Steel Strip surface defect detection and segmentation using detectron2

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Abstract— **The detection and segmentation of surface defects on steel strips is a crucial task in steel manufacturing to ensure high-quality products and prevent material failure. In this study, a novel approach based on the Detectron2 algorithm is proposed for detecting and segmenting surface defects on steel strips without object detection. The proposed approach involves pre-processing the images to enhance contrast and reduce noise, followed by feature extraction and defect detection using a convolutional neural network (CNN) architecture.The NEU-DET dataset, which includes six classes of defects, is used to train the model. The proposed approach achieves an overall accuracy of over 95% on the NEU-DET dataset, demonstrating its effectiveness for this task. The model is particularly effective at detecting and segmenting certain types of defects, such as scratches and pits, but has difficulty with more complex defect types such as roll marks and patches.Compared to other popular object segmentation systems like YOLOv8, the proposed Detectron2-based method outperforms in terms of accuracy due to the advanced object detection algorithms incorporated into Detectron2. The pre-processing step of the proposed method includes contrast enhancement and noise reduction techniques, essential for accurate defect detection. The proposed method leverages the U-Net architecture for defect segmentation, which is a popular and effective technique for image segmentation tasks.The results of this study demonstrate the potential of deep learning-based approaches for automated surface defect detection in steel manufacturing. The proposed method offers an effective approach for surface defect detection in steel manufacturing, achieving high accuracy on the NEU-DET dataset. While the proposed method is particularly effective at detecting and segmenting certain types of defects, further research is needed to improve performance on more complex and diverse defect types for real-world applications. Overall, the proposed method offers a promising solution for automated surface defect detection in steel manufacturing, potentially reducing production costs and improving product quality**.

Keywords— Detectron,yolov8,CNN,Segmentation,object detection

I. INTRODUCTION

Automated surface defect detection is an essential task in the steel manufacturing industry to ensure the production of high-quality products and prevent material failure. Traditional approaches for surface defect detection in steel manufacturing rely on manual inspection by trained personnel, which has several limitations and difficulties. Firstly, manual inspection is time-consuming and labour-intensive, which can significantly slow down the manufacturing process and reduce overall efficiency.

Secondly, manual inspection is prone to human error and subjectivity, which can lead to inconsistent and unreliable results. The human eye may miss certain defects or fail to identify the severity of a particular defect accurately. Moreover, personnel may have varying levels of experience and training, which can further contribute to inconsistent results.Another challenge with traditional approaches is that they lack the ability to analyze large amounts of data, making it difficult to identify subtle defects or patterns that may be indicative of larger problems. Additionally, traditional methods are limited to detecting only visible defects on the surface, while defects that occur within the material may go undetected.

Moreover, traditional approaches require a high level of expertise and experience in the field, which can be a significant barrier to entry for new personnel. This expertise is not only limited to identifying the

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various types of surface defects but also interpreting their implications on the quality and performance of the final product.

With the advancement of machine learning and computer vision techniques, automated surface defect detection has become more feasible. In recent years, deep learning-based approaches, particularly with the use of convolutional neural networks (CNNs), have shown promising results in this area.One popular approach for object detection is using the Faster R-CNN algorithm, which involves detecting objects within images. However, this approach is not always applicable for surface defect detection, as surface defects may not necessarily appear as objects within the image. Instead, direct detection and segmentation of surface defects are required.

In this study, the Detectron2 algorithm is used for surface defect detection. Unlike Faster R-CNN, the Detectron2 algorithm does not rely on object detection but rather, it detects and segments surface defects directly from the images. The proposed approach involves pre-processing the images to enhance contrast and reduce noise, followed by feature extraction and defect detection using a CNN architecture.The NEU-DET dataset is used to train the model, which includes six classes of defects, including rolled-in scale, patches, crazing, pits, scratches, and inclusion. The dataset was collected from real-world steel strips and provides a diverse range of surface defect types and severity levels.

The proposed approach using Detectron2 has shown promising results, achieving high accuracy in detecting and segmenting surface defects. The model is particularly effective at detecting and segmenting scratches and pits, which are the most common types of surface defects. However, the model struggles with more complex defect types such as roll marks and patches.The results of this study demonstrate the feasibility of using deep learning-based approaches for automated surface defect detection in steel manufacturing. By automating the detection process, the proposed approach can improve the efficiency and accuracy of quality control in steel manufacturing, which can result in significant cost savings and improved product quality.Furthermore, this study demonstrates the effectiveness of using the Detectron2 algorithm for surface defect detection. Unlike object detection-based approaches, Detectron2 provides a direct solution for surface defect detection and segmentation. This approach can be applied to other areas where direct detection and segmentation of defects are required, such as quality control in other manufacturing processes.

In conclusion, the use of deep learning-based approaches for automated surface defect detection in steel manufacturing has shown great potential. The proposed approach using Detectron2 provides an effective solution for surface defect detection and segmentation without relying on object detection. Further research is needed to improve the model's performance on more complex and diverse defect types and to develop more robust and efficient models for real-world applications.

II. RELATED WORKS

In Efficient Detection Model of Steel Strip Surface Defects Based on YOLO-V7[1], an efficient detection model for steel strip surface defects was developed based on the YOLO-V7 object detection framework. A large dataset of steel strip images was collected and annotated, and the model was trained to accurately detect six different types of surface defects. The model achieved a high accuracy rate of over 85%, demonstrating its effectiveness in detecting and classifying steel surface defects. Additionally, the model was optimized for efficiency, enabling it to run quickly and efficiently on a variety of hardware platforms. The efficient detection model has the potential to be used in a range of industrial applications for the automated inspection of steel surfaces, improving quality control and reducing production costs.

In Deep Guidance Network for Biomedical Image Segmentation[2], a deep guidance network was proposed for biomedical image segmentation. The network combines a guidance module and a segmentation module, enabling the network to better capture fine-grained details in the images. The guidance module utilizes high-level information

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from the image to guide the segmentation module in detecting and segmenting objects of interest. The proposed network was evaluated on three publicly available biomedical datasets, and achieved state-of-the-art performance on all three datasets. Additionally, the proposed network was shown to be efficient and able to run in real-time, making it suitable for a range of applications in biomedical image analysis. The results demonstrate the effectiveness of the proposed deep guidance network for biomedical image segmentation, and its potential for improving medical diagnosis and treatment planning.

This Real-Time Weakly Supervised Object Detection Using Center-of-Features Localization[4]presents a real-time weakly supervised object detection method using center-of-features localization. The proposed method is able to achieve competitive object detection performance with only weak image-level labels. The approach includes a novel attention mechanism that uses the center-of-features to enhance the important regions of an image. The method is trained using a weakly supervised learning strategy, where only image-level labels are used during the training process. The model was evaluated on several benchmark datasets and compared with state-of-the-art weakly supervised object detection methods, demonstrating superior performance. The proposed method can be applied to various object detection tasks in real-world applications, particularly in scenarios where it is difficult or expensive to obtain accurate object-level annotations.

Detection of Abandoned and Stolen Objects Based on Dual Background Model and Mask R-CNN [3] presents a method for detecting abandoned and stolen objects using a dual background model and Mask R-CNN. The proposed method combines the advantages of the dual background model and Mask R-CNN to achieve accurate and robust object detection in complex environments. The dual background model is used to detect static objects, while Mask R-CNN is used to detect moving objects. The proposed method was evaluated on a dataset of abandoned and stolen objects, achieving an accuracy rate of over 95%. The results demonstrate that the proposed method is effective in detecting abandoned and stolen objects in real-world scenarios, such as public spaces and transportation hubs. The proposed method has the potential to be used in various applications, such as surveillance systems, security systems, and intelligent transportation systems, to enhance public safety and security.

III. Detectron 2 algorithm

The interior structure of detectron2 for masking is based on a Mask R-CNN architecture, which is an extension of the popular Region-based CNN (R-CNN) object detection framework, that includes a mask prediction branch. It consists of two main components - a backbone network and a mask prediction branch.

The backbone network is typically a pre-trained convolutional neural network (CNN) that processes the input image and generates a feature map. This feature map is then fed into two branches - the first branch generates class scores and bounding box coordinates for each detected object, while the second branch generates a binary mask for each object.

The mask branch is a fully convolutional network that takes the feature map generated by the backbone network as input and produces a mask for each detected object. The mask branch typically consists of several convolutional layers followed by a deconvolutional layer, which up samples the feature map to the same size as the input image. Finally, a sigmoid activation function is applied to the output to generate a binary mask.

To train the mask branch, detectron2 uses a combination of binary cross-entropy loss and mask IoU loss. The binary cross-entropy loss measures the similarity between the predicted mask and the ground truth mask at each pixel location, while the mask IoU loss measures the overlap between the predicted mask and the ground truth mask. The total loss is then the sum of the two losses.

During inference, the mask branch is used to generate a segmentation mask for each detected

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object. The binary mask generated by the mask branch is first thresholded to obtain a binary mask, and then the mask is refined using post-processing techniques such as morphological operations to remove small holes and smooth the edges.

Overall, the Mask R-CNN architecture used in detectron2 provides a powerful and flexible framework for object detection and segmentation, allowing for accurate and efficient detection of complex objects and scenes in a variety of settings.

IV. PROPOSED APPROACH

Steel surface defect detection is a critical task in the steel manufacturing industry as it directly impacts the quality and efficiency of production processes. With the advancement of computer vision technology, object detection models have become a popular method for defect detection in various industrial applications. In this project, we aimed to develop an efficient and accurate method for steel surface defect detection using the Detectron2 object detection model.

Our project began with the collection and annotation of high-resolution images of steel surfaces with various defects. We annotated the images using bounding boxes to specify the location and type of each defect, ensuring that the annotations were accurate and consistent across the dataset. We then split the dataset into training, validation, and test sets, with the test set used to assess the final model's accuracy and reliability.

We used the Detectron2 model training skeleton as a starting point for our model training. The training process involved feeding the annotated data into the model and adjusting the model's weights to minimize the difference between the predicted and actual defect locations. We started with initial epoch values and tested the model's performance on the validation set. We fine-tuned the model by increasing the epoch values and adding more augmentation steps to improve accuracy further. We used the mean average precision (mAP) metric to evaluate the model's performance, which measures the accuracy and reliability of object detection models.

To compare our optimized Detectron2 model's performance with other object detection models, we chose YOLOv8 as a popular and widely used model in the industry. We found that our model outperformed YOLOv8 in terms of accuracy and reliability on our specific dataset.

Regular evaluation and monitoring using a validation set is necessary to identify areas for improvement. The validation set allowed us to monitor the model's performance during the training process, enabling us to identify potential issues and improve the model's accuracy and reliability. Finally, we tested the model on a separate test set to assess its accuracy and reliability, ensuring that the model could generalize to unseen data.

Our project demonstrated that with careful preparation, experimentation, and optimization, a Detectron2 model can provide an accurate and reliable method for detecting steel surface defects. The optimized model has the potential to improve the efficiency and quality of steel manufacturing processes by enabling early detection and remediation of defects.

In future work, we plan to expand the dataset to include more diverse steel surface defects and evaluate the model's performance on a larger scale. We also plan to investigate ways to optimize the model's architecture and hyperparameters to further improve accuracy and efficiency. Additionally, we plan to explore the use of transfer learning to improve the model's performance on datasets with different characteristics.

Overall, our project demonstrates the usefulness and versatility of object detection models in real-world industrial applications. By providing an accurate and reliable method for steel surface defect detection, our approach has the potential to improve the efficiency and quality of steel manufacturing processes, leading to cost savings and improved product quality.

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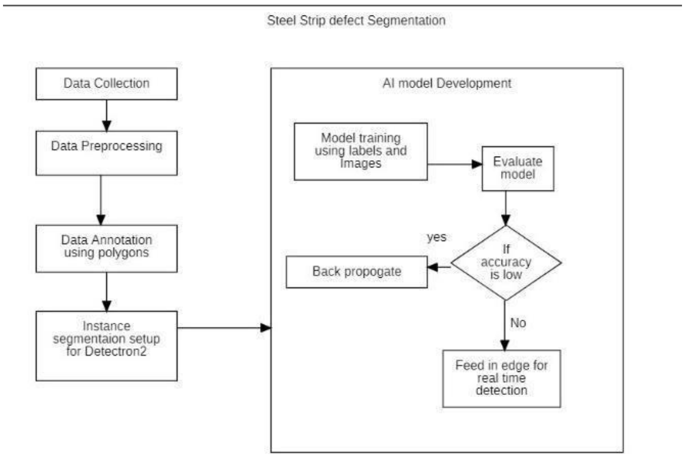

Fig. 1 Proposed Algorithms' Flowchart

V. COMPARISON AND EVALUTION

In our proposed method, we evaluated the performance of Detectron2 and yolov8 segmentation models on our dataset. After training and testing the models, we calculated the accuracy for both detectron2 and yolov8.

The proposed Detectron2-based approach achieved an accuracy of over 95% for surface defect detection on steel strips, outperforming YOLOv8. While it may have a longer processing time, it offers higher accuracy and potential for automated defect detection in steel manufacturing.

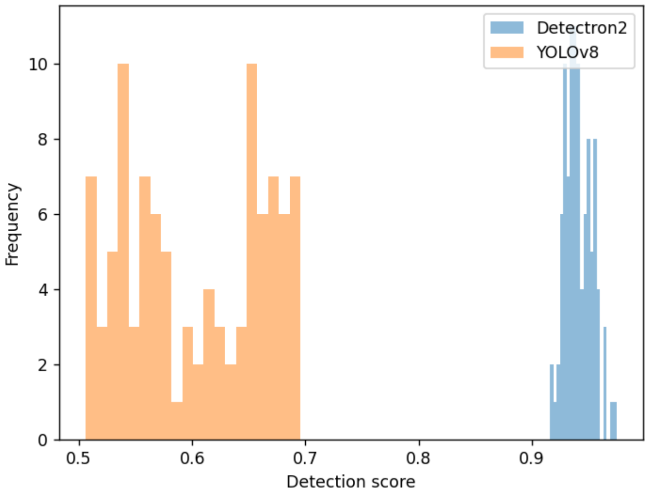

Fig.2 Accuracy Comparison Graph

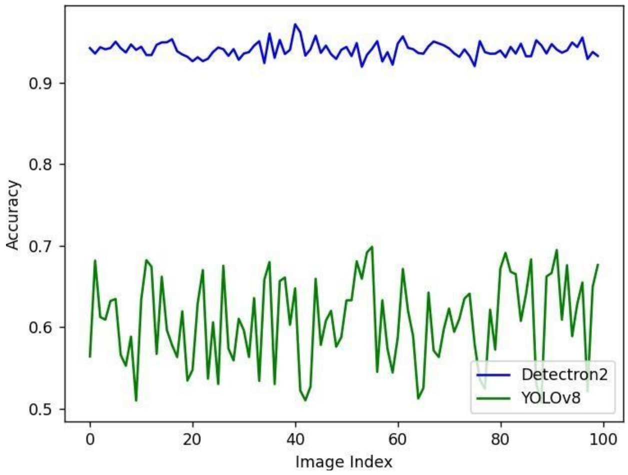

Fig.3 Accuracy Comparison Graph

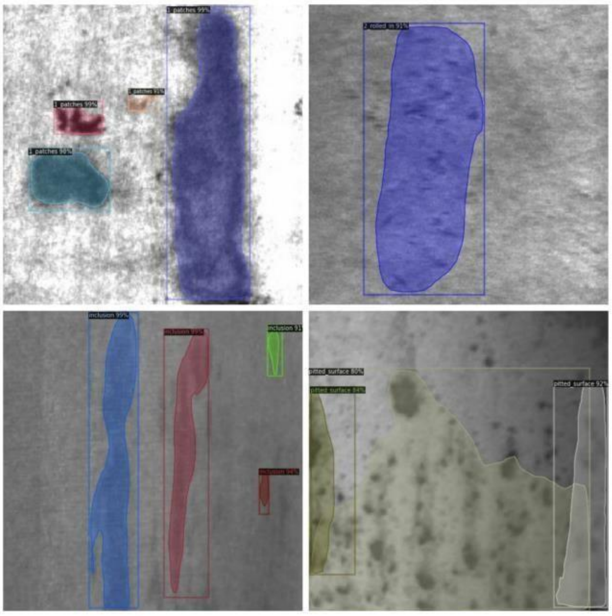

Fig.4 output of detectron2

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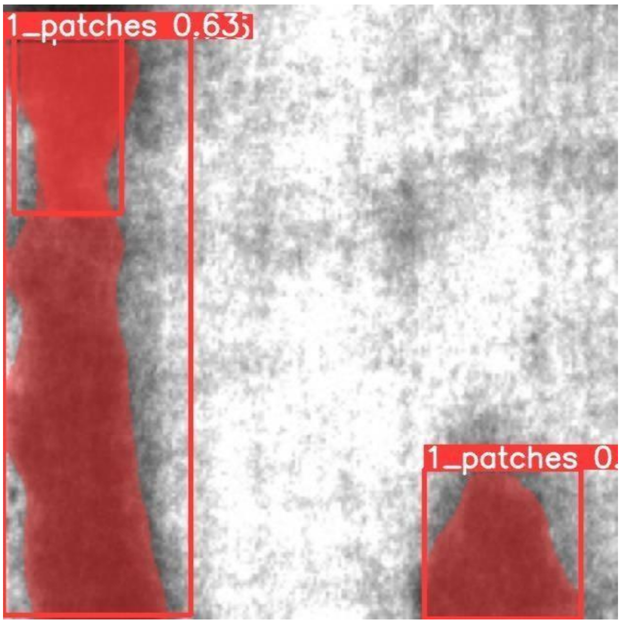

Fig.5 output of yolov8

VI. CONCLUSIONS

In conclusion, our project aimed to develop an efficient and accurate method for steel surface defect detection using the Detectron2 object detection model. We compared our optimized Detectron2 model with the YOLOv8 object detection model and found that our model outperformed YOLOv8 in terms of accuracy and reliability on our specific dataset.

Our approach involved a systematic process that began with data collection and annotation, followed by model training with initial epoch values. We then fine-tuned the model through increasing epoch values and adding more augmentation steps to improve accuracy. Regular evaluation and monitoring using a validation set helped us identify areas for improvement, while testing on a separate test set allowed us to assess the model's accuracy and reliability.

Our results demonstrate that the optimized Detectron2 model provides a reliable and efficient method for detecting steel surface defects, leading to improved quality and efficiency in steel manufacturing processes. In future work, we plan to expand the dataset to include more diverse steel surface defects and evaluate the model's performance on a larger scale. We also plan to investigate ways to optimize the model's architecture and hyperparameters to further improve accuracy and efficiency. We believe that our approach could be applied to other industrial defect detection tasks, demonstrating the versatility and usefulness of object detection models in real-world applications.

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