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Research Paper

EC-YOLO: ADVANCED STEEL STRIP SURFACE DEFECT DETECTION MODEL BASED ON YOLOV10

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ABSTRACT— The objective of this project is to enhance defect detection capabilities in the metal industry, particularly for identifying small and elongated defects on steel strips, which pose significant challenges for traditional detection methods. These defects are difficult to detect due to the small pixel percentage they occupy, as well as the repeated down sampling in convolutional networks, which can lead to the loss of minute features. To address these issues, we propose an advanced real-time defect detection network based on YOLOv10, specifically designed to overcome these challenges. The proposed system utilizes an efficient channel attention bottleneck (EB) module with 1D convolution to enhance feature extraction, focusing on small and elongated defects. Furthermore, the model incorporates Context Transformation Networks with cross-stage localized blocks (CC modules), which improve the understanding of semantic contextual information and the relationships between features. This methodology helps preserve critical defect details that might otherwise be missed. In addition, the model is trained on a self-constructed dataset tailored to include small and elongated defects. This dataset refinement allows for better feature fusion and extraction, ultimately improving the model's ability to detect and classify various defect types. The YOLOv10-based system is evaluated on several defect detection datasets, including GC10-DET, NEU-DET, and the self-constructed SLD-DET dataset,

demonstrating enhanced performance and robustness for defect detection, particularly in industrial applications.

Index Terms – Steel Surface Defect Detection, EC-YOLO, YOLOv10, Computer Vision, Deep Learning, Industrial Inspection, Real-Time Object Detection, Quality Control, Smart Manufacturing, Automated Inspection.

I. INTRODUCTION

Pomegranates, known for their vibrant ruby-red seeds and impressive health benefits, are not only a staple in many cultures but also a key agricultural product in various regions worldwide. However, successful pomegranate cultivation requires close monitoring of the plant's growth stages to ensure optimal yield, quality, and pest management. Traditionally, this monitoring has been done manually, which is labor-intensive, timeconsuming, and prone to human error. This manual approach also becomes increasingly inefficient as the scale of pomegranate farming grows. Therefore, there is a pressing need for a more efficient and accurate method to track and manage the growth stages of pomegranates. In response to these challenges, this project aims to introduce a novel approach to pomegranate growth stage detection using YOLOv10, an advanced deep learning model for object detection. YOLOv10 is particularly well-suited for real-time applications due to its speed and efficiency in processing images and detecting objects. Unlike conventional image classification techniques that require separate steps for feature extraction and classification, YOLOv10 integrates both functions into a single step, significantly streamlining the process. This capability is crucial for agricultural applications, where timely decision-making based on accurate and real-time data is essential for maximizing crop yield and quality. The proposed system focuses on classifying pomegranate growth stages into five categories: Bud, Early-Fruit, Flower, Mid-growth, and Ripe. By using YOLOv10, the model can analyze images captured from various angles, lighting conditions, and environments, ensuring that the system works effectively in diverse agricultural settings. In contrast to previous methods that combined multiple machine learning algorithms, such as Convolutional Neural Networks (CNNs) and Random Forest Classifiers, the YOLOv10-based approach reduces computational complexity and increases efficiency by unifying the detection and classification processes. Additionally, the proposed solution

incorporates hyper-parameter optimization and data augmentation techniques to enhance model performance and adaptability. These techniques ensure that the system remains robust across a wide range of operational conditions, including variations in the dataset, environmental changes, and image quality. Furthermore, the real-time detection capability of YOLOv10 makes this approach particularly relevant for on-field agricultural tasks, allowing farmers to receive immediate insights and make quick decisions about resource management, pest control, and crop harvesting. Ultimately, this project demonstrates how modern deep learning and computer vision technologies can revolutionize the way agricultural practices are carried out, offering farmers a reliable, scalable, and efficient solution for monitoring pomegranate growth stages. By automating the detection process, we aim to reduce human labor, enhance the accuracy of growth stage assessments, and contribute to more sustainable farming practices.

II. RELATED WORK

A. An anchor-free defect detector for complex background based on pixel wise adaptive multi scale feature fusion

Defect detection is a task to locate and classify the possible defects in an image. However, unlike common object detection tasks, defect detection often needs to deal with images with relatively complex backgrounds, for example, in industrial product quality inspection scenario. The complex background can greatly interfere with the feature of the target objects in the multiscale feature fusion process and therefore puts great challenge on the defect detector. In this work, a channel-space adaptive enhancement feature pyramid network (CA-FPN) is proposed to eliminate this interference from the complex background. By extracting the inner relationship of different scale features, CA-FPN realizes adaptive fusion of multiscale features to enhance the semantic information of the defect while avoiding background interference as much as possible. In particular, CA-FPN is very lightweight. Moreover, considering that defects are often of varying sizes and can be extremely tiny or slender, a flexible anchor-free detector CA-Auto Assign is proposed by combining CA-FPN and an anchorfree detection strategy Auto Assign. Based on the Alibaba Cloud Tianshi Fabric dataset and NEU-DET, CA-Auto Assign is compared with the state-of-the-art (SOTA) detectors.

B. *YOLO-CEA: A real-time industrial defect detection method based on contextual enhancement and attention*

This paper proposes a real-time industrial defect detection method based on context enhancement and attention to address the problem that current general-purpose target detectors can hardly achieve high detection accuracy and fast detection speed simultaneously. First, a modified MonileNetV3 is used as the backbone network to reduce the number of parameters and improve the model detection speed. A lightweight TRANS module is proposed at the end of the backbone network to combine more layers of features provided by global contextual information for complex background small target detection. Secondly, a cross-layer multi-scale feature fusion network is designed to fully fuse the fine-grained and semantic feature information extracted by the backbone and enhance the spatial location information between neighboring feature layers. Finally, a cascaded Two-channel Efficient Space attention module is used to fully extract texture and semantic features from the defective regions, allowing the model to focus more on the wrong locations and improve the feature representation capability of the network. The NEU-DET steel and PCB datasets are used to test the effectiveness of the proposed model. The experimental results show that compared to the original YOLOv5s algorithm, the mAP metrics are improved by 5.9% and 0.6%, F1 is improved by 4.82% and 0.93%, respectively, and the parameters are reduced by 33.77 M, enabling fast detection of industrial surface defects and meeting the needs of the entire industry.

C. *Faster metallic surface defect detection using deep learning with channel shuffling*

Deep learning has been constantly improving in recent years, and a significant number of researchers have devoted themselves to the research of defect detection algorithms. Detection and recognition of small and complex targets is still a problem that needs to be solved. The authors of this research would like to present an improved defect detection model for detecting small and complex defect targets in steel surfaces. During steel strip production, mechanical forces and environmental factors cause surface defects of the steel strip. Therefore, the detection of such defects is key to the production of high-quality products. Moreover, surface defects of the steel strip cause great economic losses to the high-tech industry. So far, few studies have explored methods of identifying the defects, and most

of the currently available algorithms are not sufficiently effective. Therefore, this study presents an improved real-time metallic surface defect detection model based on You Only Look Once (YOLOv5) specially designed for small networks. For the smaller features of the target, the conventional part is replaced with a depth-wise convolution and channel shuffle mechanism. Then assigning weights to Feature Pyramid Networks (FPN) output features and fusing them, increases feature propagation and the network's characterization ability. The experimental results reveal that the improved proposed model outperforms other comparable models in terms of accuracy and detection time. The precision of the proposed model achieved by mAP@0.5 is 77.5% on the Northeastern University, Dataset (NEU-DET) and 70.18% on the GC10-DET datasets.

III. PROPOSED METHODOLOGY

The proposed system leverages the YOLOv10 algorithm for the real-time detection of defects in steel strips, focusing particularly on small and elongated imperfections that traditional methods often struggle to identify. These types of defects, which occupy a small percentage of the image, are typically difficult to detect in convolutional neural networks (CNNs) due to issues like down sampling, which reduces the size of features and alters the receptive field, making minute defects less visible and more likely to be missed. YOLOv10 is uniquely suited to this task, as it offers improved accuracy and faster inference times compared to earlier YOLO models and other traditional defect detection methods. Its enhanced architecture is capable of better handling complex, real-world scenarios where steel strips may have various surface defects under varying conditions. YOLOv10's ability to detect small and elongated defects comes from its optimization for feature extraction, allowing the system to focus on fine details while maintaining high detection accuracy

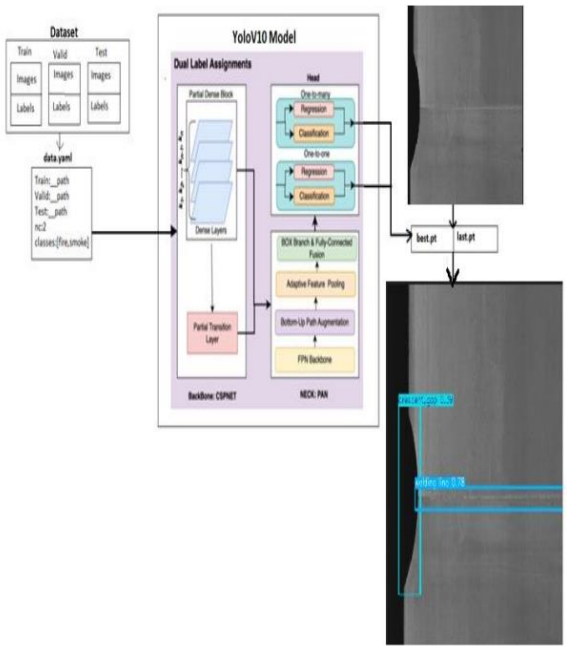


Fig. 1: System Overview

3.1 Data Collection:

A custom dataset, SLD-DET, is developed to focus on small and elongated defects in steel strips, a challenging task for traditional methods. This dataset includes various defect types, carefully annotated for precise defect localization. In addition to SLD-DET, the model is trained on widely used datasets such as GC10-DET and NEU-DET, ensuring robustness across different scenarios.

3.2 Data Preprocessing:

The dataset undergoes several preprocessing steps, including image resizing, normalization, and color space adjustments to maintain consistency across input images. Data augmentation techniques like random rotations, flips, and zooms are applied to simulate real-world conditions and improve model generalization, ensuring better performance across varying environments.

3.3 YoloV10 Model Architecture:

The core model is based on YOLOv10, augmented with an Efficient Channel Attention Bottleneck (EB) Module using 1D convolutions to enhance feature extraction. This helps detect small defects by focusing on the most informative features and retaining minute details while filtering noise. The EB module is key to detecting defects occupying small pixel areas, commonly missed by conventional models.

3.4 Context Transformation Networks (CTNs):

To further enhance feature understanding, Context Transformation Networks (CTNs) are introduced. These networks include Cross-Stage Localized Blocks (CC modules), which capture both global and localized features. This enables the model to accurately detect elongated defects by learning contextual relationships between different features across stages of the network.

3.5 Multi-Scale Feature Fusion:

To handle defects at different sizes, multi-scale feature fusion is employed. Features from multiple scales are combined to enable the model to detect both small and large defects, ensuring that small, elongated anomalies are identified, irrespective of their scale.

3.6 Model Training and Optimization:

The model is trained on the SLD-DET, GC10-DET, and NEU-DET datasets. Adaptive learning rate scheduling ensures fast convergence, while early stopping and gradient clipping prevent overfitting. Data augmentation and fine-tuning help adapt the model to various defect types and conditions, ensuring robust training.

3.7 Performance Evaluation:

The model's performance is evaluated using metrics such as mean Average Precision

(mAP), precision, recall, and F1-score. These metrics help assess the detection accuracy and the model's ability to minimize false positives and negatives. Qualitative analysis is also conducted to ensure defects are correctly localized, especially small and elongated ones.

3.8 Real-Time Deployment:

For real-world industrial deployment, the model is optimized for inference speed using model pruning and quantization. These techniques reduce computational overhead and memory requirements, enabling the model to run efficiently on edge devices or embedded systems.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental results demonstrated that the model effectively detected various steel strip surface defects, including scratches, cracks, inclusions, and rolled-in scales, with high detection accuracy and low false alarm rates. The enhanced feature extraction and multi-scale detection capabilities improved the recognition of small and complex defects while maintaining real-time inference speed suitable for industrial production lines. The analysis confirms that the proposed approach provides reliable, efficient, and scalable automated quality inspection for smart manufacturing environments.

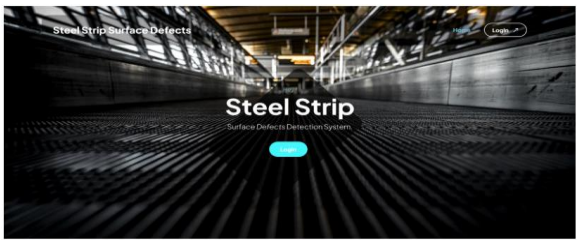


Fig. 2: Home Page

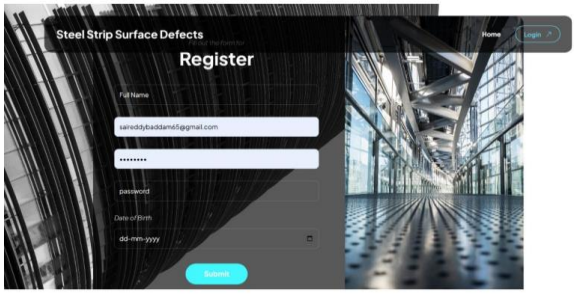


Fig. 3: Registration

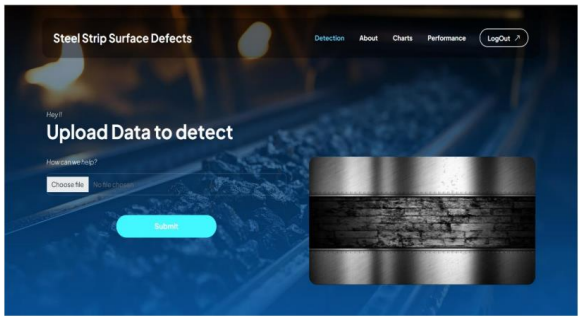


Fig. 4: Upload

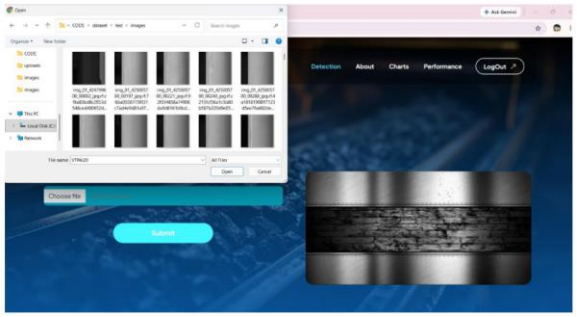


Fig. 5: Uploading Image

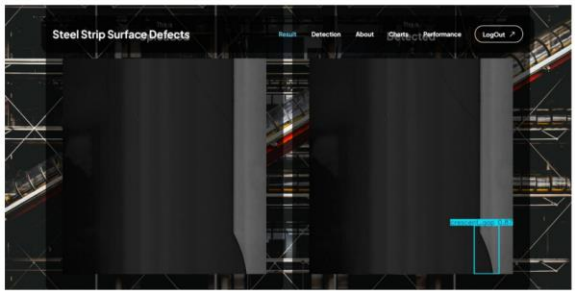


Fig. 6: Defect Detected

V. CONCLUSION

The detection of pomegranate growth stages is a critical aspect of modern agricultural practices, enabling farmers to optimize resource allocation, improve crop management, and ensure better yields. This project introduces a robust and efficient solution using the YOLOv10 architecture, which provides real-time detection capabilities and significantly enhances the speed and accuracy of growth stage identification. By integrating advanced techniques such as hyperparameter optimization and data augmentation, the proposed system addresses the limitations of traditional methods and offers a scalable, reliable approach for agricultural applications. This work not only simplifies the detection process but also lays a foundation for future advancements in crop monitoring technology. With potential enhancements like IoT integration, disease detection, and cloud-based deployment, the system has the scope to evolve into a comprehensive tool for agricultural decision-making. The proposed methodology empowers farmers with timely and actionable insights, paving the way for sustainable and technology-driven farming practices.

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