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Revolutionising Visual Bridge Inspection: A Deep Learning Approach for Automated Concrete Bridge Distress Identification & Analysis of Results

Shyam Saseethar[1], Dilip Narkhede[2]
[1]M-Tech (Structures), Faculty of Civil Engineering, College of Military Engineering
Dapodi,Pune, India
sshhar.018m@gov.in ; di_narkhede@yahoo.com
[2] Professor, Faculty of Civil Engineering, College of Military Engineering
Dapodi,Pune, India

***Abstract* -** Concrete bridges are vital infrastructure assets, yet their inspection often relies on labour-intensive, time-consuming, and sometimes subjective visual assessments. This study addresses these challenges by harnessing the power of Artificial Intelligence (AI) and Deep Learning (DL) for streamlined bridge inspection. Building upon the limitations of traditional methods, an enhanced YOLOv8s model is developed and trained on a refined CONBRID-YOLOv8 dataset. This dataset is specifically designed to minimize false positives, a common issue in concrete bridge defect detection. The integration of real-time data visualisation tools further empowers inspectors to optimize maintenance planning, ultimately enhancing bridge safety and longevity. The model exhibits exceptional performance in detecting and classifying prevalent concrete defects such as cracks, spalling, exposed bars, corrosion stains, and efflorescence. Through rigorous experimentation and analysis, the new model achieved a strong F-1 score of 0.75 and a mAP of 0.738 after 300 epochs. Real-world field testing underscores the model's practical effectiveness. Pioneering data visualisation techniques provide inspectors with the tools to rapidly interpret complex results and confidently prioritise maintenance strategies. This AI-powered approach represents a significant advancement in bridge inspection practices. By addressing the limitations of traditional methods & existing DL models, this study offers a more efficient, accurate, and objective solution for ensuring the safety and longevity of critical infrastructure assets.

***Keywords*: Concrete Bridge Distress Identification, Damage Assessment of Concrete Bridges, Computer Vision, Deep Learning, YOLOv8, Machine Learning, Data Visualisation, Result Extraction**

1. Introduction

Bridges globally play a vital role in transportation networks, reducing travel time and providing crucial links during emergencies. They enhance urban planning, ease congestion, and foster economic activities. Artificial Intelligence (AI) and Machine Learning (ML), especially in computer vision, have emerged as disruptive and transformative forces across multiple domains and civil engineering is no exception [1].

Concrete bridges are critical infrastructure assets, but their inspection can be costly, time-consuming, and prone to error. This study introduces a novel approach to bridge inspection using an enhanced YOLOv8s model and the improved CONBRID-YOLOv8 dataset. The new system discussed in this paper is specifically designed to reduce false positives and improve efficiency for bridge inspectors by integrating real-time data visualisation tools, enabling optimized maintenance planning and ultimately enhancing bridge safety and longevity.

This paper is organised into the following sections as follows: Section 2 gives an overview of the Bridge Inspection methods and their limitations from a global and Indian perspective; Section 3 discusses existing Deep Learning (DL) algorithms, the YOLO framework & limitations of the previous study; Section 4 describes the present study, scope & objectives, and methodology Section 5 explains the field testing of the model, extraction of predicted results, data visualisation & analysis. Section 6 summarises the findings & provides future work.

2. Bridge Inspection: Present Global Scenario & Limitations of Traditional Methods

Bridge inspections are critical for maintaining infrastructure safety and functionality. Globally, different standards govern inspection processes. In the USA, the National Bridge Inspection Standards (NBIS) and Federal Highway Administration (FHWA) regulations ensure safety [2]. They conduct visual inspections using the National Bridge Inventory (NBI) Condition Rating System to evaluate bridge conditions [3] [4] [5]. Europe relies on standards from the European Committee for Standardization (CEN) and the TU1406 specifications [6].

India follows IRC-SP:35 and the Bridge Inspector's Reference Manual for its inspection methodology [7]. They utilize a three-tiered system of Routine, Principal, and Special Inspections, emphasizing visual assessment. A preventive maintenance [8] approach, guided by a detailed condition assessment methodology, is central to the bridge management process.

2.1 Manual Inspection & Limitations

Traditional manual bridge inspection methods, while effective, come with limitations. Reliance on visual inspection incurs high resource costs and introduces inefficiencies due to subjective factors [9]. Human error can compromise accuracy, especially in challenging or high-risk locations, potentially overlooking critical issues and requiring additional safety measures, increasing costs. Moreover, traditional methods often cause disruptions for road users, necessitating lane closures or diversions. This logistical challenge, significant for heavily trafficked bridges, leads to time-consuming processes and longer intervals between inspections, potentially allowing issues to escalate before detection. Computer vision tech subsequently emerged as an augmentation technology that can aid and assist bridge inspectors in their manual visual inspection.

2.2 Traditional Computer Vision & Image Processing

To address the constraints of manual inspections, various research efforts have explored integrating advanced technologies like drones, sensors, and digital monitoring systems to improve the efficiency, effectiveness, and safety of bridge assessments. Traditional image processing techniques have been used for identifying defects in bridges by analysing visual data to detect anomalies or structural issues. Their non-destructive nature is advantageous for routine inspections, prioritizing the preservation of the bridge's integrity. Traditional image processing technology uses RGB images to conduct defect detection on a bridge structure’s surface. The traditional image processing technology generally needs to set the features manually, based on features such as colour, shape [10], texture [11] and others. Manual Pre-processing of images is also required to improve the accuracy of defect identification. However, the experimental results show that the detection method is complex, time-consuming, and has difficulty meeting the requirements of real-time performance.

3 Machine Learning & DNN in Bridge Defects

The swift progress in computer hardware and increased GPU computing power has significantly expanded the applications of computer vision (CV) and image processing, particularly in object detection using Deep Learning (DL) theory. The object detection based on DL has a better performance compared to the traditional image processing methods in terms of generalisation and robustness [12]. In DL-based object detection, models are generally categorized into two main architectures: two-stage (or two-step) detectors and single-stage detectors. These distinctions refer to the number of stages or steps involved in the detection process.

3.1 Two Stage Detection Algorithm

The two-stage detection algorithm in Deep Learning follows a two-step object detection process. It first proposes regions of interest (RoIs) in the input image, refining them in the second stage for final detection results, as seen in Faster R-CNN [13]. Although two-stage detectors achieve high accuracy, their complex architectures make them computationally intensive and challenging to train. They also exhibit slower inference speeds critical for real-time applications like video analysis. Moreover, deploying two-stage detectors may require more computational resources compared to single-stage alternatives.

3.2 Single-Stage Detection Algorithm

The single-stage detection algorithms usually complete feature extraction, classification and prediction in one step without the need for a separate region proposal step. These models directly predict bounding boxes and class probabilities for each anchor or pixel in the input image.

Single-stage detectors excel in speed, making them ideal for real-time applications like video analysis. Their simpler architectures facilitate easier implementation, training, and fine-tuning. These detectors efficiently handle objects of various sizes without requiring specialized design considerations. Reduced complexity translates to fewer computational resources, making them suitable for resource-constrained environments. Their straightforward workflow caters to practitioners of varying expertise levels and allows deployment on diverse platforms, including edge devices with limited computational capabilities. YOLO (You Only Look Once) and SSD (Single Shot Multibox Detector) are examples of single-stage object detection architectures.

3.3 YOLO Framework: YOLO V8

YOLO (You Only Look Once) is a widely adopted object detection and image segmentation model created by Joseph Redmon and Ali Farhadi at the University of Washington. Initially launched in 2015, it swiftly gained recognition for its high speed and accuracy. YOLOv8, the latest version by Ultralytics introduced in 2023, builds on the success of its predecessors with new features and enhancements. As a cutting-edge state-of-the-art (SOTA) model, YOLOv8 excels in performance, flexibility, and efficiency, supporting various vision AI tasks like detection, segmentation, pose estimation, tracking, and classification [14]. With a new backbone network, anchor-free detection head, and loss function, YOLOv8 is versatile, running seamlessly on a range of hardware from CPUs to GPUs.

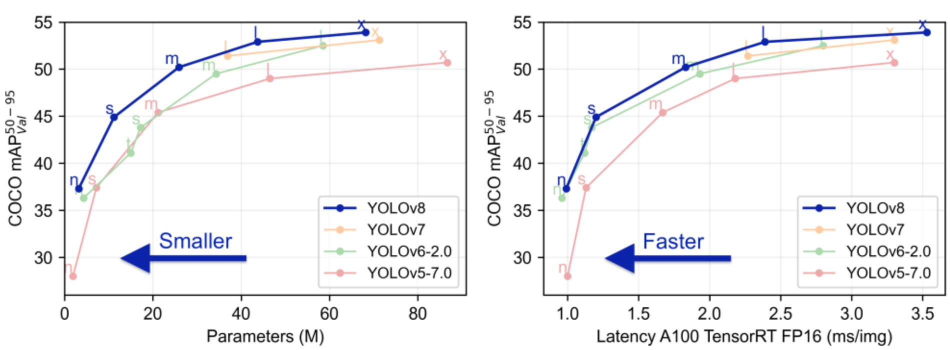

Fig 1 YOLO-v8 comparison with predecessors [14]

3.4 DNN Models in RCC Bridge Defect Detection

Despite the extensive research being conducted in various defect detection domains, the predominant focus remains on pavement defects, particularly cracks and potholes [13]. In contrast, there is a noticeable lack of attention to defect detection in computer vision technology for load-bearing structures of bridges. Computer vision methods provide a promising solution, effectively reducing detection costs, ensuring worker safety, and enhancing overall efficiency compared to alternative approaches.

The necessity to develop a multi-class, multi-target defect detection algorithm for a composite material such as concrete was achieved by Mundt et al. [15] who introduced the novel CODEBRIM dataset for multi-target classification of five commonly appearing concrete defects and developed a Meta-learning CNN.

Licun Yu et al [16] realised the detection of bridge damage by improving faster R-CNN and achieved higher accuracy, however, the Faster R-CNN model is large, flexibility is poor and detection speed is slow thereby negating its practical applications in real-time applications [17].

Khaled R. Ahmed [18], carried out a comparative experimental study of three algorithms—YOLOv5, YOLOR, and Faster R-CNN—for road surface defect detection. The findings indicate that the YOLOv5 model demonstrates exceptional flexibility and is well-suited for real-time detection scenarios on embedded devices. However, there is room for improvement in terms of accuracy, with the mean Average Precision at a confidence threshold of 0.5 (mAP@.5) reported at 58.9%.

Ma, D et al [19] improved the YOLOv3 network model to detect cracks and the detection speed has improved compared to the two-stage detection algorithm. However, the model only performs single classification and hence its application for practical projects is limited.

Sergio et al [20] carried out study on YOLOv5 framework for six defect classes-cracks, corroded steel, deteriorated concrete, honeycombs, moisture spots & pavement degradation as per Italian guidelines using images of bridges in Italy. The mean average precision mAP value of the best model was 20.66%.

3.5 Prototype Development: Inferences & Limitations

In the previous study [21], a custom de-nova dataset named CONBRID-YOLOv8 was developed, containing 831 images with an 8:1:1 split for training (658), validation (87), and testing (86). The dataset consisted of five major concrete defects namely cracks, spalling, corrosion stains, exposed bars, and efflorescence as per Indian Road Congress (IRC) guidelines. These defects can be found visually through signs of damage. The annotation of the images derived from the original CODEBRIM dataset was done accurately using the Roboflow platform [22]. A prototype YOLOv8s model was initially trained from scratch without image augmentation. This resulted in poor performance, yielding a mean average precision (mAP) score of 0.165 after 150 epochs. Subsequent improvements and key limitations include:

- Implementation of Mosaic Augmentation significantly enhanced model performance, achieving a mAP of 0.714 and effectively expanding the training set to 1974 images.
- Extending training to 200 epochs further increased model accuracy to a mAP of 0.756.
- Despite an acceptable mAP, the model tended to false positives when tested with pre-recorded videos. Common misidentifications included humans and everyday objects such as pens, name tags, and hats.

4 Present Study & Objectives

The present study seeks to address the limitations identified in previous research and achieve the following objectives:

- Conduct a comprehensive comparison of all YOLOv8 framework models utilising the enhanced CONBRID-YOLOv8 (2.0) dataset whilst solving the problem of false positives.
- Identify a suitable lightweight YOLOv8s model for on-site testing.
- Evaluate the shortlisted model in a field test on a concrete bridge for distress detection, generating predicted images and video.
- Extract relevant data from the predicted images and video to develop data visualisation tools, including bar graphs and time-history graphs.

4.1 Improved Dataset: CONBRID- YOLOv8 (2.0)

The enhanced dataset consists of 1500 images, 171 of which are designated as 'null'. 'Null' images are devoid of any of the five defect classes, yet contain coordinate label files with null values. Their integration into training, validation, and testing procedures is intended to mitigate the occurrence of false positives. The null images shown in Fig 2 consist of common objects, humans, and name tags that are likely to be encountered and captured during photography/videography of the distresses during a bridge inspection.

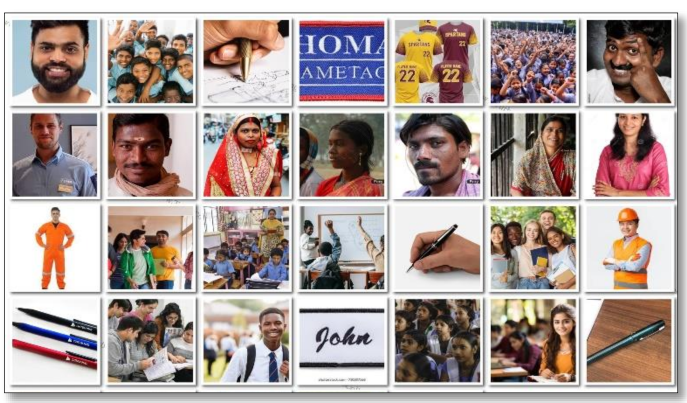

Fig 2 Sample Null Images added to the Dataset

4.2 Model Training & Evaluation Metrics

In this study, a comprehensive evaluation of all YOLOv8 framework models (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x) on the enhanced CONBRID-YOLOv8 (2.0) dataset has been carried out. All models were trained using identical hyperparameters for 150 epochs. To ensure sufficient computational resources, training was performed on Google COLAB Pro with access to A100/V100 GPUs. Preprocessing of the dataset involved two key steps: auto-orientation and mosaic augmentation. Model performance was assessed using established industry metrics, including F1-score, mean average precision (mAP), and precision-recall curves.

4.3 Evaluation of Results

Table 1 displays the performance of all five YOLOv8 models, including their training duration. As anticipated, larger models (YOLOv8x, YOLOv8l, and YOLOv8m) demonstrate superior performance metrics compared to the lighter YOLOv8s model. YOLOv8n, being the smallest, exhibited the lowest performance. The results are compared against the YOLOv5 study by Sergio et al [20] for similar datasets and hyperparameters as shown in Table 2. Despite minor differences in defined classes, YOLOv8 models achieve higher mAP values, indicating greater accuracy and suitability for practical applications.

Table 1: Comparison of YOLOv8 Models trained on CONBRID-YOLOv8 (2.0)

Models/Metrics	YOLOv8n	YOLOv8s	YOLOv8m	YOLOv8l	YOLOv8x
mAP@0.5	0.575	0.700	0.758	0.760	0.76
F1 –Score	0.59	0.70	0.76	0.76	0.76
Time Taken	1.755 Hrs	1.277 Hrs	1.875 Hrs	2.844 Hrs	2.126 Hrs
Hardware	Google COLAB Pro: A100/V100 GPU				

Table 2: Comparison of mAP values with YOLOv5 Models for similar dataset

YOLOv5 (Ver 6)	mAP @0.5	YOLOv8	mAP@0.5
YOLOv5n	17.06	YOLOv8n	57.5
YOLOv5s	18.38	YOLOv8s	70.3
YOLOv5m	20.66	YOLOv8m	75.8

Given the objective of selecting a lightweight model suitable for deployment on edge computing devices (e.g., Android mobiles), the YOLOv8s model was shortlisted for further experimentation and field trials. Initial analysis of the precision-recall (P-R) curve revealed significant variance in mean average precision (mAP) across individual defect classes. As depicted in Fig 3(a), mAP values ranged from 0.592 for cracks to 0.769 for effloroscence. To mitigate this variance and improve overall model performance, transfer learning techniques were leveraged, and training epochs were increased to 300. This resulted in a substantially tighter class distribution within the P-R curve, see Fig 3(b), with all classes achieving mAP values above 0.70. Table 3 provides a comparative analysis of class-level mAP values between the two model iterations.

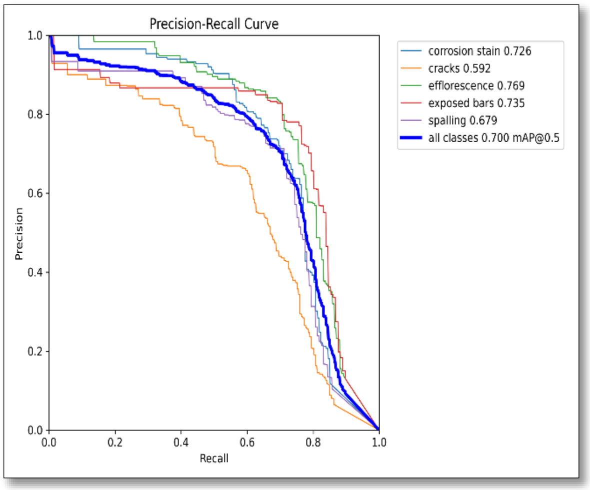

Fig. 3 (a) : P-R Curve of YOLOv8s – 150 Epochs

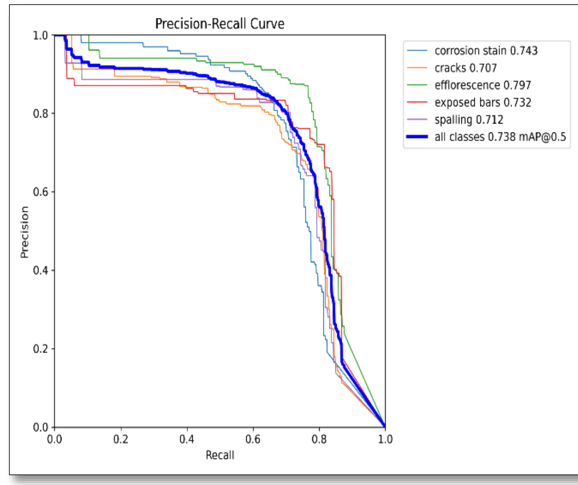

Fig. 3 (b): P-R Curve of YOLOv8s – 300 Epochs

Table 3 : Comparison of Class wise mAP values of both YOLOv8s Models

Classes/ Model	Corrosion Stain	Cracks	Efflorescence	Exposed Bars	Spalling
YOLOv8s (150 Epochs)	0.726	0.592	0.769	0.735	0.679
YOLOv8s (300 Epochs)	0.743	0.707	0.797	0.732	0.712

5 Field Testing of YOLOv8s for Concrete Bridge Inspection

The enhanced YOLOv8s model underwent field testing in Pune, a city in western India. The test site was a concrete bridge named "Sadhu Vaswani Pul." Images and video recordings of a specific pier were captured using an Android mobile device.

5.1 Model Evaluation Process

To evaluate the model's performance in a real-world setting, the following procedures were conducted:

- Image Data: Raw images of the pier were directly fed into the model. The model then generated predicted images highlighting the identified defects.
- Video Data: A video of the pier was recorded and processed by the model. This resulted in a predicted video output containing defect classifications for each frame.
- Fig 4 and 5 visually demonstrate the model's ability to detect and classify the five defect classes within the bridge images as well as video under site conditions.

5.2 Data Extraction & Visualisation: A Pioneering Innovation

The YOLOv8s framework's versatility and Python compatibility enable seamless result extraction during the prediction process. Label data was obtained from both predicted images and videos, including vital information such as bounding box coordinates and corresponding defect classes. Additionally, the video prediction was fine-tuned to generate individual image frames with associated label data. This comprehensive dataset allowed for the construction of distribution graphs for both image and video data, as illustrated in Fig 6 (a), (b) & (c). The generation of a time-history graph is also demonstrated using data extracted from individual frames in Fig 7.

To the best of current knowledge, this work introduces the first application of result extraction and data visualization techniques for concrete bridge distress assessment using detection models within the YOLO framework. This approach demonstrates the practical applications of the DL model. By providing a comprehensive overview of distress distribution and temporal tracking, these tools facilitate informed decision-making about repair measures and resource allocation.

Fig 4(a) : Raw Images from Pier

Fig 4(b) : Predicted Images

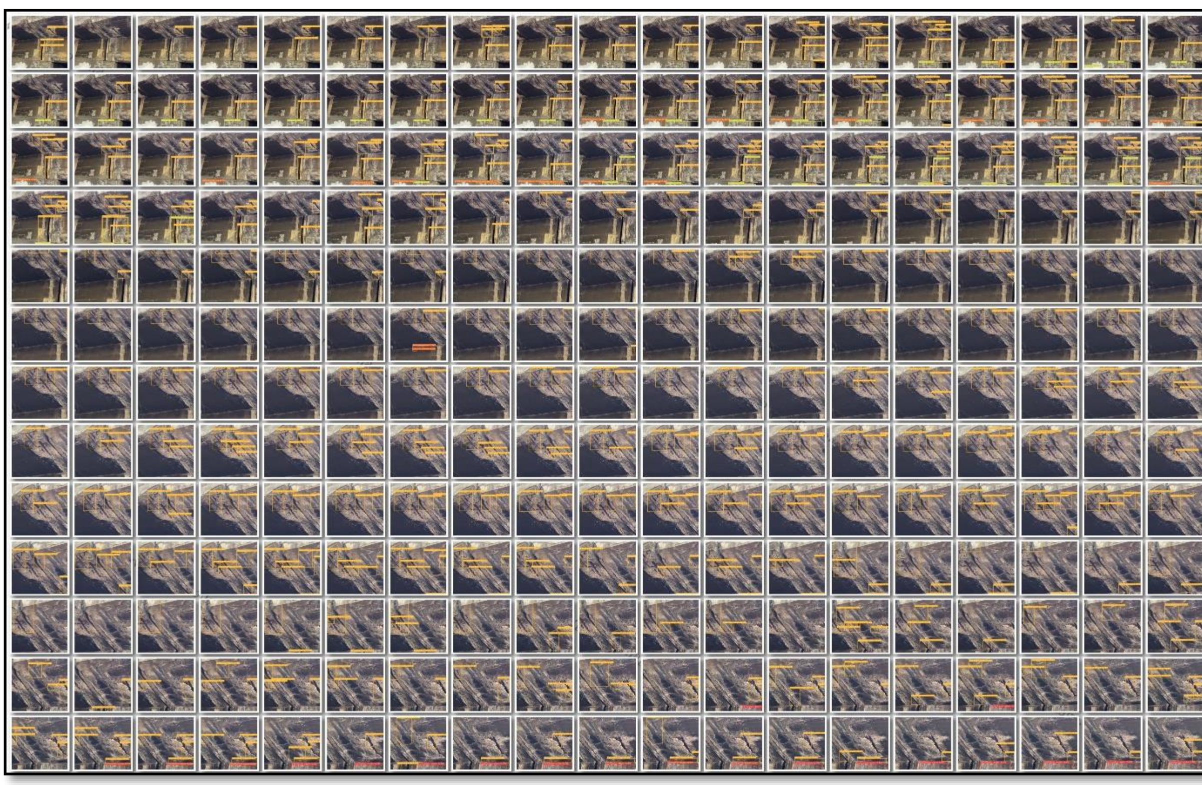

Fig 5: Predicted Video File shown as Frames

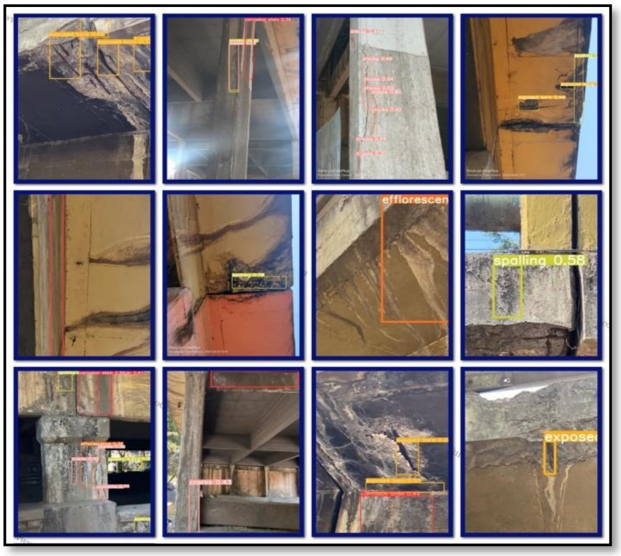

Fig 6(a) : Predicted Images of Pier

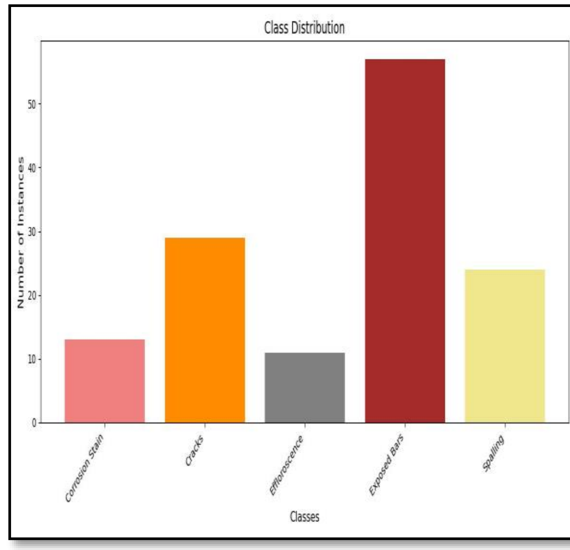

Fig 6(b): Distress distribution on the predicted Images

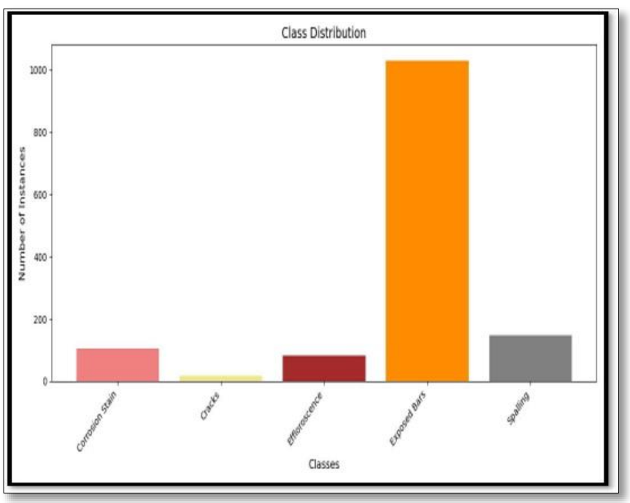

Fig 6 (c) : Distress distribution on Predicted Video

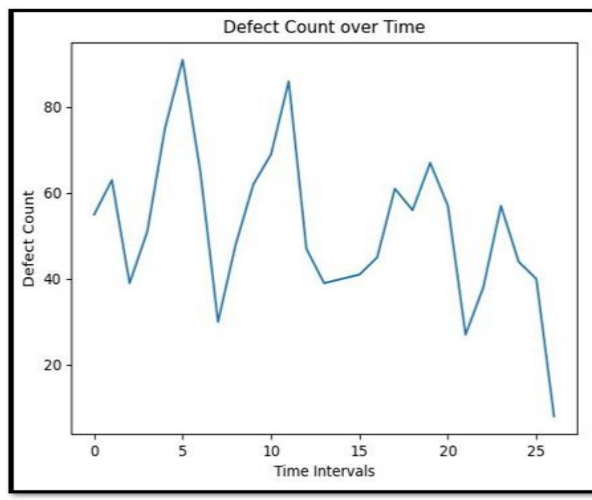

Fig 7: Time-History Graph on Predicted Video

6 Conclusion & Prognosis

This study addresses the limitations of the original YOLOv8 framework by developing an enhanced CONBRID-YOLOv8 dataset and a lightweight YOLOv8s model to reduce false positives in concrete bridge inspections. Through experimentation and analysis, the new model achieved an F-1 score of 0.75 and a mAP of 0.738 after 300 epochs. Real-world field testing demonstrated its effectiveness, and the pioneering work on data visualization provides tools for bridge inspectors to quickly interpret results and optimize maintenance planning. To further enhance the system, future work will focus on expanding the dataset with high-altitude images and additional defect classes specifically, moss, honeycombs, and pavement degradation. Many more real-time data visualisation techniques like heat mapping of distresses using JSON capabilities of the model, Metadata & GPS coordinate extraction from drone images will be created enabling inspectors to make informed decisions with greater speed and clarity. This approach has the potential to significantly improve bridge inspection efficiency, reducing costs and enhancing infrastructure safety.

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