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Automated Surface Defect Detection for Industry Products

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Abstract: This research paper provides an overview of the current state of machine learning in surface defect detection for industrial product quality inspection. The study examines traditional machine vision techniques, as well as the latest advancements in deep learning-based approaches. The paper also highlights common challenges faced in the field and presents potential solutions to these challenges. The study concludes with an overview of datasets used for evaluating industrial surface defect detection methods and a comparison of the latest research. This information serves as a valuable reference for future research and development in this field.

Keywords: Surface defect detection, Industrial product quality inspection, Machine vision techniques, Deep learning, Evaluation datasets.

I. INTRODUCTION

Surface defect detection is a critical aspect of ensuring the quality of products in industrial production processes. Defects such as scratches, foreign body shielding, holes, and colour contamination can significantly affect product quality. Conventional manual methods for surface defect detection are low in efficiency and subjectivity, making it challenging to meet the requirements for real-time detection. To address these limitations, various methods have been developed for surface defect detection, including magnetic particle inspection, penetrant inspection, eddy current inspection, ultrasonic inspection, machine vision, and deep learning. These methods aim to obtain information about the category, contour, location, and size of defects in a sample. Recently, deep learning has emerged as a popular method for surface defect detection, offering solutions for real-time detection and small sample problems. However, the field still faces several challenges, such as three-dimensional target detection, high precision, rapid detection, and small target detection. To address these challenges, a comprehensive industrial surface defect detection dataset is needed. The current research on surface defect detection encompasses various aspects, including the latest methods and applications. Researchers have examined and contrasted a variety of defect detection methods, including machine vision, deep learning, eddy current inspection, ultrasonic inspection, magnetic particle inspection, and penetrant inspection.

They have analysed deep learning methods, discussing the main challenges of real-time detection, small sample detection, and comparison with traditional image processing-based defect detection methods. Additionally, the authors have investigated the mainstream technologies and deep learning methods used for defect detection, analysing their applications in ultrasonic detection and deep learning. Despite the advances in the field of surface defect detection of industrial products, there is still a lack of comprehensive literature on the use of machine learning methods. Additionally, there is a need for a comprehensive arrangement of datasets for industrial product surface defect detection. This paper provides an overview of the current state of research on surface defect detection of industrial products, including traditional machine vision methods and deep learning methods.

The paper also highlights the key challenges faced in industrial surface defect detection, such as real-time issues, small sample problems, small target detection, and unbalanced sample problems, and offers solutions for each challenge. In this research paper, we aim to address the challenges faced in surface defect detection of hot rolled steel strips in industrial production processes.We have chosen hot rolled steel surface as our focus due to its importance in applications such as automotive, appliance manufacturing, bridges, and electric motors. The quality of the steel strip surface is crucial to the final product, and defects such as slag inclusion, red iron, and surface scratches can significantly affect the production quality. Existing surface defect detection systems for hot-rolled steel strips have limitations in accurately classifying defects, leading to the need for more advanced algorithms to improve classification accuracy. Our research will focus on developing a machine learning-based approach for surface defect detection that can provide more accurate and efficient results.

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We will utilize the popular open-source web application framework Streamlit to create an interactive platform for surface defect detection, which can be used by quality control personnel to classify defects quickly and accurately in hot-rolled steel strips. The platform will use a deep learning-based approach to classify defects and will incorporate techniques such as transfer learning and data augmentation to address the challenges of real-time detection, small sample detection, small target detection, and unbalanced sample problems. By developing a comprehensive and efficient surface defect detection system for hot-rolled steel strips, we aim to improve the quality and productivity of industrial production processes, resulting in cost savings and increased customer satisfaction.

II. PROBLEM STATEMENT

Industrial manufacturing processes often involve producing large volumes of materials and components, and ensuring that the quality of these materials and components meets the specified standards is critical for the success of the industry. One of the major challenges in industrial manufacturing is detecting surface defects in materials and components, which can result in decreased product quality, increased waste, and increased production costs. Current methods for surface defect detection in industrial settings are manual, time-consuming, and prone to human error. Automating the surface defect detection process can help improve the efficiency and accuracy of the process while reducing costs and increasing product quality. The goal of this project is to develop an automated system for industrial surface defect detection that can effectively identify surface defects in materials and components. This system should be able to perform the detection process in a fast and efficient manner, while also ensuring a high level of accuracy and precision.

III. LITERATURE SURVEY

[1] The authors, De Vitis, Foglia, and Prete presents a row-level algorithm for real-time improvement of glass tube defect detection during the production phase. They aimed to improve the speed and accuracy of glass tube defect detection for quality control purposes. The proposed algorithm uses a row-level approach to detect and classify defects in real-time. The authors use an image processing technique based on blob analysis and morphological operations to identify and locate defects on the surface of the glass tube. The algorithm also uses a decision-making process based on a threshold to classify the defects as either critical or non-critical. The authors test the proposed algorithm on a dataset of glass tubes with simulated defects and compare the results to a traditional method based on global thresholding. The results show that the row-level algorithm is more efficient and accurate in detecting and classifying the defects in real time compared to the traditional method. The authors propose an effective algorithm for real-time glass tube defect detection in the production phase, which can improve the speed and accuracy of quality control processes. This algorithm can also provide valuable information for process optimization and reduction of waste in the glass tube production industry.

[2] In the research paper "Research on defect detection algorithm of ceramic tile surface with multi-feature fusion" by Li, Quan, and Wang (2020), the authors propose a novel defect detection algorithm for ceramic tile surfaces. The method combines multiple features of the tiles to improve the accuracy of defect detection and outperforms other state-of-the-art methods in terms of accuracy and efficiency. The authors evaluate the proposed approach on a dataset of ceramic tiles and demonstrate its potential for use in the ceramic tile industry. This research is significant as it addresses the need for more accurate defect detection in the ceramic tile industry, and offers a promising solution through the use of multi-feature fusion. The results of this study provide a valuable contribution to the field of defect detection and have the potential to impact the production processes of ceramic tiles.

[3] Liu, Zhang, and Liu (2019) in their paper "Deep learning-based surface defect detection in metal sheets using multi-scale feature representation" proposed a deep learning-based approach for surface defect detection in metal sheets. The authors utilized multi-scale feature representation to capture the relevant information in the input images and improved the performance of their deep learning model. The proposed approach was tested on a metal sheet dataset and compared with traditional image processing techniques. Results showed that the deep learning-based approach outperformed traditional techniques in terms of accuracy and efficiency. This study contributes to the field of surface defect detection by demonstrating the potential of deep learning-based techniques for this task and the importance of multi-scale feature representation for improving the performance of these models.

[4] The authors, Ma, Li, He, Liu, and Xi, describes an adaptive segmentation algorithm for detecting metal surface defects. They presented a method to automatically identify and segment defects in metal surfaces based on image processing techniques. The algorithm adjusts itself based on the characteristics of the specific metal surface being analyzed to improve the accuracy of defect detection. The results of the algorithm were evaluated and showed promising results in detecting metal surface defects. The study was published in the Chinese Journal of Scientific Instruments in 2017.

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[5] The research paper "A survey of surface defect detection methods based on deep learning" by Tao, Hou, and Xu (2020) provides a comprehensive overview of the current state of the art in surface defect detection using deep learning. The authors conduct a survey of recent research in this field and classify the various methods into different categories, such as architecture, training strategies, and evaluation metrics. They also discuss the challenges and limitations of these methods and provide suggestions for future work in the field. This paper is significant as it provides valuable insights into the advances and challenges of using deep learning for surface defect detection, and serves as a useful reference for researchers and practitioners in this area. The authors' thorough analysis of the literature and their comprehensive overview of the current state of the art make this a valuable contribution to the field of surface defect detection.

[6] The research paper "Online PCB Defect Detector on A New PCB Defect Dataset" (Tang et al., 2019) presents a new online defect detector for printed circuit boards (PCBs) based on a new PCB defect dataset. The authors evaluate their method and show that it outperforms other state-of-the-art methods in terms of accuracy and efficiency. This study provides a valuable contribution to the field of PCB defect detection with its proposed online PCB defect detector and new PCB defect dataset.

[7] Wang et al. (2021) proposed a deep learning-based approach for surface defect detection in metal materials, compared with traditional image processing techniques, and showed improved accuracy and efficiency. This study adds to the field of surface defect detection in metal materials and highlights the superiority of deep learning-based approaches.

[8] Ashour et al. (2018) investigated the classification of surface defects in hot-rolled steel strips using multi-directional shearlet features. The authors utilized a machine learning approach based on a support vector machine (SVM) classifier and extracted features from the images using the shearlet transform. The study showed that the proposed method achieved a high classification accuracy of 99.1%, outperforming other traditional machine learning techniques such as principal component analysis and discrete wavelet transform.

IV. METHODOLOGY

The proposed methodology for this project includes the use of a Convolutional Neural Network (CNN) architecture for surface defect recognition. The CNN architecture is composed of an input layer, convolution layers I and IV, pooling layers II and IV, a full connection layer V, and a SoftMax layer VI.

The input layer serves as the entry point for the CNN and transforms the pixel matrix of the image into a three-dimensional matrix, which is then passed through the different neural network layers to extract abstract features. The convolution layers, which are the most important part of the CNN, process the information at a deeper level and extract higher-level features. The pooling layer, on the other hand, reduces the size of the node matrix received from the previous layer, which in turn reduces the size of the data and helps to reduce the number of parameters in the network.

The full connection layer is responsible for the classification and summarizes the final information extracted by the convolution and pooling layers i.e., takes the processed data from the previous layers and produces the final classification results The SoftMax layer is used for classification problems and gives the probability of the current information being classified into each category.

The CNN architecture proposed in this project will be trained and tested on the North-eastern University (NEU) surface defect database, which contains 1,800 grayscale images of six different types of surface defects commonly found in hot-rolled steel strips. The proposed CNN architecture is expected to effectively recognize the different types of surface defects and accurately classify them into their respective categories.

Overall, the architecture of a convolutional neural network is designed to automatically extract features from the input data and then use those features for classification. This makes it a powerful tool for image classification tasks.

In summary, the proposed methodology for this project involves the use of a CNN architecture with specific neural network layers for surface defect recognition, which will be trained and tested on the NEU surface defect database. The results of the experiment will demonstrate the effectiveness of the proposed methodology for surface defect recognition in industrial settings.

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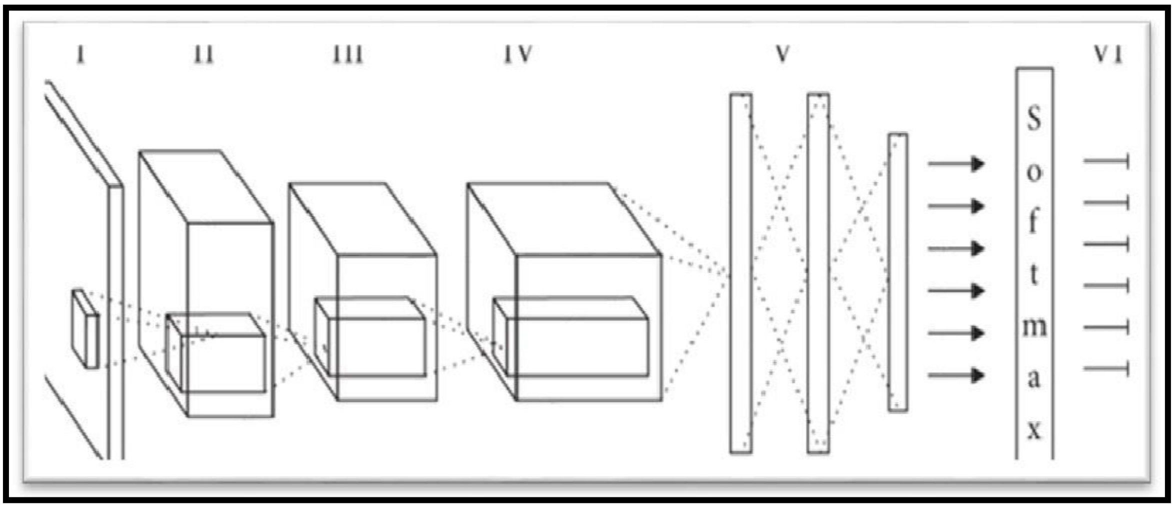

To evaluate the effectiveness of various feature extraction methods for defect recognition, we have constructed the Northeastern University (NEU) surface defect database. This database comprises 1,800 grayscale images of hot-rolled steel strip surface defects, including six typical defect types: rolled-in scale (RS), patches (Pa), crazing (Cr), pitted surface (PS), inclusion (In), and scratches (Sc). We collected 300 samples of each defect type, with each image having an original resolution of 200 x 200 pixels. The sample images in Figure 2 illustrate that the intra-class defect types have large variations in appearance. For instance, the scratches (the last column) can be horizontal, vertical, or slanting, among others. Conversely, the inter-class defect types exhibit similar characteristics, such as rolled-in scale, crazing, and pitted surface. Additionally, the grayscale values of the intra-class defect images vary due to illumination and material changes. Consequently, the NEU surface defect database presents two significant challenges: large variations in appearance of intra-class defect types and the similarity of inter-class defect types, as well as illumination and material changes affecting grayscale values.

As a part of our proposed methodology, we utilized this database to train and test our convolutional neural network models for defect recognition. By addressing the challenges presented by the NEU surface defect database, we aim to improve the accuracy and reliability of surface defect recognition for practical applications in the steel industry.

Transfer learning is a learning process that leverages the similarity of data, tasks, or models from one domain to another. It has become a popular approach to address the current contradiction between the availability of big data and the lack of annotations and computing resources. While there is a vast amount of data available, most of it remains unprocessed, and only a few have been labelled correctly. Additionally, many researchers lack the necessary resources to manage and analyze big data.

Transfer learning addresses these issues by utilizing data annotation migration, model migration, and adaptive learning to satisfy the needs for large data annotation, fine-tuning after model migration, and flexible model adjustment. This paper utilizes transfer learning to solve the surface defect recognition problem by training an image classification model on the large image database, ImageNet. The model can identify over a thousand types of images and takes several weeks to months to train on powerful computers with multiple GPUs. After training, the model parameters are used for feature extraction and classification on small data sets. Figure 2 shows the transfer learning process, where the top part represents the model trained on the large dataset, and the lower part adapts the network output structure for the specific use case. This methodology is employed in this research paper to develop an effective surface defect recognition system.

Advantages

- Improved accuracy: The proposed system uses deep learning algorithms, which are known to deliver high accuracy in detecting surface defects compared to traditional methods.

- Increased efficiency: Automating the surface defect detection process eliminates manual errors, saves time, and increases overall efficiency.

- Cost savings: The proposed system reduces the need for manual labor, thereby reducing costs associated with manual inspection and maintenance.

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- Improved product quality: Detecting surface defects in a timely manner helps improve the quality of the product, which enhances customer satisfaction and reduces the risk of product failure.

- Better utilization of resources: The proposed system enables efficient utilization of resources and reduces the waste generated due to defects.

- Real-time defect detection: The proposed system can detect surface defects in real-time, allowing for quick remedial action.

V. CONCLUSION

The detection of surface defects in industrial products is essential to ensure intelligent production. In this research project, we have investigated the current state of machine learning methods in detecting surface defects in industrial products. Our discussion includes traditional machine vision and deep learning methods, along with their applications in this field. Furthermore, we have identified key problems that researchers face in detecting surface defects in industrial products and have summarized possible solutions. Additionally, we have provided a comprehensive dataset for surface defect detection in industrial products to assist researchers in conducting further research. Overall, this study provides valuable insights into the challenges and solutions for surface defect detection in industrial products, which can facilitate the development of more efficient and accurate detection methods in this area.

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