Chapter 18
Surface Defect Detection Using Deep Learning: A Comprehensive Investigation and Emerging Trends

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Abstract Surface defect detection is currently a topic that contributes important things in identifying and assessing defects based on surface appearances, finding widespread applications in diverse manufacturing industries. This approach involves the effective handling and analysis of surface appearances using image processing techniques, coupled with the utilization of deep learning methods for defect detection in several materials such as fabric, steel, aluminum, welding, and others. However, the existing research in this field is confronted with several limitations pertaining to the accuracy, speed, and balance of defect detection outcomes. In response to these challenges, this research paper presents a comprehensive investigation into deep learning techniques for surface defect detection in some applications in industries. With the growing demand for efficient and accurate defect detection in various industries, this study aims to explore the current state of research, identify key research gaps, and shed light on the emerging trends in leveraging deep learning for surface defect detection. Through a meticulous review investigation of relevant literature and an in-depth analysis of existing studies, this research provides valuable insights into the advancements, challenges, and potential future directions in this topic area.

18.1 Introduction

The indicator of an advanced civilization is marked by the process of transformation in industries known as industrialization. Industrialization entails a shift in manufacturing processes from human labor to machine power, also referred to as the industrial revolution [1]. The current industrial revolution has shifted toward technological advancements. The development of technology has made manufacturing

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processes increasingly complex, as technological advancements bring forth demands for process improvement [2].

Since its inception in the eighteenth century, the industrial revolution has undergone remarkable transformations with the objective of enabling companies to maintain their existence and continuously improve in response to evolving market demands and product requirements [3]. The current peak of the industrial revolution is supported by rapidly advancing technologies and their integration into cyber-physical systems [4], as predicted by numerous experts [5] smart technology, artificial intelligence, automation, robotics, and algorithms, collectively referred to as STARAA, encompass the broad categories of technological advancements [5, 6].

The application of technologies such as digital technology has shown positive and significant impacts on economic and environmental performance in manufacturing companies in China [7]. Similarly, in a different region, South Africa, a positive relationship has been found between the adoption of technology, namely knowledge of big data analytics (BDA) and artificial intelligence (AI), and sustainable manufacturing and circular economy capabilities in the automotive component and related product manufacturers [8]. These empirical findings align with the research findings of [9]. Indicating that the economic performance, environmental performance, and operational performance of companies receive positive influence from the implementation of technologies such as Industry 4.0, with the greatest impact observed in the operational performance [10].

Digital disruption and technology, in essence, serve as complements to technological advancement, with the aim of achieving leaner, more flexible, and even more complex production processes [11]. However, the implementation of digital disruption is currently limited to certain industries, and the diffusion of these technologies may not occur in the near future, at least not in smaller industries [12].

Studies and research on the application of innovation technology in the textile industry are predominantly limited to literature review research [13-17], and some studies focus on bibliometric analyses [18, 19]. Furthermore, research applying quality improvement with innovation technology only focuses on defect detection for a single type of defect, such as hairiness detection in fabric [20] or yarn breakage prediction [21, 22]. Moreover, no research has utilized innovation technology for quality improvement involving multiple defect categories, nor has any research integrated it to support decision-making processes related to these defects.

18.2 Methodology

This study's methodology employs a comprehensive investigation technique, which includes searching the Scopus database for relevant scholarly papers. The retrieved papers will then be evaluated with VOS Viewer software to gain an overview of the scope of study on the issue and to investigate the chronological distribution of these studies (Fig. 18.1).

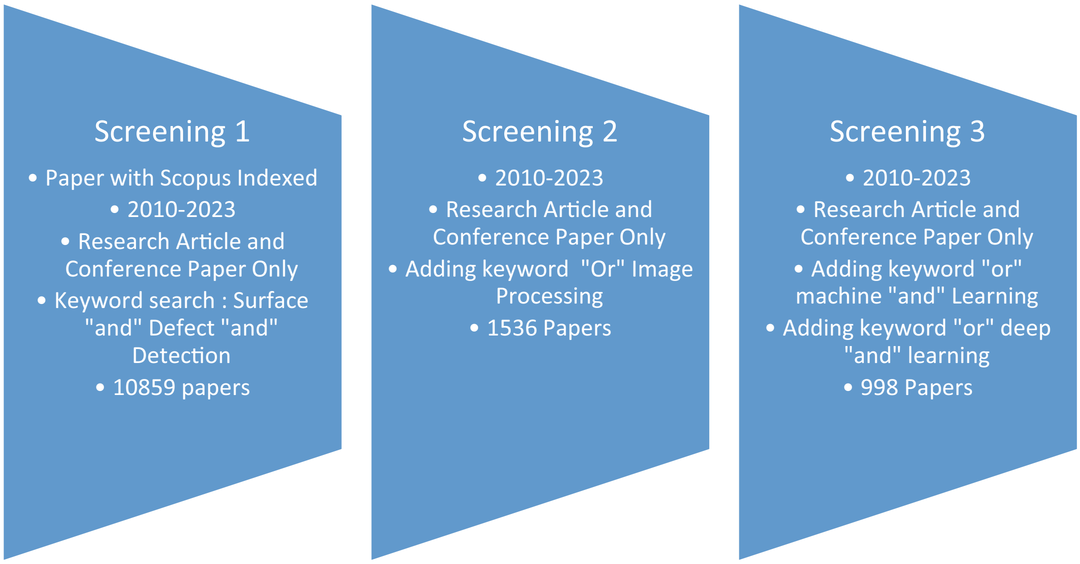

Fig. 18.1 Screening the literature

The papers were acquired using the Scopus paper database in three steps. The first stage was to limit the filter year to only research articles and conference articles from 2010 to 2023. Following that, conduct a keyword search for surface "and" defect "and" detection, yielding 10,859 papers. Using the same filter as the first, the second stage adds keywords "or" picture "or" processing, yielding 1536 papers. The third stage is the same filter as the first and second steps, with the addition of keyword search "or" machine "or" deep "and" learning, yielding 998 papers.

Following a screening process, 998 papers were determined as being highly related to the research topic. Following that, use VOS Viewer to view the classification and clustering of these publications, as well as to find notable research groups that are constantly increasing. This analysis also sheds light on prospective future research areas that might be pursued within the subject.

18.3 Result

The final visualization map is shown below after completing an analysis on 998 papers using VOS Viewer and applying "binary counting" and "occurrence" approaches for ten selected terms. The resulting visualization map is presented in Fig. 18.2.

According to the network visualization, research development is classified into numerous dominant hues. The green color represents the dominance of the topic "surface defect detection," the blue color represents discussions about attention and defect samples, the red color represents discussions about cracks, machine learning, and techniques, and the yellow color represents discussions about crack images and scores (Fig. 18.3).

Fig. 18.2 Network visualization

Fig. 18.3 Overlay visualization

Table 18.1 Top ten occurrences based on VOS Viewer

Rank	Keywords	Number of occurrence	Total link strength
1	Deep learning	414	720
2	Defect detection	222	394
3	Convolutional neural network	76	156
4	Machine vision	73	162
5	Machine learning	87	133
6	Surface defect detection	68	124
7	Image processing	55	114
8	Computer vision	52	107
9	Transfer learning	48	93
10	Object detection	40	87

Meanwhile, for the overlay visualization, also known as the co-occurrence map, the research is color-coded and organized by year. The darker colors represent the years preceding 2020, while the brighter colors, particularly yellow, depict the more recent years beginning in 2021.

The next step is to look at the top ten most frequently occurring keywords from the 889 papers linked to the previously defined topic.

Deep learning, defect detection, and convolutional neural network (CNN) are the three highest co-occurrences among the top ten co-occurrences in Table 18.1. The next step is to identify the top ten papers that are most relevant to these three co-occurrences by filtering out papers with the highest level of relevance.

18.3.1 Deep Learning

18.3.1.1 A Learning-Based Approach for Surface Defect Detection Using Small Image Datasets (2020)

The problem in this research is to reduce and solve the unbalanced image representation in rare defect detection accuracy, with the aim that it can be applied in the manufacturing industry practically. In addition, the research approach aims to reduce as much as possible the false negative rate (FNR), because FNR can interfere with and reduce the accuracy of surface defect detection [23].

The research methodology of this paper is based on learning based on small-size image datasets and ensures automatic defect detection can work. By using Wasserstein generative adversarial nets (WGANs) which is a transfer learning technique used on feature extraction and a multi-model ensemble framework [23].

18.3.1.2 Automated Visual Inspection of Fabric Image Using Deep Learning Approach for Defect Detection (2021)

The main challenge in this research is to automatically detect fabric damages in complex scenarios, involving the complexities of textile textures, defects, and intraclass differences [24].

This study introduces a dual-phase method that merges innovative and conventional algorithms to improve image and defect detection. The initial phase employs a unique fusion of domain-centered local and global image improvement algorithms, utilizing block-based alpha-rooting. The subsequent phase involves creating a neural network using modern frameworks for the precise identification of fabric defects. This approach permits more precise defect localization compared to conventional machine learning and state-of-the-art deep learning techniques [24].

18.3.1.3 An Automatic Welding Defect Location Algorithm Based on Deep Learning (2021)

The study focuses on assessing defects in welded joints on various items, leveraging deep learning's strong feature representation abilities. An automated technique for locating defects is introduced, utilizing an improved Unet network and digital X-ray images. This approach incorporates data augmentation and strategies for defect localization [25].

For improved localization accuracy, data augmentation is utilized to expand the dataset of defects welds for network training. Using this, an enhanced defect localization approach is suggested, employing a Unet network, to attain automated and highly precise defect detection [25].

18.3.2 Defect Detection

18.3.2.1 A Public Fabric Database for Defect Detection Methods and Results (2019)

The study aims to mitigate errors in textile industry inspections by creating a publicly annotated database containing plain fabrics with and without defects, characterized by uniform fabric textures. This facilitates precise comparisons among existing methods and potential future investigations. Thus, the benefits of each approach can be thoroughly understood through this database [26].

The applied analysis techniques encompass tasks related to texture, such as classification, segmentation, synthesis, shape analysis, and image restoration within the database. The defect detection approach employed for testing images from the presented database in this study involves the utilization of Gabor filters. Gabor filters, which are spectral methods rooted in texture analysis, are widely used for defect detection. Among non-feature extraction detection methods, Gabor filters are recognized as highly effective for identifying fabric defects. The objective of this research is not to establish the superiority or appropriateness of specific methods, nor is it focused on method comparison. Instead, it aims to illustrate instances using the proposed database in this investigation [26].

18.3.2.2 EDDs: A Series of Efficient Defect Detectors for Fabric Quality Inspection (2021)

The research is addressing fabric defect detection through the utilization of a streamlined deep convolutional neural network (DCNN) architecture, an evolved iteration of the convolutional neural network (CNN) [27].

The strategy adopted in this study to enhance fabric defect detection efficiency is known as efficient defect detection (EDD). In detail, the approach consists of these key elements: opting for a lightweight backbone from Efficient-Nets, incorporating L-FPN for effective multi-scale feature integration, and employing a structure reminiscent of Retina-Net for tasks involving classification and bounding box regression. This section can be adjusted using the recommended R compound scaling approach to create a variety of detectors suitable for various resource limitations [27].

18.3.2.3 Unified Detection Method of Aluminum Profile Surface Defects: Common and Rare Defect Categories (2020)

Automating the visual identification of defects on aluminum profile surfaces (APSD) is a complex task owing to the varied classes, irregular forms, haphazard arrangement, and skewed sample distribution. By harnessing attention mechanisms, a comprehensive approach for defect detection is put forth, aimed at overcoming these difficulties for both prevalent and rare defects [28].

In this study, the approach is structured as a derivation of multiple learning algorithms, designed to identify both prevalent and uncommon defect classes. Initially, a category representation network is utilized to extract common category maps (CCMs). Following this, a subject module is introduced to create proposal maps (PMs) for individually infrequent classes. Lastly, the transformation of rare category maps (RCMs) from CCMs is guided by the information present in PMs [28].

18.3.2.4 Multistage GAN for Fabric Defect Detection (2020)

Fabric (textile product) defect detection presents an intriguing and demanding subject. Numerous approaches have been suggested to address this issue, but they remain less than ideal due to the intricate variety of fabric textures and defects [29].

This study introduces a framework for fabric defect detection based on generative adversarial networks (GANs). Addressing real-world complexities, the proposed system learns from available fabric defect examples and flexibly adjusts to diverse fabric textures across distinct application scenarios. The core of this approach involves the adaptation of a deep semantic segmentation network, enabling the identification of diverse defect types. Furthermore, our efforts include training a hierarchical GAN to artificially create convincing defects within new defect-free samples [29].

18.3.3 Convolutional Neural Network (CNN)

18.3.3.1 Mobile-Unet: An Efficient Convolutional Neural Network for Fabric Defect Detection (2020)

The existing fabric manufacturing conditions demand methods with enhanced real-time capabilities. Furthermore, fabric defects, when used as samples, are significantly less common compared to normal samples, leading to imbalanced data. This, in turn, poses a challenge for training deep learning-based models [30].

To accomplish end-to-end defect segmentation, a notably well-organized convolutional neural network named Mobile-Unet is put forth. The irregular distribution of defect instances is leveraged to tackle the concern of defect sample representation. Moreover, Mobile-Unet integrates depth-wise independent convolutions, significantly diminishing computational complication and network size. The architecture comprises two segments: an encoder and a decoder. The MobileNetV2 has a feature extractor functions as the encoder, followed by the inclusion of five deconvolutional layers to serve as the decoder [30].

18.3.3.2 Fabric Defect Detection System Using Stacked Convolutional Denoising Auto-encoders Trained with Synthetic Defect Data (2020)

With the growing diversity and advancement in machine vision-based defect detection, the utilization of deep learning methods is becoming more prevalent. Lately, various investigations have been conducted regarding defect identification and categorization through image segmentation, detection, and classification. These techniques yield positive results; nevertheless, they necessitate a substantial volume of authentic defect data. Yet, procuring an ample amount of genuine defect data within industrial environments presents a considerable challenge [31].

The study introduces an approach for identifying defects through the application of stacked convolutional autoencoders. The devised autoencoder is trained solely on defect-free data and artificially generated flawed data, which is created based on expert knowledge-driven defect attributes [31].

18.3.3.3 Detecting Textile Micro-defects: A Novel and Efficient Method Based on the Visual Gain Mechanism (2020)

Considered a crucial technique in machine learning, the faster region-based convolutional neural network (Faster RCNN) has surfaced as a hopeful framework, exhibiting commendable efficiency in object detection. Nonetheless, the detection of diminutive entities like micro-defects within textiles continues to be a complex endeavor for the Faster RCNN [32].

Creating an innovative detection model to enhance the capacity for detecting small-sized entities. Initially, through an examination of the interplay between reading and visual mechanisms enhancement process, it's discerned that mechanisms connected to attention-driven visual enhancement can modify response amplitudes while retaining selectivity, consequently ameliorating visual perception acumen. Subsequently, these pertinent mechanisms are integrated into the Faster RCNN framework, culminating in the formation of a novel model termed Faster VG-RCNN. To assess the suggested class of detection, a distinctive micro-textile defect database is established as a reference point for micro-defect detection. Additionally, spacious experimental validation is carried out, encompassing diverse design alternatives [32].

Furthermore, Table 18.2 illustrates the positions and comparisons of the ten selected papers, highlighting their relative strengths and weaknesses. The table provides insights into the existing gaps in the research and identifies potential areas for future research and development. This analysis aids in understanding the current landscape of the field and guides further investigations to advance the research in this area.

Table 18.3 illustrates that within the context of defect detection, the topic of automatic defect detection remains a substantial and ongoing concern. Scholars continue to advance their understanding in this domain by delving into relevant literature through the examination of citations. This underscores the evolving nature of research endeavors in this particular area.

18.4 Discussion

This paper presents a comprehensive review of research studies indexed in Scopus that are closely related to surface defect detection. The reviewed papers focus on various aspects of surface defect detection analysis, including subjects, methods, and reference outcomes. Some studies aim to enhance defect quality and refine detection methods, while others explore cost–benefit analyses to uncover differences in defect reading approaches. The findings from these papers have significantly influenced the topic area of surface defect detection, particularly in terms of tested samples.

However, despite the progress made, there remain several aspects that require further improvement and development to achieve an optimal defect detection model. These aspects include the selection of derivative methods for artificial intelligence, types of defect readings, accuracy, error reduction, and addressing the issue of false

Table 18.2 Paper method comparison and future research

	A	B	C	D	E	F	G	H	I	J	K
1	√	√	√	√							
2	√				√	√					
3	√			√			√				
4	√				√			√			
5	√								√	√	
6	√			√					√		
7	√			√	√						
8	√			√	√	√					
9	√			√	√	√					√
10	√			√	√			√	√		
11	√			√	√	√		√			
12	√			√	√		√		√	√	
13	√										
14	√		√	√	√	√	√	√	√		√

Table description:
A = Surface defect detection
B = Wasserstein generative adversarial nets (WGANs)
C = Multi-model ensemble framework
D = Fabric/textile industry
E = Convolutional neural network (CNN)
F = Computer processing/machine learning
G = Image processing/computer vision
H = Automatic defect recognition
I = Deep learning
J = UNet framework efficient
K = Defect detectors (EDDs)
1 = Le et al. (2020)
2 = Fu et al. [33]
3 = Silvestre-Blanes et al. [26]
4 = Gao et al. (2020)
5 = Yang et al. [25]
6 = Jin and Niu (2021)
7 = Li et al. (2019)
8 = Wei et al. [32]
9 = Zhou et al. [27]
10 = Han and Yu [31]
11 = Liu et al. [35]
12 = Jing et al. [30]
13 = Zhang et al. [28]
14 = Future research

Table 18.3 Paper method comparison based on citation

Article	Google Scholar citation	Scopus citation
Le et al. (2020)	57	47
Fu et al. [33]	4502	3100
Silvestre-Blanes et al. [26]	74	48
Gao et al. [34]	26	23
Yang et al. [25]	57	41
Jin and Niu (2021)	126	58
Wei et al. [32]	26	23
Zhou et al. [27]	13	11
Han and Yu [31]	18	13
Liu et al. [35]	1653	4173
Jing et al. [30]	71	123
Zhang et al. [28]	29	26

negative ratio. Collectively, these factors highlight the need for continued attention and research in the field of surface defect detection.

To address these research gaps, this study aims to elaborate on the existing literature and introduce innovative technology in surface defect detection within the manufacturing industry. Specifically, the use of convolutional neural networks (CNNs) for fabric defect detection will be explored, aiming to refine and reduce errors encountered in previous CNN research [36].

Processing data grids, images, and videos is the main function and special design of CNN which is a neural network architecture. It effectively recognizes patterns and features present in spatial data. Training CNN involves the use of deep learning techniques, specifically backpropagation, which iteratively adjusts network weights and parameters to minimize prediction errors. This process allows CNN [36] to automatically learn relevant structures from input data deprived of the need for manual feature engineering.

CNN has emerged as a highly successful architecture in image processing and computer vision, surpassing traditional methods in several tasks including image classification, object detection, segmentation, and face recognition. Moreover, CNN [36] has found applications in other domains such as natural language processing, speech recognition, and bioinformatics.

Given these reasons, the field of artificial intelligence focused on image detection, particularly CNN, is highly relevant for future research and aligns with the identified research gap. Additionally, CNN is particularly well-suited for texture-based readings, making it an optimal choice for surface defect detection in materials like fabric.

18.5 Conclusion

This paper discusses potential directions for further research in the field of defect detection analysis, focusing on the incorporation of multiple methods to enhance the detail and accuracy of defect identification. Furthermore, the introduction of AI-based decision-making techniques is proposed to support stakeholders in making informed decisions concerning defective products. By integrating these aspects, this research aims to contribute to the existing body of knowledge, which can be further developed from various perspectives, utilizing different tools and samples. Additionally, the measurement and comparison of research outcomes are emphasized to showcase how emerging technologies can effectively assist industries in improving product quality.

Defect detection, particularly in the domain of fabric or textile product defect detection, has generated a considerable body of related literature. These connections can be categorized into various sub-connections, including object relevance, employed methods, obtained results, branches of science employed, and functional relevance. To gain a comprehensive understanding of these relationships, it is necessary to explore specific research gap topics that identify areas requiring further investigation to ensure continued relevance and advancement in the field.

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