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Original Article

Automated Diagnostic System for Bridges through Artificial Intelligence and Image Processing: Case Study in Lima, Peru

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Abstract - *This research addresses the gap in comprehensive automated bridge damage diagnosis systems by developing and implementing a system based on Artificial Intelligence (AI) and image processing to diagnose damage to bridges in Lima, Peru. Using the YOLOv7, YOLOv8, and YOLOv10 models, a comparative analysis was performed regarding accuracy, sensitivity, and mAP. The results show that YOLOv8 achieved a mAP50 of 47% and a mAP50-95 of 32%, significantly outperforming YOLOv10 (21% and 9%, respectively) and YOLOv7 (9% and 3.8%). In addition, YOLOv8 obtained a precision of 60% and a recall of 50%, positioning itself as the most effective model for detecting cracks, corrosion, and concrete spalling. The CRISP-DM methodology was selected for the development process, from collecting a robust dataset of 7,934 images to implementing a web application that automates the diagnosis. The system generates detailed reports and specific recommendations, optimizing efficiency and reducing inspection times by up to 40%. The field validation included 202 images collected from Lima bridges, demonstrating the applicability and reliability of the system in real scenarios. This solution, in addition to improving the safety and sustainability of infrastructures, represents a significant advance in the automation of structural inspections, promoting the adoption of innovative technologies in civil engineering.*

Keywords - *Artificial Intelligence, Damage detection, Road infrastructure, Cracking, Corrosion.*

1. Introduction

Structural damage detection using artificial intelligence techniques has gained relevance in recent years. Convolutional Neural Networks (CNNs) have been applied to identify patterns in medical diagnosis [1] and evaluate concrete strength [2]. In the field of civil engineering, these techniques have been adapted for structural damage detection, including the use of fully convolutional neural networks [3], the extraction of precise urban features for inspection [4], and deep learning methods [5]. Furthermore, innovative approaches such as ProtoNet-based few-example learning have been developed for damage detection with limited samples [6] and unsupervised machine learning approaches that increase the effectiveness and efficiency of inspections [7]. In this context, adapting methodologies such as CRISP-DM to digital medical image processing [8] offers a framework to structure data analysis projects in various fields, including structural engineering. The proposal of a Data Analytical Problem Structure (DAPS) [9] contributes to the definition phase of analysis projects. Regarding challenges, literature related to issues such as quality control in constructing roads and bridges through three-dimensional laser scanning was addressed [10], and reviews have been carried out on the use of technologies based on image processing for monitoring structural health [11].

In terms of infrastructure, road infrastructure is key to cities' economic and social development, and bridges are essential for efficient and safe transportation. The inspection of structural damage in bridges is critical, but “traditional” methods are limited in precision, time, and resources [12]. These approaches depend heavily on the experience of engineers, which can generate variability and risks, especially in the face of aging and deterioration of infrastructure [13]. Internationally, a study applied to bridges in New South Wales, Australia, developed an unsupervised methodology based on computer vision for Bridge Structural Health Monitoring (BSHM) and used the drive-by inspection technique [14]. On the other hand, in a study conducted at a university in China, they investigated the damage evolution behavior of corroded steel cables under alternating loads, with a focus on cable-stayed bridges [15]. Said established a model of damage evolution based on the theory of continuous damage mechanics. In another study in China, on the Dashengguan Bridge on the Yangtze River, they developed a three-dimensional detection and localization method for surface damage on bridges, combining computer vision, deep learning, and 3D reconstruction [16]. In the Peruvian context, a group of researchers carried out a study to develop a damage model for El Niño events in Peru using data mining techniques [17]. The research was based on a national building survey conducted after the 2017 El Niño event, which caused heavy rain, flooding, and landslides.

Based on this background, this research is justified by developing and implementing a comprehensive Artificial Intelligence (AI) system that encompasses more than simple damage detection, providing a complete diagnosis of bridges in Lima, Peru. This work contributes through (1) the implementation and comparison of three YOLO models (v7, v8, and v10) specifically for bridge damage diagnosis, (2) the development of a web application that automates the entire diagnostic process from image capture to report generation, and (3) field validation through 202 images collected from Lima bridges with demonstrated efficiency improvements of up to 40% in inspection times. This comprehensive approach addresses the complete diagnostic workflow: detection, classification, and report generation (quantification) for specific damage types (cracks, corrosion, and concrete spalling).

Despite the advances in structural damage detection through AI, which are documented in the literature, a significant gap persists in the development of automated systems for comprehensive bridge damage diagnosis. The documented studies primarily focus on detecting individual damage patterns in infrastructure but do not provide a holistic approach that combines detection, classification, and quantification of detected damage to generate specific recommendations. This limitation is particularly critical in contexts such as Peru, where adaptation of solutions to local infrastructure conditions is required.

This research aims to address the absence of comprehensive automated systems for structural damage diagnosis in bridges in Lima, Peru, considering that these systems must detect, classify, and quantify damage in bridge infrastructure. The combination of the country's varied geography and traditional diagnostic methods (which depend on the inspector's experience) requires considerable investment in resources such as time and money. These considerations compromise the safety and sustainability of the city's road infrastructure (and other regions of the country).

Finally, this study was aligned with the UN Sustainable Development Goal 9, which promotes industry, innovation and resilient infrastructure. By improving efficiency and accuracy in damage diagnosis, the proposed system extends the useful life of bridges and reduces the need for costly reconstructions, minimizing the environmental impact associated with large infrastructure works. This represents a significant advance in the practical application of AI in civil engineering and demonstrates how the technology can be leveraged to address critical infrastructure challenges in emerging economies.

This paper is structured with the following sections: Section II presents the literature review, Section III explains the materials and methods used, Section IV details the methodology used, Section V shows the results of the study, Section VI presents the findings of the discussion regarding the Project, and finally, in Section VII, the conclusions and recommendations for future work are presented.

2. Literature Review

Artificial intelligence (AI) and image processing offer a promising alternative to automate and improve reviews and inspections ranging from agricultural disciplines [18], intelligent tutoring systems [19], object detection and tracking [20], to any kind in general [21, 22]. In this sense, there are various techniques and tools for image processing. These differences must be measured and compared to proceed with the selection of the most appropriate ones for research [23]. As a result, these technologies allow damage or obstructions to be identified and classified more accurately and quickly, reducing dependence on manual methods [24]. Techniques for image processing of mode shapes have been investigated using CNN to identify damage [25], as well as image stitching methods based on accelerated robust features (SURF) to analyze cracks from different angles [26]. Additionally, photometry and the use of drones [27] have expanded inspection possibilities, while techniques such as YOLO have been applied specifically for crack detection [28]. These technologies have proven to be particularly useful in the visual inspection of reinforced concrete bridges [29].

In this technological framework, the diagnosis of structural damage in bridges, through AI and image processing, is a rapidly evolving field within civil engineering. This section explores the key concepts of recent studies that support this research in the context of Lima, Peru. In particular, convolutional neural networks excel in automated image analysis for structural damage detection and classification. According to recent studies, CNNs improve accuracy and reduce inspection time, identifying everything from microscopic cracks to major deformations [30]. However, high precision requires a large sample of training images (datasets). This can be avoided by using pre-trained networks [31].

Especially in the field of application, AI systems not only detect but also classify different types of damage caused by weather or natural disasters [32], facilitating the planning of more efficient and detailed maintenance interventions [33]. In this context, corrosion is a critical factor in the deterioration of structures. Research has been carried out on the influence of corrosion on the seismic behavior of viaducts, considering the impact of climate change [34]. The use of Machine Learning for corrosion detection [35] and the study of the impact of corrosion on Ground Penetrating Radar responses [36] are significant advances in this field. As a result, these techniques contribute to the early detection and effective maintenance of structures such as bridges [37]. In the local context, the lack of an automated and efficient system for diagnosing bridges in Lima represents a risk for both safety and resource management. Consequently, the use of AI can optimize inspections of different types of damage [38], avoiding late or inaccurate diagnoses and reducing maintenance costs. Therefore, researching and developing a diagnostic system based on AI and image processing for Lima's bridges is essential to improve its road infrastructure's safety, efficiency and sustainability. Table 1 below shows a comparison of recent studies with regard to the variables under investigation.

Table 1. Summary of relevant studies on bridge damage diagnosis

Study	Summary Description	Relevance	Models / Algorithms Used	Metrics
[14]	Bridge monitoring with drive-by inspection and unsupervised learning (CVAE and CAAE), reducing training time by 60%.	Efficiency in contexts with limited damage data.	CVAE (Convolutional Variational Autoencoder) and CAAE (Convolutional Adversarial Autoencoder)	Training time, detection accuracy (exact values not specified)
[15]	ANSYS model to evaluate corrosion in cable-stayed bridge cables; crack nucleation represents ~80% of fatigue life.	Provides the basis for corrosion assessment in critical elements.	Continuous damage mechanics model, traffic–bridge–wind simulation in ANSYS 2020R2	Fatigue life, stress concentration
[16]	UAV + 3D reconstruction and YOLOv7 for damage detection with centimetre-level accuracy and damage mapping.	Combines aerial inspection and computer vision for accurate diagnosis.	YOLOv7, 3D reconstruction with photogrammetry	Positioning accuracy (cm), detection accuracy (m)
[17]	Post–El Niño 2017 damage classification in Peru using data mining and remote sensing on more than 10,000 records.	Methodology applicable to damage assessment for extreme weather events.	Random Forest, unsupervised clustering	Damage probability by levels (D1–D4), explanatory variables
Study Proposal	Development and implementation of an AI and image processing system for damage diagnosis in bridges in Lima.	Improves inspection accuracy and efficiency, contributing to road safety and infrastructure sustainability.	YOLOv7, YOLOv8, YOLOv10	mAP50, mAP50–95, precision, recall, F1-score

3. Materials and Methods

This work employed an approach based on pre-trained models optimized through transfer learning to detect and classify bridge damage. Three main architectures were selected to evaluate their performance in identifying cracks, corrosion, concrete spalling, and exposed surfaces. Steel. The materials and methods used are described in detail. Below.

3.1. Dataset

The study used two sets of data. The first was a public set that included 7,934 labeled images from online repositories specializing in structural damage. These images covered varied scenarios and diverse environmental conditions, ensuring adequate representation of typical damages. The second set was prepared independently, comprising 202 images captured on bridges in Lima, Peru. These images were taken using high-resolution cameras and different lighting configurations to expand the diversity of the set. Both sets were preprocessed. The images were resized to 640x640 pixels, their color values were normalized, and data augmentation techniques such as rotation, brightness adjustment, and cropping were applied. This improved the robustness of the models against variations in input conditions.

3.2. Pretrained Models

Three widely recognized deep learning architectures were used in object detection tasks: YOLOv7, YOLOv8, and YOLOv10. These architectures stand out for their ability to perform accurate and real-time detections. YOLOv7, known for its efficiency, was selected for its low computational requirements. YOLOv8 introduced significant improvements in accuracy, while YOLOv10 represented the latest iteration with advanced optimizations for multi-class tasks. The models were implemented in Python, using the Ultralytics library. Using pre-trained weights in ImageNet, the models were fitted with the described data sets. The hyperparameters used during training are summarized in Table 2.

Table 2. Hyperparameter table

Hyperparameter	Value	Description
Lot size	Values	Number of images processed simultaneously during a training iteration. A smaller size allows for greater precision at the cost of more time.
Epoch	Values	Total number of completed passes over the training set. More epochs can improve accuracy, but increase the risk of overfitting.
Evaluation Metrics	Values	mAP evaluates the average precision at different IoU thresholds. Precision measures the proportion of correct predictions over the total, and recall measures the correct detections of real objects.

3.3. Experimental Process

The experimental process included data loading and processing, the training and validation phase of the models, and the evaluation of their performance. During loading and processing, the data were divided into subsets for training, Validation, testing, and maintaining a ratio of 70%, 20%, and 10%, respectively.

Additionally, custom scripts were developed to convert the tags between YOLO, COCO, and Pascal VOC formats. In the training stage, the models were fine-tuned using an NVIDIA RTX 3060 GPU with CUDA support, allowing for accelerated calculations. Precision and recall metrics were continuously monitored to evaluate learning progress. The models were evaluated by analyzing their ability to detect and classify defined structural damages. The main metrics were precision, recall, mAP50 and mAP50-95.

3.4. System Design

The design of the proposed system included data processing, damage prediction, and report generation modules. This system was implemented in a web environment, where the most efficient model was integrated for practical use. The web application allows users to upload images of bridges, receive automatic predictions of detected damage, and get specific suggestions for repair.

4. Solution Methodology

For the development of this Project, the CRISP-DM methodology was selected because it provides guidelines for the development process of the data mining application to achieve the defined objectives [39, 40]. "Bridges located in Lima, Peru, in the year 2024" were defined as the study population and those bridges that were not accessible for the analysis were excluded, or those that, due to their physical characteristics, do not allow their evaluation with the proposed solution. This research used a data set of cracks, corrosion, exposed steel, detachment and crocodile skin (crack group) in bridges from online data sets and 202 images collected from bridges in the city of Lima, Peru.

The YOLOv7, YOLOv8 and YOLOv10 models were used. The models were used to detect and compare the effectiveness in identifying the previously mentioned damages in the analyzed images. This comparison allowed us to determine which of the models offers the best results in terms of precision and performance in detecting the aforementioned damages. The stages of the design and application of the CRISP-DM methodology, which summarize the phases of the project process, are presented below, as shown in Figure 1: (A) Business Understanding, (B) Data Understanding, (C) Data Preparation, (D) Modeling, (E) Evaluation, and (F) Deployment.

In the (A) "business understanding" phase, an in-depth analysis of the Project's specific needs and objectives was carried out, focusing on the automated diagnosis of bridge damage. This began with a comprehensive review of current literature on monitoring and detecting damage in civil infrastructure, especially bridges. Both traditional and novel approaches were investigated, and emerging technologies were proven effective in addressing challenges in this area. The review included methodologies, techniques, and tools applied to damage detection, highlighting the use of Artificial Intelligence (AI) algorithms and image processing.

In the (B) "data understanding" phase, data collection began with a search for reliable sources that would provide labeled damage-related datasets. Among the available options, the Roboflow platform was selected due to the diversity and quality of its resources, which are categorized and, in many cases, accurately labeled. Damage types relevant to this study include corrosion, cracks, and the phenomenon known as alligator skin on pavements, selected for their direct impact on bridge integrity. Initially, 1,848 images were obtained from this platform, organized into specific classes such as cracks (946 images), corrosion (627 images), and alligator skin (287 images) (See Figure 2).

Data collection included both public sources and a proprietary database, ultimately resulting in a robust dataset of 7,934 images that also included additional samples of exposed steel and concrete spalling. To enhance the dataset with local representativeness, 202 images of Lima bridges were collected during 2024, captured under various lighting conditions and angles. This combination of high-quality external data and local samples provided technical robustness, realism, and regional representativeness to the model training and validation process. In the (C) "data preparation" phase, a detailed evaluation of class identifiers was performed to ensure correct representation during model training. One of the main challenges was the diversity of annotation formats, as some datasets were in YOLO format while others used Pascal VOC or COCO. Custom scripts were developed to convert and unify these formats, allowing the datasets to be integrated into a consolidated set and minimizing annotation errors. Before modeling, the images were reviewed to ensure labeling quality and consistency.

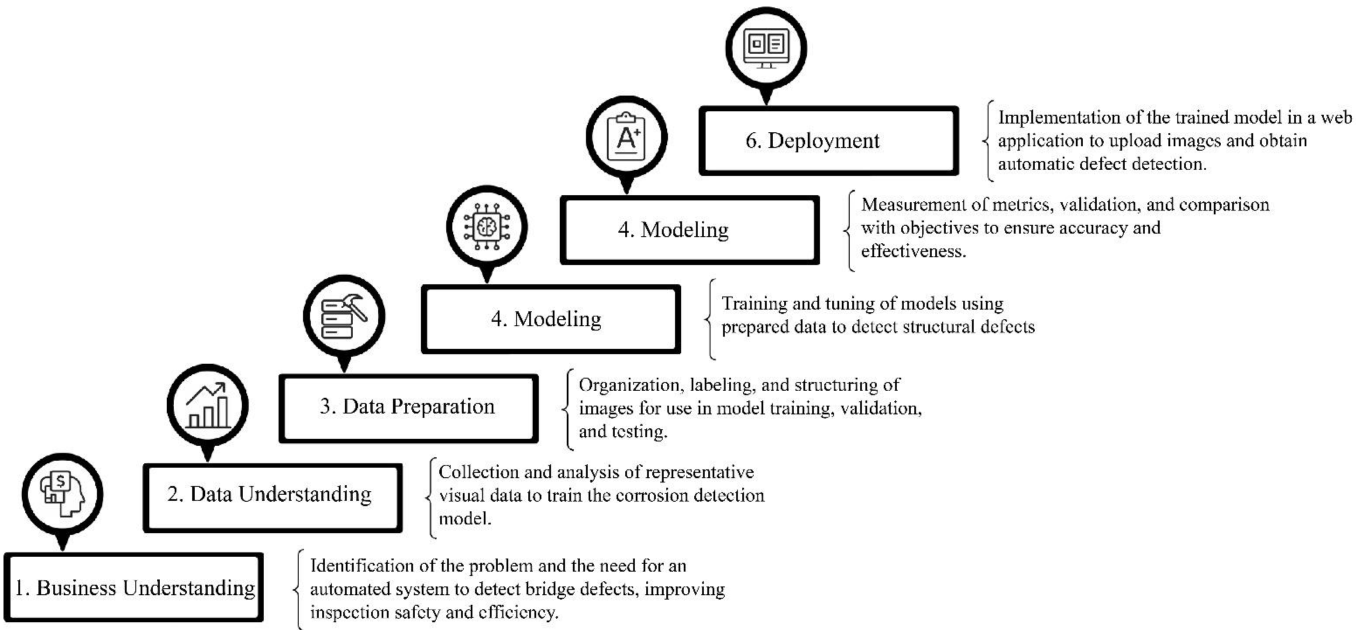

Fig. 1 Representation of the CRISP-DM methodology phases

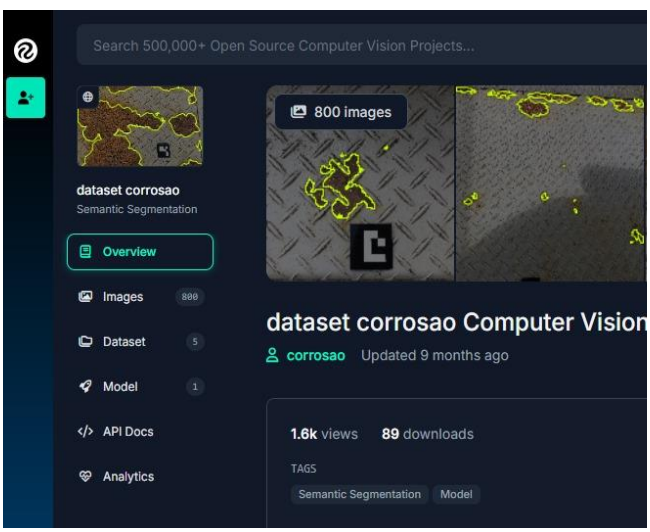

Fig. 2 Roboflow platform screenshot

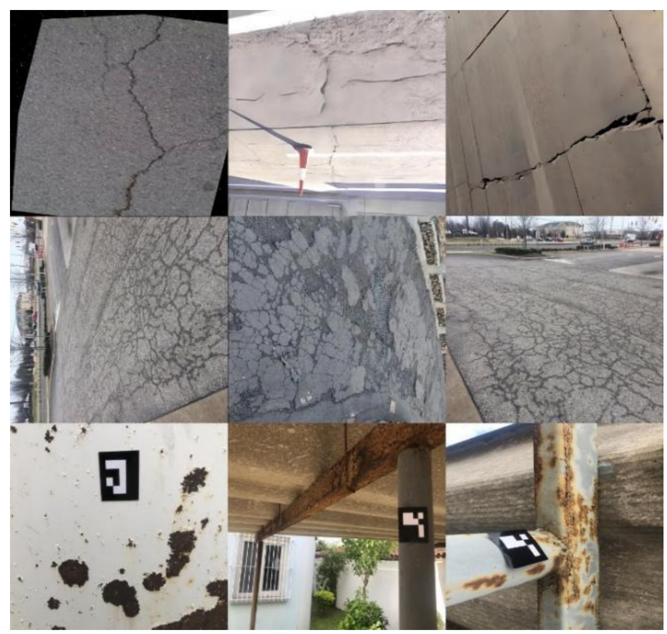

Fig. 3 Set of images from the dataset

Two working configurations were defined: a lightweight dataset of 1,848 images for initial testing and a robust dataset of 7,934 images for final training. Data augmentation techniques, including rotations, flips, brightness changes, and crops, were subsequently applied to improve model generalization. Additionally, all images were normalized to 640x640 pixels to optimize processing. Finally, the data was divided into training (70%), validation (20%) and testing (10%) subsets to ensure a robust evaluation of the model's performance (See Figure 3).

In the (D) “modeling” phase, the YOLOv7, YOLOv8, and YOLOv10 models were trained in the PyCharm Community development environment, using Python 3.9.0 and the Ultralytics library. The official repositories for each model were cloned and configured in virtual environments, ensuring the correct installation of dependencies. Pre-trained weights (transfer learning) were used, and a 100-epoch training session was defined with a batch size adapted to the available resources. Tests were run on an NVIDIA RTX 3060 GPU with CUDA support. During this phase, the data.yaml files were configured with the dataset and class paths, and key hyperparameters such as learning rate and momentum were tuned to improve convergence (See Figure 4).

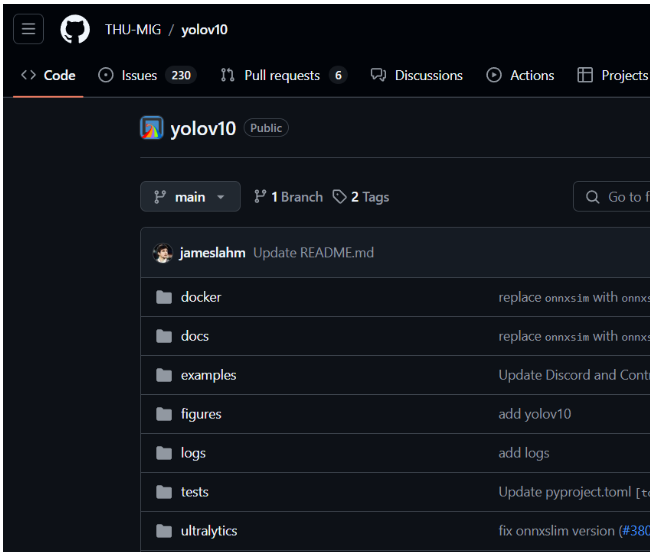

Fig. 4 YOLOv10 repository

In the (E) "evaluation" phase, model validation was performed using the test dataset and labeled assets in the "valid" folder, allowing a direct comparison between model predictions and expected results. Three versions of YOLO were evaluated: YOLOv7, YOLOv8, and YOLOv10. Although they follow the same convolutional neural network-based approach for object detection in static images, they exhibit key differences in their performance. Results were measured using standard computer vision metrics: precision, recall, F1 score, mAP@50, and mAP@50-95, allowing the strengths and limitations of each YOLO version to be identified. Results showed poor performance for YOLOv7, intermediate performance for YOLOv10, and improved performance for YOLOv8, which achieved an mAP@50 of 47% and an mAP@50-95 of 32% on the robust dataset (See Figure 5).

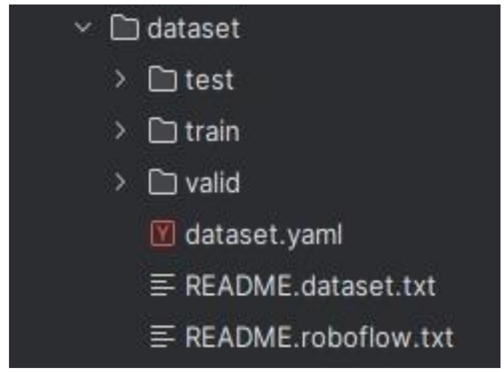

Fig. 5 Valid folder

In the final (F) "deployment" phase of the Project, the selected model (YOLOv8) was integrated into a structural diagnostic web application. The system allows the user to upload bridge images and obtain automatic damage detection results with graphical visualization and detailed reports that include maintenance recommendations. The interface was designed to be intuitive and accessible, helping to reduce inspection times and facilitating decision-making in road infrastructure management.

One of the main challenges encountered was the diversity in the labeling formats of the collected datasets, since some datasets came in YOLO format, while others used the Pascal VOC and COCO formats. To solve this incompatibility problem, it was necessary to develop a series of custom scripts that allowed the conversion of tags between the three formats. A diagram detailing the labeling formats found is shown in Figure 6.

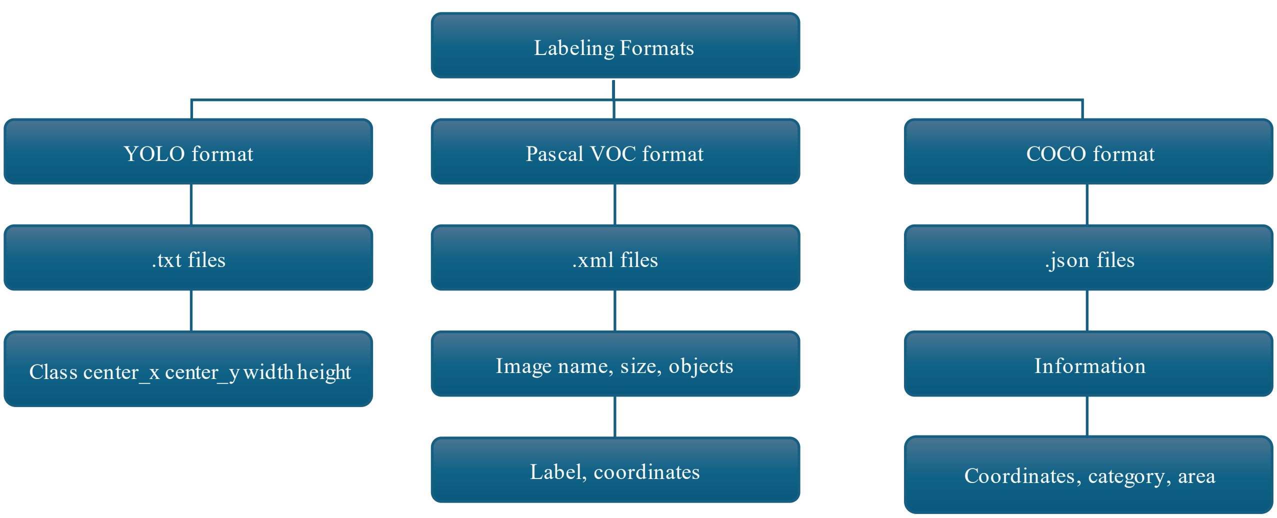

Fig. 6 Labeling formats

Subsequently, the different collected datasets, which were initially separated by damage types, were combined into a single unified dataset. Likewise, it facilitated the training of the models by having a single set of images and labeling. For this task, a "light" and a "robust" data set were used. The structure and values of the dataset labels were validated through the creation of additional scripts. These validations consisted of identifying and correcting possible errors in the labels, such as missing identifiers or inconsistencies in the coordinates of the labeled objects.

5. Results

5.1. About the Models

In this research, the YOLOv7, YOLOv8, and YOLOv10 models were evaluated in the detection of structural damage in bridges in Lima, using key performance metrics, such as precision, sensitivity (recall), mAP50 and mAP50-95. These metrics allowed for a rigorous comparison of the performance of the models in Terms of damage detection and classification. YOLOv7 presented the lowest values in all the metrics evaluated, with a mAP50 of approximately 9% and a mAP50-95 of 3.8%. The precision and recall of this model remained around 20%. This reflects significantly limited performance, as the model showed a low ability to correctly detect areas of interest and failed to identify a considerable proportion of the corrosion instances present. This combination of low precision and recall suggests that YOLOv7 generates a considerable number of false positives and misses many correct detections, limiting its applicability in the context of structural inspection (See Figure 7).

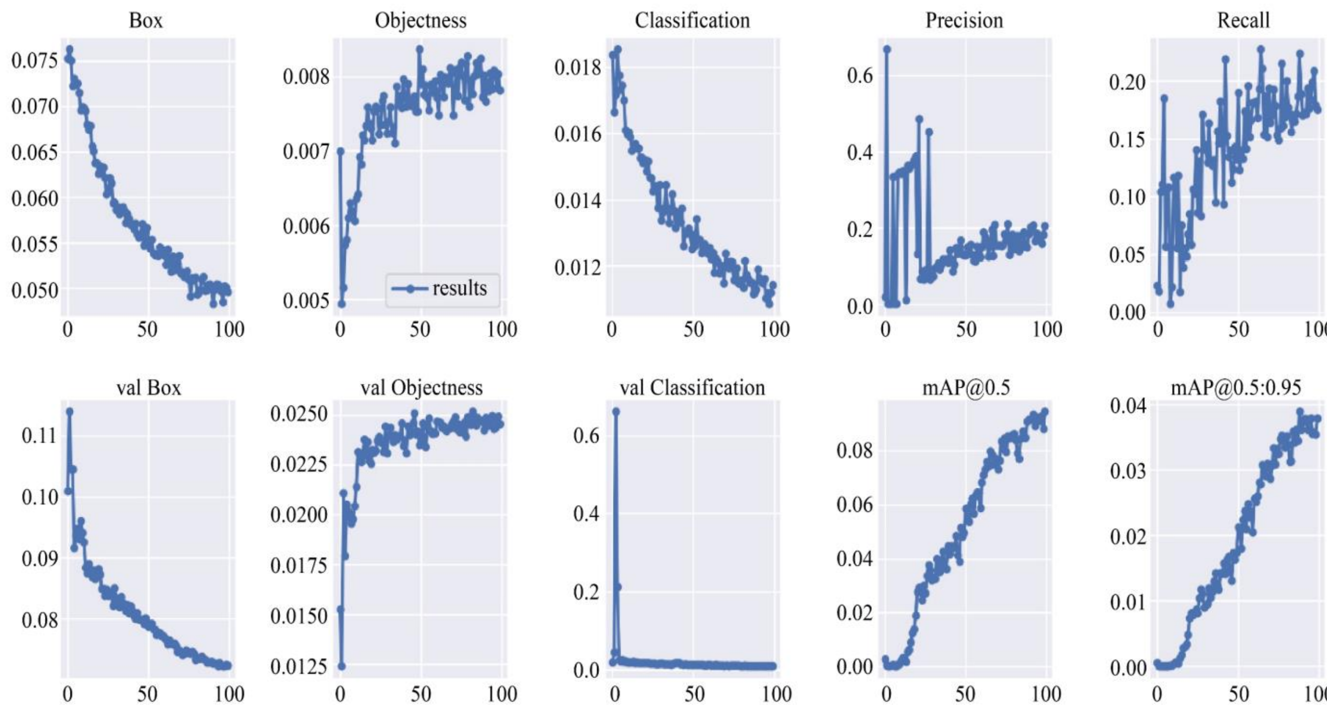

Fig. 7 YOLOv7 model results

On the other hand, YOLOv8 proved to be the most robust model, achieving a mAP50 of 28% and a mAP50-95 of 14%. Its precision fluctuated between 40% and 60%, while its recall remained around 30%. These results indicate that YOLOv8 can perform a higher number of correct detections and maintains a better balance between the number of true positives and the number of correctly detected instances.

The higher precision suggests that YOLOv8 is more reliable in reducing the number of false positives, while its better recall ensures that it detects a greater number of corrosion areas (See Figure 8).

YOLOv10, although inferior to YOLOv8, showed intermediate performance with a mAP50 of 21% and a mAP50-95 of 9%. Its precision was approximately 40%, and its recall reached 25%. These results position YOLOv10 as a model that balances accuracy and detection capacity reasonably well, although it does not reach the level of effectiveness of YOLOv8.

The accuracy of YOLOv10, similar to that of YOLOv8, indicates an acceptable ability to minimize false positives, but its lower recall suggests that it may miss more instances of corrosion than YOLOv8 (See Figure 9).

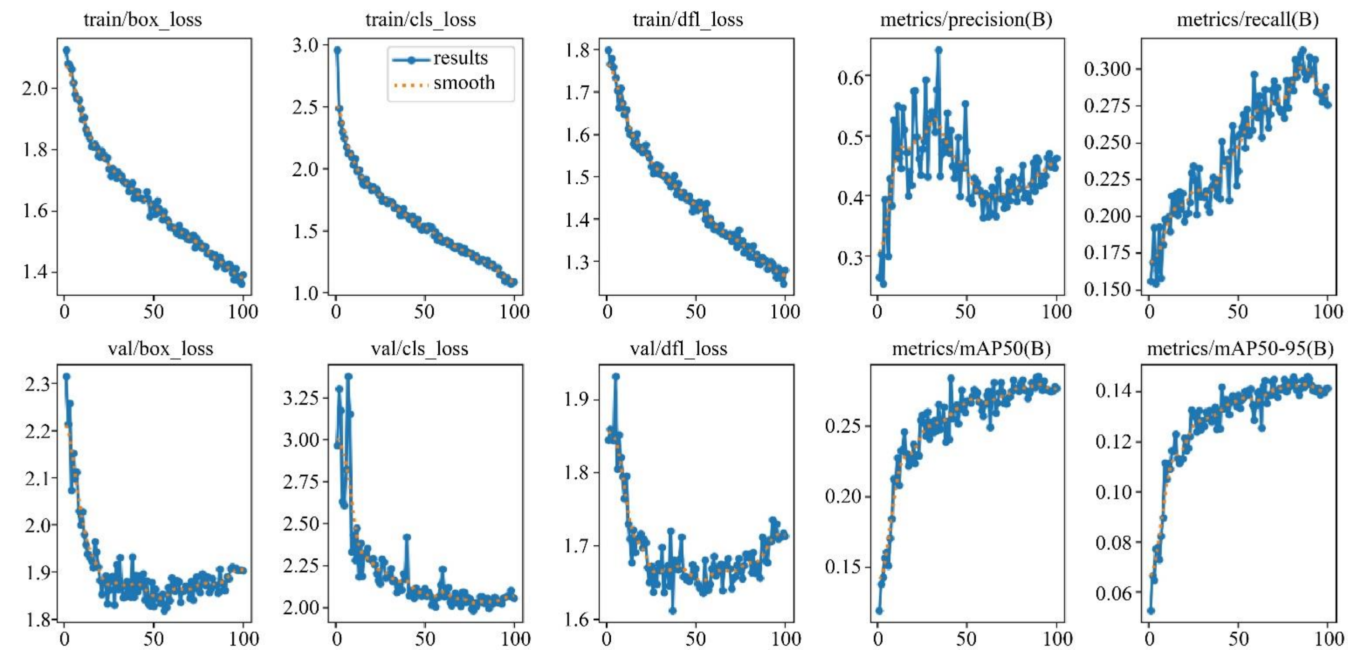

Fig. 8 YOLOv8 model results

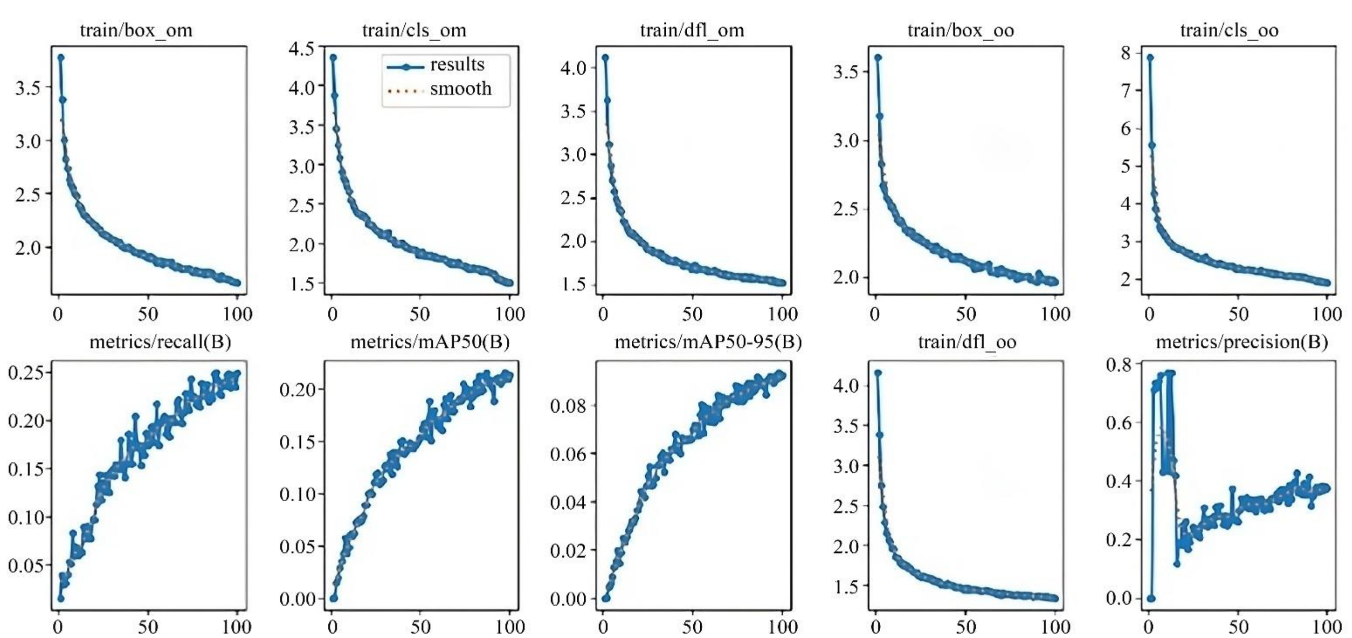

Fig. 9 YOLOv10 model results

Table 3. Training results table

<table>
<tr><th rowspan="2">Models</th><th colspan="4">Table Header</th></tr>
<tr><th>mAP50</th><th>mAP50-95</th><th>Precision</th><th>Recall</th></tr>
<tr><td>YOLOv7</td><td>9.0%</td><td>3.8%</td><td>20.0%</td><td>20.0%</td></tr>
<tr><td>YOLOv8</td><td>28.0%</td><td>14.0%</td><td>40.0% - 60.0%</td><td>30.0%</td></tr>
<tr><td>YOLOv10</td><td>21.0%</td><td>9.0%</td><td>40.0%</td><td>25.0%</td></tr>
</table>

Table 3 shows that the analysis of the results shows that YOLOv8, with both the light and robust data sets, significantly outperforms the YOLOv7 and YOLOv10 models. This indicates that it can allow for more precise and balanced detections. Training with the robust data set further improved the results of YOLOv8, reaching a precision of 60.0% and a recall of 50.0%. Furthermore, the mAP50 and mAP50-95 values also increased considerably, with a mAP50 of 47.0% and a mAP50-95 of 32.0% (See Figure 10).

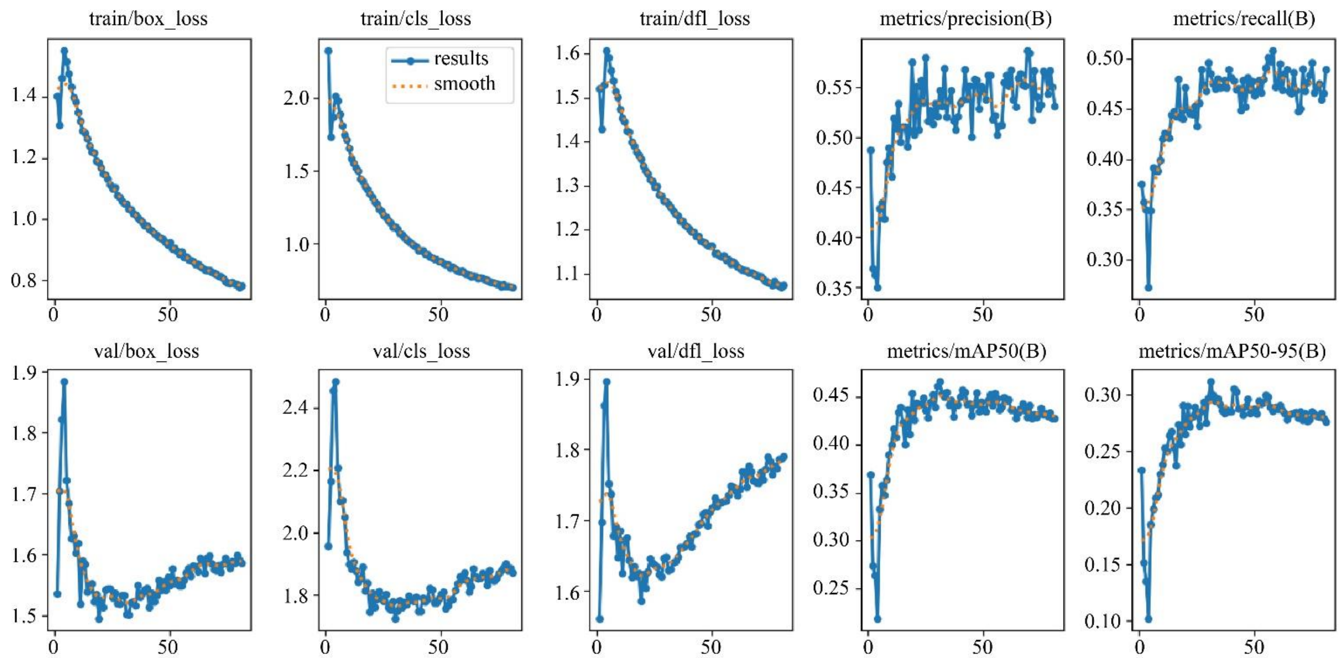

Fig. 10 Results from the robust YOLOv8 model

Fig. 11 Lima bridges dataset 2024

YOLOv7 shows limited performance, with precision and recall values of around 20.0% and a mAP50 of only 9.0%. These results indicated a high rate of false positives and omissions of important detections, making them unsuitable for application in this Project. For its part, YOLOv10 offers intermediate performance, but still below YOLOv8, with a precision of 40.0% and a recall of 25.0%. This suggests that although it reduced false positives, it still missed a considerable number of relevant instances. The comparison shows that YOLOv8 is the most suitable model for bridge diagnosis, due to its ability to balance precision and sensitivity, minimizing false positives and maximizing damage detection. For the validation stage of the proposed software, a total of 202 images were collected from six bridges located in Lima, Peru. This data set includes general images of the bridges and more specific snapshots of areas with obvious structural defects. The collection covered a variety of bridges, from vehicular traffic bridges to pedestrian bridges, providing a representative spectrum of the city's road infrastructure (See Figure 11). The diversity of this proprietary data set is particularly relevant, as it includes examples of different types of damage that may not have been sufficiently represented in the initial training datasets. While the training data focused on high-resolution images labeled for corrosion, cracking, spalling, and rebar obtained from global sources, the proprietary dataset provides local context, reflecting specific conditions and challenges of Lima's infrastructure. This diversity allows us to evaluate the model's ability to adapt and generalize to real-world situations, improving its applicability and reliability in the diagnosis of structural damage.

5.2. Acerca del Sistema Web

The damage detection model was implemented in a web application designed to offer an optimal user experience. Once the images are entered into the system, the processing is activated using the trained model, applying object detection algorithms that have proven effective in identifying damage patterns in bridge structures (See Figure 12). For crack and corrosion detections, the system identified the affected areas with high precision, providing the exact location and an estimate of the confidence level associated with each prediction. Representative examples of detections performed on processed images are presented in Figure 13. In these illustrations, predictions are marked with outlines indicating the affected areas and the type of damage identified.

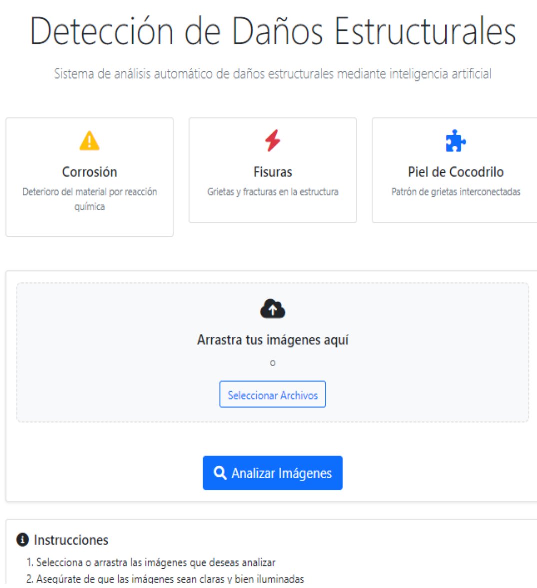

Fig. 12 Software main screen

Fig. 13 Crack and Corrosion Detection

On the other hand, the detections of significant detachments focused on areas where the exposure of steel or loss of concrete material was evident. These damages represent critical risks to structural integrity, so the recommendations generated by the system focused on immediate repair strategies. Figure 14 illustrates notable examples of detachments detected in different structures. In these images, the system identifies damage and generates specific alerts to guide maintenance decisions.

A detailed breakdown of each damage detected in the images processed through the software is presented in Figure 15. As previously noted, the system provides specific information on the type of damage, along with recommendations and relevant details, such as its location within the analyzed image.

Fig. 14 Detection of Exposed Steel and Spalling

Fig. 15 Detail view of structural damage

5.3. About the Indicators

5.3.1. kpi 1: Reduction of Data Collection Time

During the validation phase, the average time required to collect images of the bridge areas without using the proposed system was measured. In this scenario, the manual capture and registration process took between 15 and 20 minutes per area. Subsequently, with the incorporation of the system, data collection was reduced to an average of 8 minutes per area, since additional manual annotations and initial damage classification were no longer required. This contrast demonstrated an approximate 50% reduction in collection time (See Figure 16).

5.3.2. kpi 2: Reduction of Inspection Time

Inspection time was evaluated in two scenarios: without the system and with the system in place. In the first, manual review of the collected images required an average of 30 minutes per image set due to the exhaustive visual analysis. The developed tool reduced this process to 10 minutes per set, as the model automatically highlighted the affected areas and provided a preliminary report of findings. The difference between the two approaches reflected a 66% reduction in inspection time (See Figure 17).

Fig. 16 KPI-1 chart

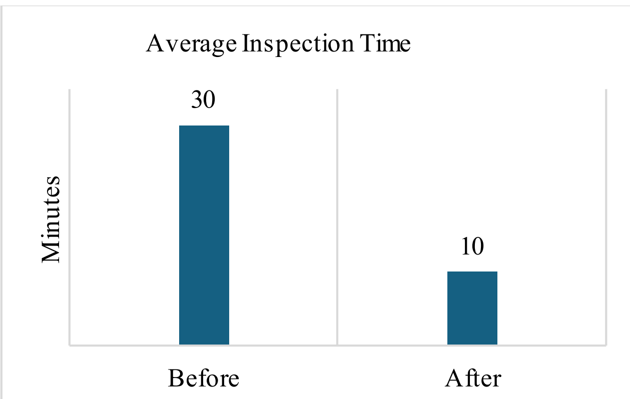

Fig. 17 KPI-2 chart

5.3.3. kpi 3: Reduction in Diagnostic Time

The total time required to complete the diagnosis was also compared between traditional methods and the proposed system. Without the software, consolidating observations and writing a diagnostic report took between 1 and 2 hours per bridge. In contrast, with the developed system, generating structured reports, including damage type, location, and recommendations, took less than 15 minutes. This represented a more than 80% reduction in diagnostic time, demonstrating the efficiency achieved after implementing the model (See Figure 18).

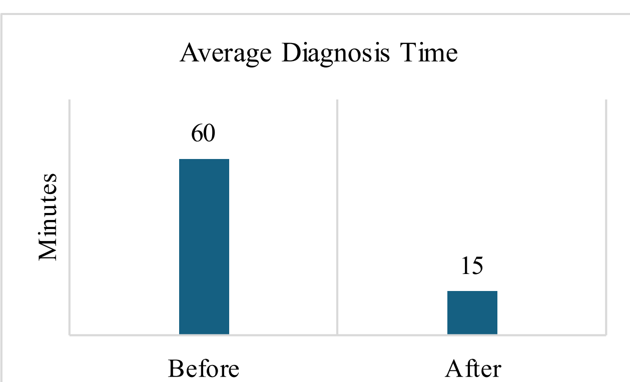

Fig. 18 KPI-3 chart

6. Discussion

The results of the evaluation of the models, YOLOv7, YOLOv8, and YOLOv10, used to detect bridge damage, were presented. The focus is on specific machine learning performance metrics, including precision, sensitivity (recall), mAP50, and mAP50-95. These metrics were essential to evaluate the capacity of the models to detect and classify damage. The implementation of artificial intelligence and image processing techniques for the diagnosis of structural damage in bridges has proven to be an effective and promising tool. Throughout the study, different object detection models were evaluated, highlighting YOLOv8 for its balance between precision and recall, which positions it as the most suitable model for this type of task.

The evaluation results show that the YOLOv8 model, trained with a robust dataset, can accurately identify various structural damages, such as concrete spalling, corrosion, and cracks. The ability of the model to correctly detect these damages in images of bridges in Lima reaffirms the viability of applying AI technologies in monitoring critical infrastructures. However, the research also reveals areas for improvement. Although the results are promising, the precision and recall of the model indicate that there is still room to increase the effectiveness of the system. This could be achieved by incorporating a more extensive and diversified dataset, including a greater variety of structural damage, lighting scenarios, and capture angles. The integration of local data, such as images of bridges in different regions and under various environmental conditions, is essential to adapt the system to the specific characteristics of each environment. This will improve the robustness of the model and ensure its effectiveness in different geographical and climatic contexts, increasing its practical usefulness.

To avoid issues related to the copyright of bridge images, all images were captured by project members, except for images from public datasets available on the internet that were used for training. Furthermore, the analyzed bridges are publicly accessible, so no regulations were violated, and no additional permits were required. It should be noted that, although ethical aspects are taken into account in the development of this Project, the results are not absolute. In other words, the results represent a quantified assessment of the damage and its relationship to the need for attention, so the final decision must always be supervised by experts in bridge structural integrity. Traditional bridge inspection methods rely heavily on inspector experience and direct visual analysis, which entails high subjectivity and inter-rater variability. Recent studies have shown that these manual inspections are slower and have accuracy limitations. For example, authors [12] report that traditional visual detection can miss up to 30% of minor damage due to eye strain and coverage limitations. Similarly, [13] emphasize that variability in crack identification can compromise the reliability of structural diagnosis. In contrast, the proposed system based on YOLOv8 reduced collection, inspection, and diagnosis times (KPIs defined in this study), generating more consistent and replicable results. Although accuracy still depends on the quality of the dataset and capture conditions, automation reduces the subjectivity of the process, which is consistent with studies such as [16], which validated that the combination of computer vision and 3D reconstruction improves the objectivity of bridge inspections. Although the results obtained demonstrate the effectiveness of the artificial intelligence-based system, there are several limitations that must be considered. First, the size and diversity of the local dataset (202 images of bridges in Lima) were limited compared to the international datasets used in training. This could affect the model's generalization ability in contexts other than Lima. Second, the system depends on the quality of the captured images; factors such as poor lighting, the presence of vehicles, or adverse weather conditions can reduce the accuracy of detections. Finally, while the system automates detection and diagnosis, it does not replace the experience of the structural engineer, as the results must be validated in the field to ensure safe decisions.

7. Conclusion

The YOLOv8 model has proven to be the most effective among those evaluated for the detection of structural damage in bridges, standing out for its ability to balance precision and sensitivity. This model allows different types of damage to be more accurately identified, such as cracks, corrosion, and detachments, contributing significantly to the automation and improvement of inspection processes in road infrastructure.

Although the results obtained are promising, the need to have a more diversified and extensive dataset is evident. The inclusion of a greater variety of images, representative of different structural conditions and types of damage, is crucial to improve the generalization capacity of the model and its applicability in more diverse real scenarios. This study demonstrates how the application of artificial intelligence can revolutionize infrastructure inspection practices, improving accuracy and efficiency in damage identification, and contributing to the safety and sustainability of road infrastructure.

The research highlights how the application of artificial intelligence and image processing can transform infrastructure management, providing more accurate and efficient tools for damage detection and diagnosis. This advance not only optimizes resources and inspection times but also improves the safety and sustainability of road infrastructure, contributing to urban development and the prevention of catastrophic failures. Finally, future research could explore different models in search of more accurate and faster results. Likewise, it is recommended that we explore more applications and different damages to evaluate, without limiting ourselves to the damages evaluated in this research.

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