especially for RD4AD, suggesting its scalability. However, precision levels for both methods remained suboptimal, emphasizing the need for further method improvement.

Table 3. Evaluation metrics for different dataset sizes. The % change was calculated considering 1k as the baseline for each method. Green indicates improvement, while red indicates degradation.

Method Used	Sample Size	AUC	Change (%)	mAP	Change (%)
DBFAD [23]	1k	0.7573	-	0.8162	-
	2k	0.7570	−0.04%	0.8199	0.45%
	4k	0.7691	1.56%	0.8293	1.60%
	8k	0.7737	2.17%	0.8301	1.70%
	16k	0.7797	2.96%	0.8354	2.35%
	32k	0.7814	3.18%	0.8429	3.27%
RD4AD [24]	1k	0.8231	-	0.8773	-
	2k	0.8189	−0.51%	0.8803	0.34%
	4k	0.8640	4.97%	0.9275	5.72%
	8k	0.8726	6.01%	0.9319	6.22%
	16k	0.8831	7.29%	0.9374	6.85%
	32k	0.8860	7.64%	0.9390	7.03%

Furthermore, precision–recall curves and ROC curves, depicted in Figures 5–8, offer visual insights into the performance of DBFAD and RD4AD across various evaluation criteria. These curves provide a nuanced understanding of the trade-offs between precision, recall, and false positive rates, aiding in the interpretation of model performance.

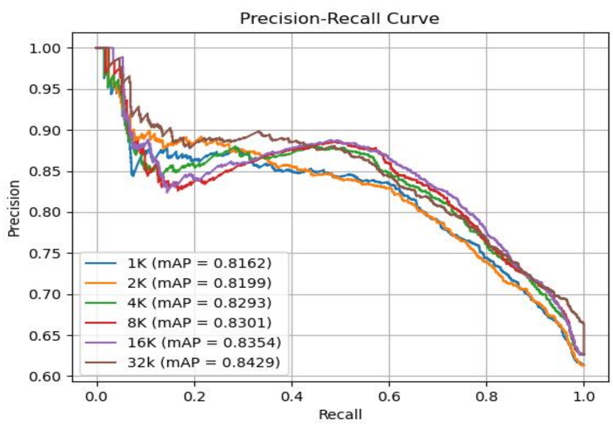

Figure 5. PR-AUC of the DBFAD model.

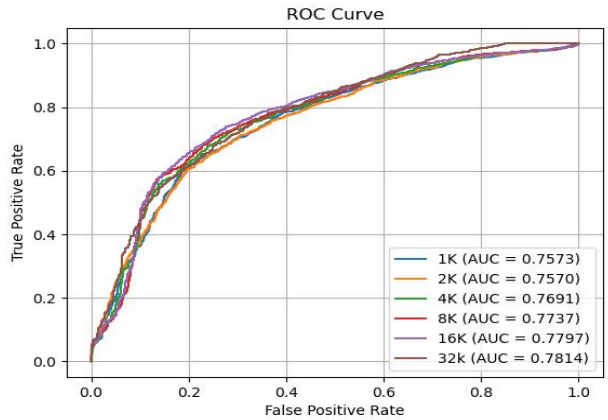

Figure 6. AUC-ROC of the DBFAD model.

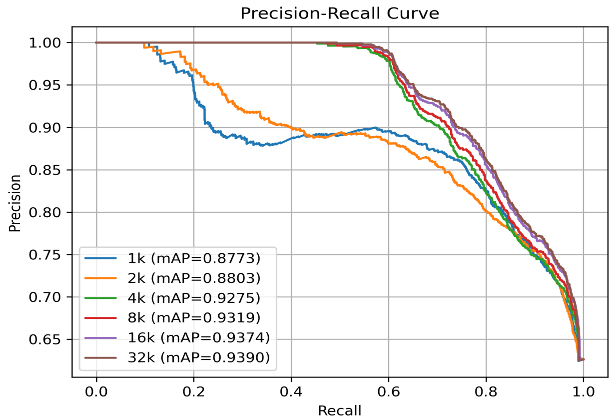

Figure 7. Precision–recall curve of the RD4AD model [24].

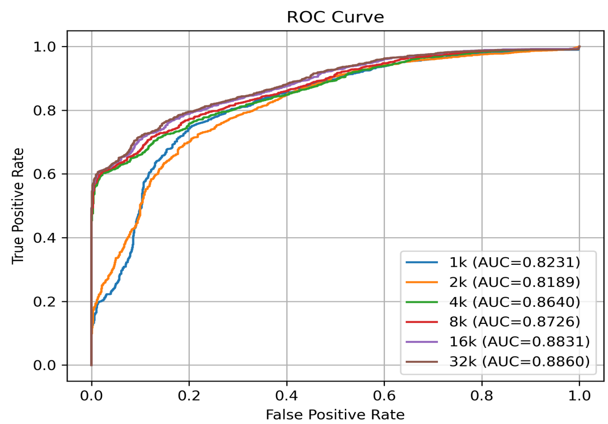

Figure 8. ROC curve of the RD4AD model [24].

5. Conclusions

We presented a new dataset to advance the area of fabric defect detection, as we concluded that there was a dearth of good, well-populated datasets in this area. To this end, we collected fabric images for three months in factory settings and obtained 32,000 images without defects, with which we created a training set. For testing purposes, we provided 1100 normal images and 1300 images with defects, also collected in factory settings. These images can thus be used in one-class anomaly detection methods.

We benchmarked this dataset against two open-source one-class anomaly detection methods and obtained results that, while suboptimal, validate the use of this dataset in this area.

In the future, we intend to continue collecting data and adding them to this dataset, testing new benchmark methods on it, and perfecting the dataset, by segregating different fabric types, better tuning lighting and camera positioning conditions, and other improvements.

We believe this dataset thus constitutes a valid contribution to this area, and we will continue expanding it in the future.

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Data Availability Statement: Our dataset is available at https://kailashhambarde.github.io/Lusitano/, accessed on 1 May 2024.

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