J Opt (April 2024) 53(2):1345–1351
https://doi.org/10.1007/s12596-023-01340-5

RESEARCH ARTICLE

A review of deep learning-based approaches for defect detection in smart manufacturing

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Received: 30 April 2023 / Accepted: 22 July 2023 / Published online: 8 August 2023

Abstract Automatic detection of surface faults or defects from images plays a crucial role in ensuring quality control in smart manufacturing. Traditional image processing techniques have limitations in handling background noise, texturing, and lighting variations. To overcome these limitations, the researchers explored deep learning for automated defect identification. The study investigates contemporary mainstream approaches and deep learning methods for flaw detection, highlighting their features, benefits, and drawbacks. The goal is to understand the potential of advanced techniques in enhancing defect identification processes. The research also evaluates the performance of the proposed method and discusses the achievements and limitations of existing defect detection methods. By identifying current challenges, the study aims to pave the way for future advancements in defect detection. It provides an outline to aid the defect detection research community in shaping a new and promising research agenda. Therefore, the study not only presents the proposed method's performance but also offers valuable insights into the strengths and weaknesses of traditional and deep learning-based defect identification approaches.

Keywords Defect detection · Quality control · Smart manufacturing · Image processing · Deep learning · Review

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Introduction

In industrial manufacturing, products may encounter various faults and defects during the production of mechanical items in complex industrial processes. Some common faults include physical defects, internal holes, pits, abrasions, and scratches [1–3]. Unfavorable working conditions as well as failures in the design and machine manufacturing equipment are the causes of these flaws [4–6]. Products that are used frequently may also corrode easily and wear out [7, 8]. These shortcomings put people's health and safety at risk and make it more expensive for businesses to operate [9]. They use a lot of resources and reduce the usable lives of manufactured objects [10, 11]. Hence, spotting errors is a crucial skill that companies should possess in order to improve the quality of manufactured goods without compromising output [12, 13]. Some of existing defects in industrial products are shown in Fig. 1.

Deep learning and teaching algorithms are as powerful method for surface defect detection that has shown impressive results in recent years [15, 16]. It involves the use of artificial neural networks and learning algorithms that are trained on large datasets of images to identify defects [17]. Deep learning models can learn complex representations of images, including color, texture, and shape, without the need for manual feature engineering [10, 18–21]. Convolutional neural networks (CNN) are a popular type of deep learning model used in various object and defect detection applications [22–24]. CNNs are trained on large datasets of labeled images to learn features that are relevant for defect detection [25–27]. The output of the network is a probability map that indicates the likelihood of a defect in different regions of the image [28–30]. The network can be fine-tuned or re-trained to adapt to new types of defects or new surface materials.

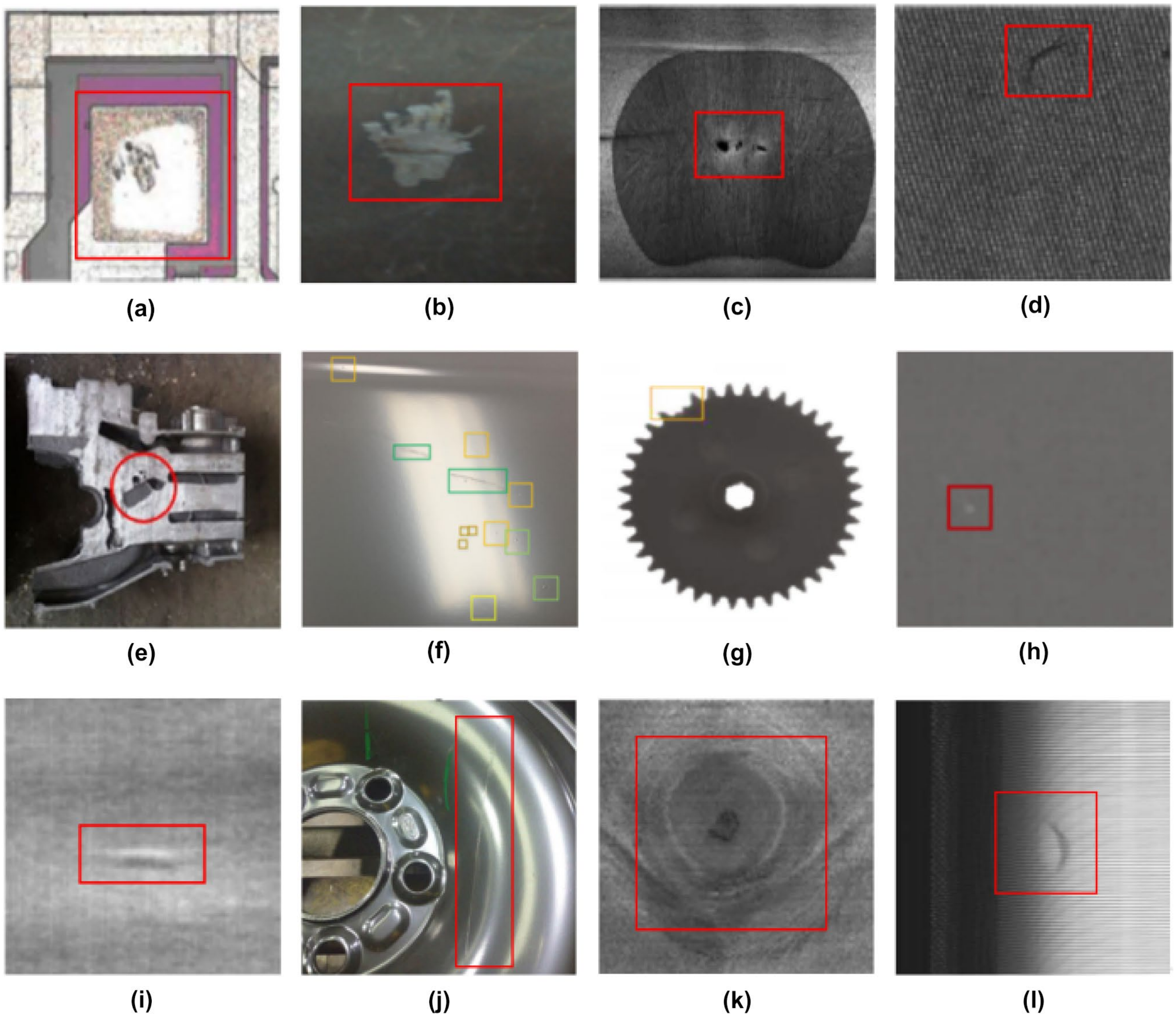

Fig. 1 Different defects in different products [14]

Deep learning (DL) models have achieved state-of-the-art performance in surface defect detection applications, outperforming traditional feature-based methods. On the other hand, real time object detection and tracking using vision based approaches are mostly used in object and defect detection applications [31]. They can detect defects in different surface materials and are robust to illumination changes, noise, and partial occlusion [32, 33]. However, they require a large amount of labeled data for training, which can be time-consuming and expensive to collect [34]. Additionally, the interpretability of deep learning models can be challenging, making it difficult to understand why a particular decision was made. Nonetheless, deep learning is a promising approach for automatic surface defect detection with many potential applications in industry and manufacturing.

In this study, deep learning is comprehensively examined in relation to its potential for automating fault detection. Moreover, the characteristics, benefits, and drawbacks of modern mainstream approaches and deep-learning methods for flaws are reviewed. Then, we describe the current achievements, limitations of the current methodologies, current research issues, and directions for future work in order to assist the defect detection research community. The study population in this research likely consists of surface defect images or datasets from various industrial manufacturing processes. Data collection methods for this study could involve gathering labeled images of surface defects from different materials and manufacturing settings.

The significance of this study lies in its comprehensive examination of deep learning's potential for automating surface defect detection, particularly in comparison to traditional feature-based techniques. Deep learning models have demonstrated state-of-the-art performance in detecting defects across various surface materials while being robust to lighting changes, noise, and partial occlusion. Despite these advantages, they require a large amount of labeled data for training, which can be costly and time-consuming to collect. Additionally, the interpretability of deep learning models poses challenges in understanding their decision-making process. Nevertheless, the study recognizes deep learning as a promising approach for automatic surface defect detection with numerous potential applications in industry and manufacturing. The originality of this research lies in its comprehensive evaluation of deep learning and mainstream approaches for flaw detection, along with an exploration of recent achievements, limitations, current research issues, and future directions. By providing valuable insights into both the strengths and drawbacks of deep learning-based defect detection, this study offers a valuable resource to the defect detection research community, aiding in the advancement of this field.

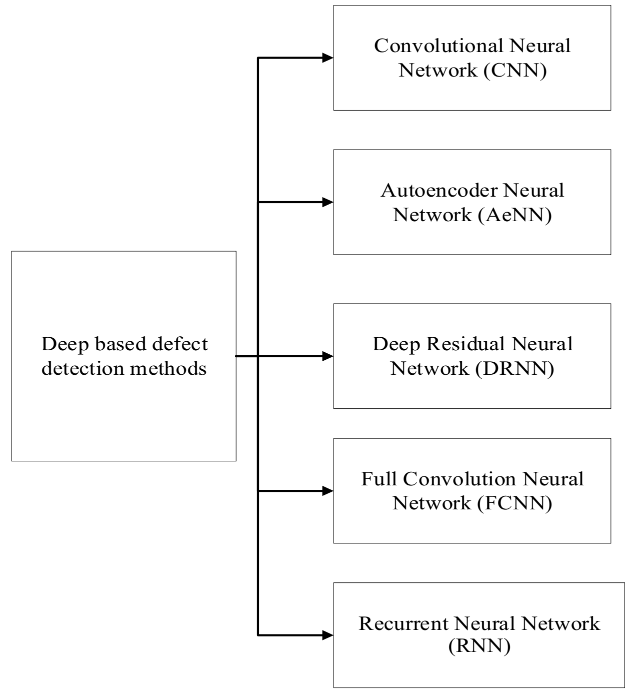

Fig. 2 Deep learning-based defect detection methods

Review of DL based approaches

Deep learning technologies have advanced quickly and achieved great success in a variety of fields [4], including object detection [35], intelligent robots [36], saliency detection [37], and event detection [38, 39], anomaly detection [40, 41], event detection [42], UAV based inspection [43–46]. Figure 2 shows categorization of deep learning-based defect detection methods.

The benefits and drawbacks of popular deep-learning techniques for detecting product defects are listed in Table 1.

Convolutional neural network (CNN) based methods

The CNNs consist of multiple layers that process images by convolving filters over the input to extract relevant features, followed by pooling layers to down sample the output [58, 59]. In surface defect detection, CNNs are trained on a dataset of images containing both defective and non-defective surfaces, allowing the network to learn to identify patterns and features specific to defects. Once trained, the CNN can classify new images as defective or non-defective.

There are various CNN-based methods used in surface defect detection, including one-shot learning, transfer learning, and multi-scale CNNs. One-shot learning involves training a CNN on a single or few images per class, while transfer learning involves using a pre-trained CNN on a different task and fine-tuning it for defect detection. Multi-scale CNNs use multiple layers with varying receptive fields to capture both local and global features of the surface.

Autoencoder neural network (AeNN) based methods

Autoencoder network-based methods for surface defect detection involve training a neural network to reconstruct an image of a non-defective surface and then using the same network to reconstruct images of potentially defective surfaces. The difference between the original and reconstructed images is used to detect defects.

The network consists of an encoder and a decoder, where the encoder compresses the image into a lower-dimensional representation and the decoder reconstructs the image. By training the network on non-defective surfaces, it learns to reconstruct them accurately. When presented with defective surfaces, the network will not be able to reconstruct them as accurately, resulting in a higher reconstruction error and indicating the presence of defects. Autoencoder network-based methods offer high accuracy and can be applied to various surface defect detection tasks, including crack detection and surface scratch detection.

Deep residual neural network (DRNN) based methods

In surface defect detection, DRNNs are trained on a sequence of images that represent the surface over time, allowing the network to learn the temporal characteristics of defects. The DRNN consists of a hidden state that is updated with each new input, allowing it to retain information about previous inputs.

Table 1 DL based analysis

Method	Applications	Benefits	Drawbacks
CNN [47, 48]	Various products	The CNN based methods enable to learn abstract, important, and high-order features from even the smallest amount of preprocessed or entirely new data and has a significant learning capacity for high-dimensional input data	The depth of the network will expand along with the capacity to communicate ideas clearly and the complexity of calculations
AeNN [49–51]	Various product	The AeNN based methods are able to represent object information, can separate the foreground area from a complicated background, and is noise-resistant	The autoencoder machine must have consistent input and output data dimensions
DRNN [52, 53]	Various product	The RNN performs better in terms of classification because it does not overfit and has reduced convergence loss	For the network's structural advantages to be fully utilized, deeper depth must work in conjunction with it
FCNN [54, 55]	Various product	Any size image can have its features extracted, and a high-level semantic prior knowledge matrix can be obtained. This has a positive impact on semantic level object detection	It is necessary to merge the underlying features with the feature matrix transformation, but the model's convergence happens slowly
RNN [4, 56, 57]	Various product	Since there are fewer sample data, we can learn the key characteristics of the data and minimize information loss during pooling	The RNN model may exhibit an overfitting phenomenon as the number of network training iterations increases

DRNN based methods can detect defects that occur over time, such as cracks that grow or scratches that appear gradually. They offer high accuracy and can be applied in various industries, including manufacturing and quality control.

Full convolution neural network (FCNN) based methods

The FCNN based methods for surface defect detection involve using a neural network that consists entirely of convolutional layers to analyze images. In surface defect detection, FCNNs are trained on a dataset of images containing both defective and non-defective surfaces, allowing the network to learn to identify patterns and features specific to defects. Once trained, the FCNN can classify new images as defective or non-defective.

The FCNN based methods offer high accuracy and can be applied in real-time scenarios due to their ability to process images quickly. They can also detect defects of varying sizes and shapes, making them suitable for various surface defect detection tasks, including surface scratch detection and surface crack detection.

Recurrent neural network (RNN) based methods

The RNN based methods for surface defect detection involve using a neural network that is designed to analyze sequential data, such as a time series of images or a video. In surface defect detection, RNNs are trained on a sequence of images that represent the surface over time, allowing the network to learn the temporal characteristics of defects. The RNN consists of a hidden state that is updated with each new input, allowing it to retain information about previous inputs. RNN based methods can detect defects that occur over time, such as cracks that grow or scratches that appear gradually. They offer high accuracy and can be applied in various industries, including manufacturing and quality control. However, they may be slower than other methods due to the sequential nature of the data.

Discussion and future study directions

Recent developments and upcoming research directions are discussed in this section. With Little Defect Data, Deep Learning is Used: People frequently have trouble locating enough data to successfully implement deep learning in defect detection applications. The number of parts produced on the production line that are defect-free is substantially larger than the number of parts that are flawed. As a result, the data with errors are naturally tiny. The limited defect data set is not an issue for a straightforward anomaly detection system that can train effectively on typical samples. The quantity of the data collection containing flaws can become a difficulty for defect localization and classification [14].

Explain ability

Users are curious as to why the system failed when a defect detection method either fails to locate a flaw or mistakenly detects a defect in an acceptable part. Unfortunately, most deep learning techniques involve complicated architecture, making it challenging for people to comprehend the decision-making process and explain why something failed. This may make deploying and enhancing system performance difficult.

Transfer-learning

The basic idea behind transfer learning is to use a pre-trained model that has already been trained on a large dataset to perform a similar task as the one we are interested in. In the case of surface defect detection, a pre-trained model could be used to detect patterns and features that are relevant to identifying surface defects. This pre-trained model can then be fine-tuned or adapted to the specific task of surface defect detection by training it on a smaller dataset of images of defective surfaces.

Fine-tuning a pre-trained model involves updating the weights of the model using the new dataset of images. This process allows the model to learn from the new data and adapt its internal representations to better detect surface defects. By using transfer learning, we can leverage the pre-trained model's ability to recognize features and patterns, which can significantly reduce the amount of data and training time required to build an accurate surface defect detection system.

Transfer learning can be implemented using a variety of pre-trained models, such as VGG, ResNet, and Inception. These models are often trained on large-scale image datasets, such as ImageNet, which contain millions of images. By using transfer learning, we can leverage the feature extraction capabilities of these models to detect surface defects with high accuracy and efficiency.

Transfer learning is an effective approach for solving surface defect challenges by leveraging pre-trained models to improve the accuracy and efficiency of surface defect detection. By fine-tuning a pre-trained model on a smaller dataset of images of defective surfaces, we can adapt it to the specific task of surface defect detection and significantly reduce the amount of data and training time required to build an accurate detection system.

Scale invariant defect detection

This is due to the fact that the CNN layers may abstract at various degrees and can extract varying amounts of structure from the patterns contained in the training pictures. These feature learning techniques take into consideration the pixel-level data in a picture. It becomes difficult to identify because the covariance surrounding each pixel varies when pictures of various sizes are present. Defects may emerge in a wide range of sizes in some applications where imaging from varied distances is necessary.

Avoiding over-fitting

Overfitting is a common problem in convolutional neural network (CNN) approaches for surface defect detection, where the model becomes too complex and starts to fit the training data too well, resulting in poor generalization performance on unseen data.

Overfitting is a challenge in surface defect detection where a model becomes too complex and starts to fit the training data too well, resulting in poor generalization performance on unseen data. In the case of surface defect detection, this can lead to inaccurate detection of defects, which can have significant consequences in industrial applications. To avoid overfitting, techniques such as data augmentation, dropout, and early stopping can be employed to ensure the model is not too complex and can generalize well to new data. To avoid overfitting in CNN approaches for surface defect detection, several techniques can be employed such as data augmentation dropout.

Conclusion

The manufacture of industrial products involves a lot of quality control, so research on defect-detection technology is quite significant in terms of practical application. Deep learning is becoming more and more popular in the defect detection field, as the literature analysis indicated. In contrast to other image analysis and object detection tasks, image-based surface defect detection using deep learning is a rapidly developing topic that has its own set of difficulties. In this paper, the current state of product defect detection technology research in intricate industrial processes is reviewed. We have talked about deep learning defect detection methods and described the experimental findings for these methods. This report also highlighted potential deep solutions now under consideration and provided information on the path future research in this field will take. The findings of this study highlight the extensive investigation into the potential of deep learning for automating surface defect detection, especially when compared to traditional feature-based techniques. A potential future work in this field could involve exploring and developing novel techniques to reduce the dependency on large labeled datasets for training deep learning models used in surface defect detection. Additionally, researchers could focus on improving the interpretability of these models to gain better insights into their decision-making process and enhance their practical applicability in industrial quality control processes.

Acknowledgements Hebei Provincial Department of Education, 2022 Hebei University Science and technology research project "Intelligent maintenance of production line based on digital twin and deep learning" (QN2022201).

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