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# Defect detection in the textile industry using image-based machine learning methods: a brief review

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# Defect detection in the textile industry using image-based machine learning methods: a brief review

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**Abstract.** Traditionally, computer vision solutions for detecting elements of interest (e.g., defects) are based on strict context-sensitive implementations to address contained problems with a set of well-defined conditions. On the other hand, several machine learning approaches have proven their generalization capacity, not only to improve classification continuously, but also to learn from new examples, based on a fundamental aspect: the separation of data from the algorithmic setup. The findings regarding backward-propagation and the progresses built upon graphical cards technologies boost the advances in machine learning towards a subfield known as deep learning that is becoming very popular among many industrial areas, due to its even greater robustness and flexibility to map and deal knowledge that is typically handled by humans, with, also, incredible scalability proneness. Fabric defect detection is one of the manual processes that has been progressively automatized resorting to the aforementioned approaches, as it is an essential process for quality control. The goal is manifold: reduce human error, fatigue, ergonomic issues and associated costs, while simultaneously improving the expeditiousness and preciseness of the involved tasks, with a direct impact on profit. Following such research line with a specific focus in the textile industry, this work aims to constitute a brief review of both defect types and Automated Optical Inspection (AOI) mostly based on machine learning techniques, which have been proving their effectiveness in identifying anomalies within the context of textile material analysis. The inclusion of Convolutional Neural Network (CNN) based on known architectures such as AlexNet or Visual Geometry Group (VGG16) on computerized defect analysis allowed to reach accuracies over 98%. A short discussion is also provided along with an analysis of the current state characterizing this field of intervention, as well as some future challenges.

## 1. Introduction

In the textile industry, a series of fabric processes using either natural or synthetic raw materials are employed to produce clothes, coatings, among many other outputs with distinct market targets (e.g., household items retail, automotive industry). Inevitably, these processes are commonly prone to originate various types of defects or flaws in the production items – mostly, during knitting activities -, inducing undesirable additional costs in the textile value chain (for example, through complains and devolutions or items that were undervalued due to imperfections), which, depending on occurrence rates, may lead to significant financial losses. As such, textile defects must be mindfully addressed, through inspection activities, to ensure high-quality standards, envisaging manifold purposes that may range from internally spotting malfunctioning machinery to preventing the delivery of low-quality materials into partners/stakeholders' hands.

Traditionally, the identification of textile defects is performed by human vision-based inspection, which is inaccurate and time-consuming. In recent years, one has been witnessing the increase of popularity of Automatic Optical Inspection (AOI) systems, due to their capabilities for providing consistent and reliable quality control process, with greater results than human vision-based inspection. AOI consists, essentially, of a set of acquisition equipment (RGB sensors, illumination kits for light uniformization, clean chambers - in case of very high precision requirements -, etc.), remote or local processing hardware (e.g., workstation) and real-time defect detection-oriented algorithms that, together, establish a powerful combination to automatically and effectively perform expeditious quality analysis and to provide pertinent decision support. As such, in the industry in general and, in particular, in the textile fabrics context, these systems have the potential of playing a significant role to ensure high-quality and high-speed production, while equipping industries with more efficient and competitive tools, capable of lowering costs [1].

Some recent surveys have been proposed focusing defect inspection, highlighting the importance of developing automated methods capable of tackling with sensitive human factors such as ergonomics, and predisposition to fatigue and flaw. In [2], a broad review transversal to industry was provided, focusing visible and palpable defects. More focused in the textile industry, another couple of recent contributions can be found, i.e., [3] and [4]. The former was a four-page review that lightly addresses the types of defects, inspection procedures and provides a few of (mainly traditional) computer vision approaches within the textile defect detection context. The later, provides an extensive review concerned with textile defect detection methods categorized into traditional algorithms and learning-based algorithms. This paper shares similar concerns, but with a stronger emphasis in the last 5 years of representative image-based machine learning approaches for textile inspection, which, moreover, can be found benchmarked nearby the end of the document, in terms of techniques and methods employed, defect types addressed, performances achieved, resorted metrics and involved datasets, thus seeking to add value over previous surveys.

This paper is organized as follows: in the next section, a brief description of the research method is given; in section 3, a background on textile defect types is provided and recent AOI approaches in textile industry are reviewed, with greater emphasis in machine learning-based methods; section 4 provides a summary of this review, wherein it can also be found a table benchmarking the different analyzed machine learning approaches; in the end, conclusions are drawn.

## 2. Review process

To produce this review, a PRISMA-like procedure was followed, whose steps are depicted in Figure 1. Relevant academic databases such as Science Direct, IEEE Xplore, ACM Digital Library, MDPI, Google Scholar, etc. were queried with the keywords "defect detection", "textile fabric", "automatic inspection", "deep learning", "machine learning", which were used alone and combined. Publications done in the latest 5 years were considered, mainly – only a reduced set of works former to this period were included for contextualization purposes. After collecting all the papers returned from the mentioned databases, a screening step took place aiming the suppression of duplicated documents. Also, by analysing the abstract, the non-relevant articles were removed, and then, the content of the articles was inspected in more detail to check the appropriateness for inclusion. Finally, the resulting hindmost set of articles were divided into a few concise topics, focusing AOI in textile industry.

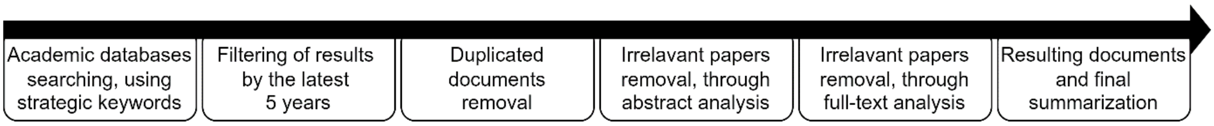


**Figure 1-** Prisma-based systematic methodology used to review image-based machine learning methods to perform defect detection in the textile industry.

## 3. Automatic optical inspection in the textile industry

In the web material manufacturing processes, visual inspection in quality control is to determine levels of product quality successfully. The manual inspection process, where much labour is involved, is highly influenced by the lack of efficiency, and it is time-consuming with low accuracy, and also prone to error due to environmental conditions and human errors. Hence the development of an AOI system using computer vision and machine/deep learning more often plays a leading role in defect detection in different industrial processes. In this section, a brief presentation of textile defects is provided, and the concept of defect detection technologies is described.

### *3.1. Types of defects*

Defects in web material manufacturing products are unavoidable due to device hardware and environmental conditions during manufacturing processes. Any abnormality in the fabric that causes the product to be rejected by the consumer is a fabric defect. The various types of defects detected during quality controls are broadly classified as follows [5]:

- Critical Defects: crucial anomalies that render an item completely unusable and could cause harm to the user of the product. These defects put businesses at serious risk of product liability issues, lawsuits, and product recalls;
- Major Defects: are those that could adversely affect the function, performance, or appearance of a product;
- Minor Defects: are usually small, insignificant issues that don't affect the function or form of the item.

Cotton Incorporate [6] has categorized the defect types into six main categories as (i) vertical lines, (ii) horizontal lines, (iii) isolated defects, (iv) pattern defects, (v) finishing defects, and (vi) printing defects (**Erro! A origem da referência não foi encontrada.**). Samples of defects such as missing yarn, broken end, needle line, oil spot, hole, press off, mixed yarn, gouts can be seen catalogued in their database (Figure 3).

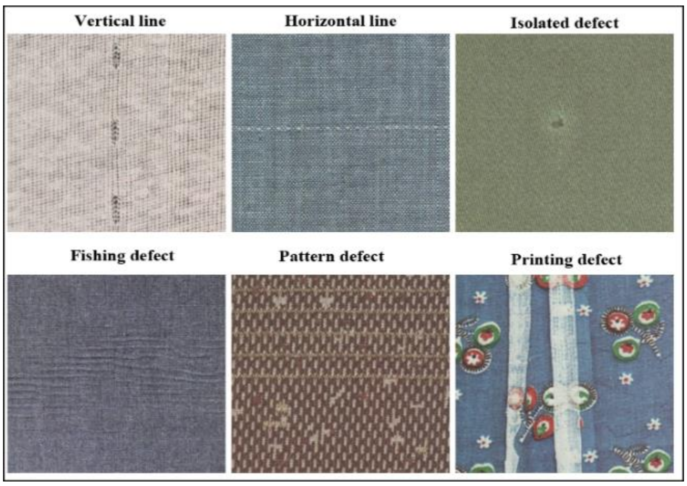


**Figure 2.** Categorization of defects [6].


**Figure 3.** Samples of defects [6].

These defects can occur periodically during the processes due to an attached object to the surface of the rolls, and it usually happens when there is more than one roll. Francisco G. Bulnes et al.[7] has solved this problem by grouping the periodical defects and cluster them.

*3.2. Defect detection methods*

Technologies using AOI shows a high potential for quality inspection and has drawn considerable interest in web material manufacturing. AOI system conclude creating image datasets and detection methods in which will let to final result and segment the defect from background (Figure 4). The fabric detection methods can be categorized into classical computer vision and machine learning methods.

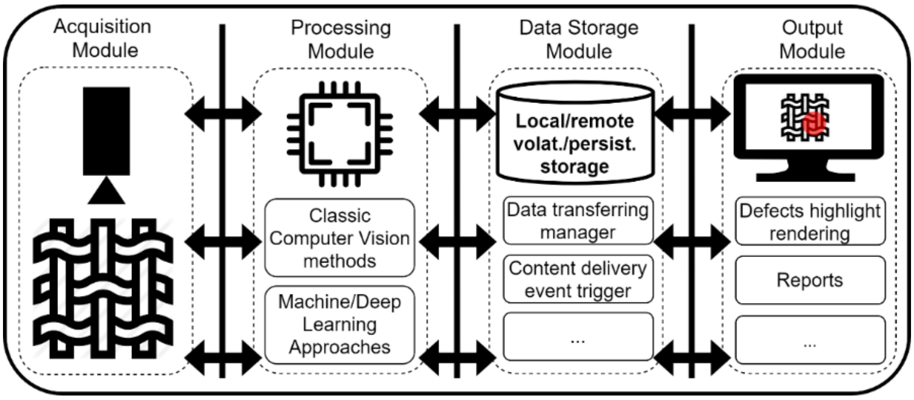


**Figure 4.** General AOI pipeline for textile quality assessment.

Relying in [8] , classic computer vision and machine learning-based methods are compared in Table 1, regarding the following defined criteria: capacity to map complex problems, margin to operate independently from structured datasets, openness to provide control over parameters extraction, level of required development effort, ability to adapt and scale to new environments and cases, low-profile hardware admissibility (performance vs. available processing power), and attainable estimation accuracy. A rating scale based on typographical symbol classification to grade each criterion was adopted, wherein a single bullet (•) refers to lowest relevance and a bullet triplet (•••) represents highest relevance.

Image-based machine learning methods, in particular, the supervised ones, are suitable to map complex problems, but they also highly rely on structured datasets to operate properly. The control over feature extraction is not as clean as in traditional computer vision, due to the automatic processes that are carried out along neural networks and preform as "black-box" operations. Other noteworthy characteristics are their ability to adapt to a certain variability of conditions (e.g., light, background) and to scale to more categories of elements within a given context, without the need for extra coding efforts. Even though machine learning methods require high-processing capabilities to operate time-effectively, they are potential estimation accuracy enhancers, as well. Complying with the goals previously defined for this paper, and considering the textile inspection context, the next subsections will be devoted to review both classic computer vision and image-based machine learning methods, with a more emphasis in the later class of approaches.

**Table 1.** Comparison between classic computer vision methods and modern machine/deep learning methods regarding problem mapping, dataset dependency, control over parameters/features extraction, adaptability and scalability for new cases, and potential for accurate estimations, from less relevant (•) to most relevant (•••).

| | Complex problem mapping capacity | Margin to work independent from structured datasets | Control over feature and parameter extraction process | Overall independence from development effort | Potential for adaptability and scalability (new cases) | Low-profile hardware admissibility | Overall estimation accuracy potential |
|---|---|---|---|---|---|---|---|
| **Classic Computer Vision methods** | • | •• | ••• | •• | • | ••• | •• |
| **Supervised image-based machine (deep) learning methods** | ••• | • | • | ••• | ••• | • | ••• |

*3.2.1.* A brief contextualization concerning classic computer vision approaches

The traditional methods of computer vision - such as binarizations, morphological operations, colour space transformations and related processing tasks, etc. – alone, usually rely on code specifically developed to address particular challenges, which are not supported by modern computational intelligence methodologies, disregarding the presence or absence of problem/conditions-oriented statistical modelling. Some of these methods can be fairly represented by Gaber filter, Wavelet transform, Fourier transform for textile defect detection. For example, S. Sadaghiyanfam [9], employed Gray Level Co-occurrence Matrix (GLCM) and three types of wavelets transform, including Haar, 2nd order Daubechies (db2), Sym4 with the different number of levels and compared the results. When the feature extraction was done for the acquired image and non-defective template, then the statistical information was compared. Both methods were successful in defect detection for the texture with high resolution.

When the GLCM is used along with other methods, it leads to a better result in defect inspection. For instance, in [10], they used a Discrete Curvelet Transform (DCT) to convert the acquired image to a binary image and then employed GLCM. They represented that this combination gives better performance when compared to GLCM-based and wavelet-based.

Such methods are suitable for textile defect inspection. Nonetheless, their problem/conditions-oriented nature constitutes a drawback in scenarios requiring tolerance for circumstantial variations affecting both elements of interest and background. More specifically, if the focus of the problem (context) shifts or the conditions (e.g., light) change, a solution developed for a very specific purpose and relying on the traditionality of computer vision will most probably have its performance degraded, as well as it will require deeper source-code reengineering. Some approaches capable of tackling such drawbacks are provided by the machine learning field, wherein training strategies are designed with the potential of generalizing, ideally, any classification problem. A key feature is the separation of the problem representation from the algorithmic approach, which supports codeless machine knowledge ground improvement strategies that rely on retraining models with datasets extended with cases never seen before. A well-known approach that can be referenced as example is active learning, which allows the improvement of inference models through expert reinforcement in dubious machine-based guesses (i.e., confidence rate below a given threshold). In the next section, machine learning approaches applied to textile defect inspection will be reviewed.

*3.2.2.* Machine/Deep Learning approaches

Computational intelligence can be integrated as an essential part of smart manufacturing to enable accurate insights for enhanced decision making across industrial activities such as - but not restricted to - production cycle itself and product quality inspection. Machine learning, and more specifically, deep learning (DL) has been widely investigated in different stages of the manufacturing lifecycle covering concept, design, evaluation, production, operation, and sustainment [11], [12].

In regard to the approaches that can be found in the literature, K. Hanbay et al. [13] proposed a new feature extraction method called DST-PCA for detection of knitting fabric defects e.g., Needle breakages, hole, press-off and gouts. They used Discrete Shearlet Transform (DST) to extract the features and then Principal Component Analysis (PCA) was employed [14] to optimize them as input for a three-layer ANN.

M. Li et al. [15] proposed a novel visual saliency–based defect detection algorithm that employs the histogram features extracted from the Context-Aware (CA) saliency maps to detect defects (Broken end, thin bar, thick bar, netting multiple, knots, hole, oil spot, and stain) in patterned and non-patterned fabric images. Such features were used to feed an SVM for classification. Three other different saliency models were used to generate the saliency maps for the fabric images (Spectral Residual (SR)[16] , Graph-based Visual Saliency (GBVS) [17] , and the third one is the model based on Covariances (COV)[18]. Also to evaluate SVM, they used Random Forest (RF) and compared the result. The K-Nearest Neighbours (KNN) algorithm is a supervised machine learning algorithm that can be used to solve both classification and regression problems. It was used by [19] for horizontal, vertical, and isolated defect inspection, more specifically, to classify coefficients matrix extracted using Discrete Wavelet Transform (DWT). V. Gnanaprakash et al.[20] extracted features e.g., contrast, correlation, cluster shade, energy, etc. from the image using GLCM and used more 3 Backpropagation Neural Network (BPNN) learning algorithms: Resilient Backpropagation, Scaled Conjugate Gradient, and Levenberg Marquardt and compared them, in which Gradient descent with adaptive learning rate showed a better performance. Also, D. Choundhury et al. [21] have used GLCM for feature extraction and fed the features to 4 types of Artificial Neural Networks (ANN): Backpropagation networks (BPN), Radial Basis Function networks (RBF), Recurrent Neural Network (RNN), Learning Vector Quantization network (LVQ), in which among them, they got the best performance using RNN to compare with others. S. Mei et al.[22] proposed a non-motif-based Multi-Scale Convolutional Denoising Auto Encoder (MSCDAE) method based on the Gaussian pyramid. This model trains the network with randomly sampled image patches from defect-free samples. Then, a batch gradient descent algorithm is applied in an error backpropagation fashion to optimize the process. They used the residual map of each image patch as the indicator for pixel-wise prediction and segmented it using a predefined threshold. The final inspection result was obtained by synthesizing the residual map reconstruction at each resolution level.

Recently, the implementation of the deep learning method in industrial applications is growing due to its ability in features extraction from raw data and automatic recognition [23]. Within this context, CNNs are becoming increasingly popular for analysing images, and are playing a main role in intelligent manufacturing [24], [25]. W. Ouyang et al. [26] developed a DL algorithm for an on-loom fabric defect inspection system to detect horizontal, vertical, and isolated defects. They improved the autocorrelation measurement by FFT in the image, which represents the motif image to be used for fabric motif generation. They employed Zero-mean Normalized Cross-Correlation (ZNCC) for generating the fabric motif map that, in turn, eliminates the weave pattern in the image but inherits the fabric defects information. They determined the probability of the defect area in the map related to the number of nodes found in the node-searching area by taking the ground image as a reference. The area with higher probability is the defect area. The fabric defect probability map undergoes to the CNNs as a Pairwise Potential Activation Layer (PPAL). To classify the fabric defect uniform textured fabrics, P. Bandara et al. [27] employed CNN and locate thread missing, oil stain and hole defects in the image. They concluded that utilizing a light beam of similar colour intensity leads to a better detection of defects than a white light. Grab cut is one of the methods used by Y. Chen et al. [28] to segment hole, knob, stain, hanging, broken warp and broken weft defect areas . Here, the advantage is the maintenance of the characteristics of defects to be used for further processes. They simplified the number of convolution layers and the number of neurons in the full connection layer in the CCN network structure of AlexNet [29] in order to reduce the parameters and then fed the samples to it for fabric defect recognition and classification. Y. Huang et al. [30] proposed an efficient CNN for defect segmentation and detection of defects (Carrying, thin bar, knots, fuzz balls, warp, weft, stain, line, broken end, hole, netting multiple, thick bar) in yarn-dyed and patterned texture fabric. They divide the network into two parts: segmentation and decision. The input image is firstly passed to the segmentation part and, then, its output is trained for the decision network. A method based on CNN and Low-Rank Representation (LRR) was proposed by [31] , in which they extracted the features of fabric image using a multi-level pyramid CNN and stored them in the feature's matrix. To speed up the training, they utilized Sparse Autoencoder in each layer. Then, a low-rank representation model and augmented lagrangian multiplier algorithm was applied to features matrix, dividing it into low-rank matrix (corresponding to the background), sparse matrix (corresponding to the defective regions) and, based in the latter, saliency maps. To locate the fabric defect region, they used a threshold segmentation algorithm to discriminate the saliency map.

H. Zhang et al. [32] proposed a method based on YOLO to detect belt yarn, knot tying, hole defects on yarn-dyed fabric . They trained the network with YOLO9000, Tiny-YOLO, and YOLO-VOC and the precision was 0%, 36%, and 86%, respectively. Based on those preliminary tests, they selected YOLO-VOC for their experiments, and to optimize the network, they changed the iterations to 20000 and 30000 with a learning rate of 0.01 that improved the precision to 94.5% and 90.6%, respectively. An effective deep learning method known as Stacked AutoEncoders (SAEs) is used by [33] to detect defects e.g., broken end, hole, netting multiple, thick bar, thin bar. Since the size of the defect in the image is tiny, to extract the right features, they applied the fisher criterion into the loss function of SAE and proposed Fisher Criterion-based Stacked AutoEncoders (FCSAE). The SAE was constructed with the encoder part of several pre-trained autoencoders. According to the context centred on the pixel, the confidence of each one is predicted by the network. Their results showed better accuracy comparatively with the Image Decomposition (ID) method [34] and the original SAE. Z.Liu et al.[35], developed an algorithm to optimize the DL network in order to detect missing yarn, scratch, twill flaw, and dye spot defects in fabric with complicated texture. They modified the original VGG16 model, which they called LZFNet. To initialize the training, they employed parameters pre-trained by ImageNet as initial values. Due to the large number of parameters, a deconvolution network was used to project feature activation back to the input pixel space and generate the map. After a detailed visualization analysis, they found out that the main features are extracted before layer 10 in the VGG16 network so that they trained the model using ten convolutional layers. Hence, the total number of fully connected layer parameters in their model was reduced to 5.3% in comparison with the original VGG16 network. Since the connection in traditional convolutional network is between each layer, G. Huang et al. [36] proposed Dense Convolutional Network (DenseNet), in which all the layers have full connection to each other in a feed-forward fashion but since its default output is 1000 categories, Z.Zhu [37] modified its network to meet their requirement which is classifying only 11 defects. In their experiments focusing data transmission, they proved that the latency with edge computing was reduced 30% when compared with cloud computing.

In the next section, a discussion is provided along with a benchmark that considers the machine learning-methods here reviewed.

## 4. Discussion

Having well-structured datasets is crucial in (supervised) machine learning methods. A valid approach may lie in using available public datasets (Table 2) that contain different types of defects. Another one is to create a customized dataset based on desired types of defects. It should be considered that the existing datasets can be augmented to create a larger number of examples for improved training stages in deep neural networks which can be done by basic operations such as rotation, flipping, translation, and random cropping [38].

Depending on the purpose, there are different methods to measure the performance of the approach such as Area under Curve (AUC), Precision, and Accuracy (ACC), F1 Score, Mean Squared Error. The screening of works analysed in this paper points out AUC, ACC, and precision as the most used metrics for the evaluation of methods.

The summary of this review is shown in table 2 and demonstrates that significant research has been reported to detect the defect by using machine learning, mostly deep learning with different type of defect e.g., hole, knob, stain, hanging, broken warp and broken weft, etc. Among them, DL has shown better performance than ML and classical methods. As it is shown in the following table, CNN with the accuracy of 98% [26] and 98.2% [28] and modified VGG16 with accuracy of 98.1% [35] for various type of defects have precise detection.

**Table 2.** Recent learning methods summary.

| Techniques | Ref | Methods | year | Defect type | Performance Metrics | Dataset |
|---|---|---|---|---|---|---|
| Spectral | [9] | GLCM and Wavelet Transform | 2018 | N/A | N/A | Self-made dataset |
| Spectral | [10] | GLCM and DCT | 2018 | N/A | N/A | N/A |
| ML | [13] | ANN | 2019 | Needle breakages, hole, press-off and gouts | ACC = 95.46% | Self-made dataset. |
| ML | [15] | SVM and RF | 2019 | Broken end, thin bar, thick bar, netting multiple, knots, hole, oil spot, and stain | ACC = 95.5% ACC = 93.5% | TILDA and self-made dataset. |
| ML | [19] | KNN | 2019 | Horizontal yarn missing, vertical yarn missing, hole, stain | ACC = 95% | N/A |
| ML | [20] | Gradient descent with adaptive learning rate, Resilient Backpropagation, Scaled Conjugate Gradient and Levenberg Marquardt | 2018 | N/A | ACC = 81%, ACC = 76%, ACC = 73%, and ACC = 72% | N/A |
| ML | [21] | BPN, RBF, RNN, and LVQ | 2018 | N/A | ACC = 90%, ACC = 60%, ACC = 96%, and ACC = 85% | N/A |

| | | | | | | |
|---|---|---|---|---|---|---|
| ML | [22] | Multi-Scale Convolutional Denoising AutoEncoder | 2018 | Oil polluted, heterozygous, scratched, flying-fiber, perforated and gauzy | N/A | Fabrics [30], KTH-TIPS [31], Kylberg Texture [32] and self-made dataset. |
| DL | [26] | CNN | 2019 | Horizontal defect, vertical defect, and isolated defect | ACC=98% | TILDA and Self-made dataset |
| DL | [27] | CNN | 2019 | Thread missing, oil stain and hole | N/A | N/A |
| DL | [28] | AlexNet-based CNN | 2017 | Hole, knob, stain, hanging, broken warp and broken weft | ACC=98.2% | TILDA |
| DL | [30] | CNN | 2021 | Carrying, thin bar, knots, fuzz balls, warp, weft, stain, line, broken end, hole, netting multiple, thick bar | N/A | Three public dataset and one self-made dataset. |
| DL | [31] | CNN and LRR | 2018 | N/A | N/A | TILDA and Defect library of the University of Hong Kong. |
| DL | [32] | YOLO-VOC | 2018 | Belt yarn, knot tying, hole | Precision=94.5% | Self-made dataset |
| DL | [33] | Stacked Auto Encoders | 2016 | Broken end, hole, netting multiple, thick bar, thin bar | ACC=85.5%, 84.4%, 82.2%, 95.3%, 86.5% respectively to Defect type. | The dataset from [29]. |
| DL | [35] | Modified VGG16 | 2019 | Missing yarn, scratch, twill flaw, and dye spot | ACC=98.1% | Xiamen Face++ Company |
| DL | [37] | Modified Dense net | 2020 | Pin holes, burl mark, chafed yarn, rough, loose warp, stretched warp, end out, overshot, stain | AUC= 18% | Alibaba Tianchi Competition |

## 5. Conclusions and future challenges

In this paper, we have presented a recent overview of defect detection for the web material manufacturing industry focused on the textile fabric. Since the manual human visual examination raises significant issues (e.g. ergonomics, subjective criteria, fatigue and proneness to failure), the inspection process must be done by using some industrial automation to enhance the quality and to decrease the production cost of the final product in which computer vision and ANN can play a main

role. In this paper, the main workflow and goals underlying these techniques and their results are represented, which seems to point out DL methods have accuracy enhancers, comparatively to other approaches. In opposition, one should bear in mind that this kind of learning methods usually require extensive and representative datasets - that are not always available -, burdensome and time-consuming training activities, as well as high-performance hardware.
Even though the machine/deep learning methods are potentially more precise than the ones relying in computer vision, when providing solutions for defect detection purposes - in fact, as in many other contexts -, aspects such as processing requirements (image resolution, flaws minimal tolerances, inspection cadence, etc.), available computation power and real-time supporting decision needs should be considered while defining an AOI system for quality assessment. Finding a compromise between classic computer vision (CV) dynamics for gross tasks, DL for sharper inference and strategies for computational resources bottleneck minimization, might be a proper way of designing responsive and precise AOI for industry. Moreover, future challenges should concern developments at two levels: a) promote the implementation of democratized multipurpose DL/CV frameworks for lego-based building solutions, scalable and flexible enough to adapt the several inspection requirements adopted across industry; and b) encourage domain-aware knowledge sharing strategies (classified imagery, annotated data, etc.) capable of leveraging integrative active learning to sustain both existing and emerging CV/DL-based tools.

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