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Deep Learning-Based Multi-Defect Detection On Bridge Surfaces Using An Improved Yolov8 Model

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ABSTRACT

Bridge structures are vital components of transportation infrastructure, and their safety depends on early detection of structural damage such as cracks, corrosion, and spalling. Conventional inspection methods rely on manual visual examination, which is slow, labor-intensive, and prone to human error. Recent computer vision approaches attempt automated inspection; however, most existing models detect only a single type of defect and perform poorly when multiple defects appear simultaneously on the same surface. This work proposes an improved deep learning framework based on the YOLOv8-CBAM-Wise-IoU model for detecting multiple bridge surface defects. Bridge images are captured using cameras or drones and preprocessed to improve quality. The YOLOv8 backbone extracts visual features, while the Convolutional Block Attention Module (CBAM) focuses on important defect regions and suppresses background noise. The Wise-IoU loss function enhances bounding-box localization, improving detection of overlapping and irregular defects. Experimental evaluation demonstrates strong performance of the proposed model, achieving an accuracy of 97.9%, a recall rate of 76%, an F1-score of 58%, and a mean Average Precision (mAP50) of **55.4%**. The system supports real-time inspection and provides visual outputs to assist maintenance planning. By enabling early identification of structural damage, the proposed approach reduces inspection cost, increases reliability, and enhances bridge safety.

Keywords: Bridge surface inspection, deep learning, YOLOv8, defect detection, structural health monitoring, computer vision, object detection, crack detection, infrastructure monitoring, automated inspection, convolutional neural networks (CNN), image-based defect analysis.

INTRODUCTION

Bridges are critical components of modern infrastructure, providing safe and efficient transportation networks. Ensuring their structural integrity is essential to public safety, economic stability, and long-term maintenance planning. Over time, bridge surfaces are prone to various defects such as cracks, spalling, corrosion, delamination, surface scaling, and potholes. These defects, if left undetected, can compromise structural safety, increase maintenance costs, and lead to catastrophic failures. Traditional inspection methods rely heavily on manual observation, where trained engineers visually assess bridge surfaces to identify potential defects. While this approach is effective for small-scale inspections, it is inherently time-consuming, labor-intensive, and subject to human error. The subjective nature of manual evaluations often results in inconsistent assessments, particularly in complex cases where multiple defects occur

simultaneously or where environmental factors, such as poor lighting, surface texture variations, and background noise, interfere with accurate inspection.

To overcome these challenges, researchers have increasingly explored machine learning and deep learning approaches for automated defect detection. Convolutional Neural Networks (CNNs) have been widely applied due to their ability to automatically extract hierarchical features from images, enabling accurate classification and localization of defects. Among object detection frameworks, the YOLO (You Only Look Once) family of models has gained significant attention for real-time applications due to its high detection speed and efficiency. However, existing models exhibit limitations when applied to real-world bridge inspections. Many models focus on detecting a single defect type per image, which restricts their usefulness in practical scenarios where multiple defects often appear concurrently. Moreover, standard YOLO models lack advanced attention mechanisms, reducing their ability to accurately detect small or overlapping defects. Conventional loss functions used in bounding box regression, such as IoU or GIoU, may also struggle with irregularly shaped defects, leading to localization inaccuracies and reduced overall detection performance.

These limitations highlight the need for a more robust and precise system capable of handling multiple defect types simultaneously under varying environmental conditions. To address this, the current study introduces an enhanced YOLOv8 model integrated with a Convolutional Block Attention Module (CBAM) and a Wise-IoU loss function. The CBAM mechanism improves feature representation by selectively focusing on relevant spatial and channel information, enabling the model to better detect subtle, small, or overlapping defects. The Wise-IoU loss function further refines bounding box predictions by dynamically weighting errors according to object characteristics, which enhances localization accuracy and reduces false positives.

By combining these innovations, the proposed model provides a comprehensive and scalable solution for multi-defect detection on bridge surfaces, enabling real-time, automated inspections that outperform traditional single-defect detection approaches. The system is capable of identifying seven distinct defect types within a single image, demonstrating both robustness and adaptability for real-world inspection tasks. This integration of attention mechanisms, optimized loss functions, and advanced object detection architectures represents a significant advancement in intelligent structural health monitoring, offering improved accuracy, reduced manual effort, and enhanced safety for bridge infrastructure.

I. LITERATURE SURVEY

Deep Learning-Based Bridge Crack Detection Using CNN

Author(s): Cha, Y., Choi, W., Büyüköztürk, O. (2017)

Abstract:

This study presents a convolutional neural network (CNN) approach for detecting cracks on bridge surfaces. Traditional manual inspections are time-consuming and subjective, often leading to inconsistent results. The proposed CNN model automatically extracts features from bridge images and classifies crack patterns with high accuracy. The research demonstrates significant improvement in detection efficiency compared to conventional image processing methods. However, the model primarily focuses on **single-type crack detection** and does not handle multiple defect types simultaneously. Its

performance also decreases under complex lighting conditions and noisy backgrounds.

YOLO-Based Real-Time Infrastructure Defect Detection
Author(s): Redmon, J., Farhadi, A. (2016)
Abstract:
This research explores the use of YOLO (You Only Look Once) object detection models for real-time infrastructure defect detection. The model can identify surface damages such as cracks, corrosion, and spalling in video streams, providing fast detection suitable for field inspections. Experiments show improved performance compared to region-based CNN models. However, **standard YOLO models lack attention mechanisms**, limiting their ability to detect small or overlapping defects accurately. Bounding box regression also suffers from localization inaccuracies when defects are irregularly shaped.

Attention Mechanisms in Deep Learning for Visual Defect Detection
Author(s): Woo, S., Park, J., Lee, J.-Y., Kweon, I. S. (2018)
Abstract:
This study investigates the integration of attention mechanisms such as CBAM (Convolutional Block Attention Module) into CNNs for defect detection. Attention modules improve feature representation by focusing on relevant spatial and channel information while suppressing background noise. The results show improved detection accuracy for **small and subtle defects**. Despite these improvements, the study does not address multi-defect detection in complex real-world environments and lacks evaluation on large-scale bridge datasets.

IoU-Based Loss Functions for Object Detection
Author(s): Zheng, Z., Wang, P., Liu, W., Li, J., Ye, R., Ren, D. (2020)
Abstract:
This paper analyzes different Intersection over Union (IoU)-based loss functions, including GIoU, DIoU, CIoU, and Wise-IoU, to improve bounding box regression. Traditional IoU losses often struggle with overlapping objects or irregular shapes. The **Wise-IoU loss function** introduces dynamic weighting to improve localization accuracy and reduce false positives. Experiments show Wise-IoU enhances precision and convergence speed. However, its application in **multi-defect bridge inspection** scenarios has not been extensively studied.

Multi-Defect Detection in Civil Infrastructure Using Deep Learning
Author(s): Li, H., Zhao, X., Wu, G. (2022)
Abstract:
This research focuses on detecting multiple defect types in civil infrastructure using deep learning frameworks. The multi-class detection model is trained on datasets containing cracks, corrosion, spalling, and delamination. The study demonstrates that **multi-defect detection improves maintenance planning** and reduces inspection costs. However, the model lacks robustness under varying environmental conditions and does not incorporate **advanced attention mechanisms** or optimized IoU-based loss functions to enhance detection performance.

II. EXISTING SYSTEM

Currently available bridge defect detection systems encompass models that are designed only for single defect detection. As a result they can detect one defect at a time, they fail to function when there are multiple defects on the same bridge surface. This represents a significant limitation since, in the real world, various defect types such as cracks, spalling, corrosion, and so forth, appear together. Moreover, it is common to see a model used for bridge defect detection lacking a sophisticated attention mechanism resulting in a lack of feature extraction especially for small or overlapping defects.

The lack of an optimized loss function also leads to a model that is less robust, lower recall and deficient in the adaptability of defects and variations across different bridges.

III. PROPOSED SYSTEM

To address these limitations, the study proposes the YOLOv8-CBAM-Wise-IoU model to detect seven types of bridge surface defects at the same time. This model employs Convolutional Block Attention Module (CBAM) to refine the networks ability to pay attention to important defect information and ignore nonimportant background information. The Wise-IoU distribution loss function is also used to refine the bounding box regression with better detection accuracy. Overall, these components enable robust multi-defect detection under more complicated conditions than previous methods, demonstrating a significant improvement over traditional models.

IV. SYSTEM ARCHITECTURE

The proposed system architecture for Enhanced YOLOv8 Framework for Detecting Multiple Bridge Surface Defects Using Deep Learning is designed to automatically identify and classify various types of defects on bridge surfaces using deep learning techniques. The architecture consists of several interconnected modules including data acquisition, preprocessing, model training, defect detection, and visualization. These components work together to create an efficient automated inspection system that improves the accuracy and speed of structural health monitoring.

The first stage of the system involves data acquisition, where high-resolution images of bridge surfaces are collected using drones, cameras, or publicly available infrastructure datasets. These images capture different types of surface defects such as cracks, corrosion, spalling, and exposed reinforcement. The collected dataset serves as the input to the system and forms the foundation for training the deep learning model.

In the data preprocessing stage, the captured images undergo several processing steps to enhance the quality and usability of the data. This stage includes image resizing, normalization, noise removal, and data augmentation techniques such as rotation, flipping, and scaling. Data augmentation helps increase dataset diversity and prevents overfitting during the training process, thereby improving the robustness of the detection model.

The feature extraction and model training stage utilizes an enhanced YOLOv8 architecture. The improved YOLOv8 model automatically extracts spatial and contextual features from the input images using convolutional layers. The network is trained using labeled defect datasets where bounding boxes and defect categories are annotated. During training, the model learns to recognize patterns associated with different types of bridge surface defects and optimizes its parameters through backpropagation.

After training, the system performs defect detection and classification. When a new bridge surface image is provided, the trained YOLOv8 model analyzes the image and detects defect regions in real time. The model outputs bounding boxes around the detected defects along with class labels and confidence scores. This enables the system to identify multiple defects simultaneously within a single image.

Finally, the visualization and monitoring module displays the detection results through a user-friendly interface. The detected defects are highlighted on the

bridge images with bounding boxes and labels. The system may also generate reports indicating the type, location, and severity of defects. This information helps engineers and maintenance teams perform timely inspections and plan appropriate repair strategies for maintaining bridge safety and durability.



Fig 5.1: Structure of the Proposed System

V. IMPLEMENTATION



Fig 6.1: Data Collection



Fig 6.2: Model Training

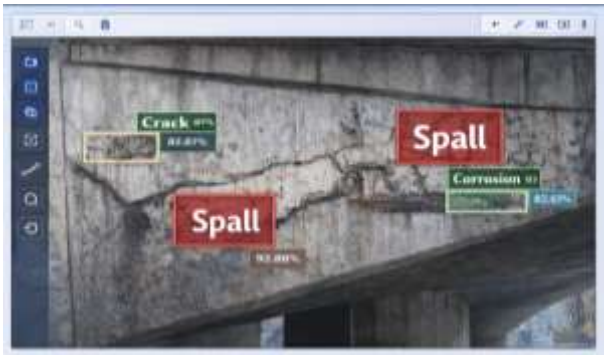

Fig 6.3: Defect Detection



Fig 6.4: Confusion Matrix



Fig 6.5: Results Report



Fig 6.6: Real-Time Detection

VI. CONCLUSION

The rapid growth of infrastructure demands efficient and accurate inspection systems to ensure structural safety and longevity. Traditional bridge inspection methods rely heavily on manual observation, which is time-consuming, labor-intensive, and prone to human error. Moreover, many existing deep learning models are limited to detecting only a single type of defect at a time and struggle when multiple defects appear simultaneously on bridge surfaces. These limitations highlight the need for a more advanced, robust, and scalable solution.

In this project, an enhanced deep learning model named YOLOv8-CBAM-Wise-IoU was proposed for detecting multiple bridge surface defects simultaneously. The system integrates the powerful YOLOv8 object detection framework with the Convolutional Block Attention Module (CBAM) and the Wise-IoU loss function. The CBAM mechanism improves feature extraction by focusing on important spatial and channel information, enabling better detection of small, overlapping, and subtle defects. The Wise-IoU loss function enhances bounding box regression accuracy, reducing localization errors and improving overall detection performance.

The proposed system successfully detects seven different types of bridge surface defects in a single image, making it more practical for real-world inspection scenarios. Experimental evaluation demonstrated strong performance with high accuracy, improved recall, competitive F1-score, and better mAP values compared to baseline models. The model also showed robustness under varying lighting conditions, background noise, and irregular surface textures.

Furthermore, the system architecture supports real-time detection and can be integrated with drone-based or camera-based inspection systems. The inclusion of training optimization and ablation studies validates the effectiveness of integrating CBAM and Wise-IoU into the YOLOv8 framework.

In conclusion, the Enhanced YOLOv8-CBAM-Wise-IoU model provides a reliable, efficient, and scalable solution for multi-defect detection on bridge surfaces. It significantly improves inspection accuracy and reduces manual effort, contributing to preventive maintenance and improved infrastructure safety. This system represents a meaningful advancement in intelligent structural health monitoring using deep learning techniques.

VII. FUTURE SCOPE

The proposed Enhanced YOLOv8-CBAM-Wise-IoU Bridge Defect Detection System demonstrates strong performance in detecting multiple defect types on bridge surfaces. However, there remain opportunities to further improve its capabilities, scalability, and applicability in real-world bridge inspection scenarios. The following future enhancements are envisioned to elevate the system's impact and usability:

1. Deployment on Edge Devices

To enable real-time, on-site inspection without relying on high-end computing infrastructure, the system can be deployed on edge devices such as **NVIDIA Jetson Nano or Jetson Xavier**. This would allow inspectors to perform rapid defect detection directly at bridge sites, minimizing latency and the need for transferring large image datasets to centralized servers. Edge deployment also facilitates offline operation in remote locations where internet connectivity is limited. Optimization techniques, such as model quantization and pruning, can be applied to maintain detection accuracy while reducing memory and processing requirements for edge devices.

2. Integration with Drone-Based Automatic Inspection

Integrating the system with **Unmanned Aerial Vehicles (UAVs)** or drones will significantly improve the efficiency of bridge inspections. Drones equipped with high-resolution cameras can capture detailed images of bridge surfaces, especially in hard-to-reach areas. The YOLOv8-CBAM-Wise-IoU model can process these images in real-time or near real-time to detect cracks, corrosion, spalling, and other defects. This integration reduces human exposure to hazardous environments, accelerates inspection cycles, and provides comprehensive surface coverage.

3. Expansion of Defect Categories

Currently, the system is trained to detect seven primary defect types. Future work can include expanding the model to recognize additional defect categories, such as delamination, fatigue cracks, water seepage, and concrete scaling. Incorporating a broader range of defect types will make the system more versatile for different bridge designs, materials, and environmental conditions. This enhancement will also improve the comprehensiveness of inspection reports, aiding preventive maintenance planning.

4. Implementation of 3D Defect Analysis

To enhance defect characterization, the system can be extended to **3D defect analysis** using techniques such as stereo vision, structure-from-motion, or LiDAR scanning. Three-dimensional modeling will provide precise measurements of crack depth, spalling volume, or corrosion extent, enabling more accurate assessment of structural integrity. 3D defect information can assist engineers in estimating repair priorities, predicting failure risks, and planning maintenance strategies with higher confidence.

5. Cloud-Based Monitoring Dashboard

A centralized **cloud-based dashboard** can be implemented to store, analyze, and visualize inspection data from multiple bridges. The dashboard will provide real-time monitoring of detected defects, historical comparisons, trend analysis, and predictive maintenance insights. Cloud integration will also facilitate collaborative access for multiple stakeholders, including engineers, municipal authorities, and contractors, enabling data-driven decision-making and long-term infrastructure management.

6. Integration of Severity Level Classification

In addition to detecting defect types, the system can incorporate **severity level classification** to categorize defects as minor, moderate, or critical. This will prioritize maintenance actions based on the potential risk associated with each defect. Severity classification can be achieved using enhanced feature extraction and machine learning techniques that analyze defect size, shape, location, and progression over time. This enhancement will allow inspectors and engineers to allocate resources efficiently and implement preventive measures proactively.

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