Available online at www.eccomasproceedia.org
Eccomas Proceedia COMPDYN (2025) 1482-1492

ECCOMAS Proceedia

COMPDYN 2025
10th ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, M. Fragiadakis (eds.)
Rhodes Island, Greece, 15-18 June 2025

CV-BASED CORROSION CLASSIFICATION TO IMPROVE FAST SEISMIC ASSESSMENT OF EXISTING RC BRIDGE PIERS

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Abstract

The paper proposes a new image-based methodology for classifying corrosion intensity to improve seismic assessment of reinforced concrete (RC) bridge piers. This work is framed within the topic of bridge and viaduct health management, in which the process of visual inspection can suggest insights about the health state of bridge components. Therefore, the aim of the study consists of automatically defining corrosion intensity values to penalize the structural performance of RC bridge piers by modifying the constitutive laws of the steel reinforcement and reducing the overall ductility capacity. To identify corrosion intensity values, computer vision (CV) techniques were used. First, a dataset of images containing exposed steel reinforcement in RC elements was collected and domain experts manually classified the images into three corrosion intensity levels. After, with the aim of extracting key features from images, a color space transformation was applied to preprocess the images, while a Convolutional Neural Network (CNN) was trained and tested to automatically classify the corrosion intensity. The prediction of the intensity class from images allows extracting penalty parameters for the steel reinforcement, in terms of mass. Finally, to predict the performance reduction of the corroded RC piers, a fiber-based modelling approach was employed, accounting for material uncertainties, and capacity curves were derived. The proposed approach tends to enhance the current methods of fast risk assessment and prioritization, for which the combination of CV and simplified structural modelling-analysis can drive road management companies to improve their maintenance efficiency.

Keywords: Bridges Assessment, Corrosion, Computer Vision, Numerical modelling.

ISSN:2623-3347 © 2025 The Authors. Published by Eccomas Proceedia.
Peer-review under responsibility of the organizing committee of COMPDYN 2025.
doi: 10.7712/120125.12504.25332

1 INTRODUCTION

Transportation infrastructure systems are critical assets for economic development, requiring structural resilience to environmental and seismic hazards [1]. Bridges, as key nodes in these networks, are particularly susceptible to structural degradation over time, primarily due to aging, environmental exposure, and increased traffic demand. In developed countries, a substantial portion of the bridge stock was built between the 1950s and the 1990s under outdated design codes, which did not adequately account for long-term durability and seismic resilience [2, 3]. As a result, a large fraction of these structures exhibits severe deterioration, requiring urgent assessment and intervention to mitigate potential failures, particularly under seismic loading conditions.

Among the various deterioration mechanisms affecting reinforced concrete (RC) bridges, steel reinforcement corrosion is a primary concern, as it significantly reduces mechanical properties and structural performance [4, 5]. Corrosion of reinforcement bars leads to a reduction of the structural flexural capacity, while corrosion of transverse reinforcement adversely affects the shear strength, potentially anticipating the failure mechanism, leading to a transition from ductile to brittle behavior. In addition, the corrosion of steel stirrups leads to significant secondary effects, including the reduction of concrete core confinement, which results in a decrease of compression ultimate strength of confined concrete, sensibly reducing the ductility [6, 7]. The latter aspect is particularly critical in bridge piers, given their essential role in dissipating energy during seismic events.

Given the extensive number of existing bridges requiring assessment, transportation management companies need to face significant challenges in implementing large-scale structural evaluations due to resource constraints. Traditional seismic assessment approaches rely on detailed finite element (FE) modelling, calibrated on experimental tests, which are computationally expensive and then, not practical for large-scale assessment. Furthermore, most of existing studies on seismic risk of bridges neglect corrosion issues, leading to potential underestimation of structural vulnerabilities [8].

Recent advancements in artificial intelligence (AI) and machine learning (ML) can offer a transformative solution for seismic risk assessment of corroded RC bridge piers [9]. ML techniques have proven to be effective in predicting structural responses, estimating residual capacity, and identifying failure mechanisms, significantly reducing computational effort [10]. However, the existing literature specifically focusing on AI-based assessment of corroded RC bridge piers remains limited, indicating a critical research gap [11].

On this way, this study proposes a novel AI-driven computer vision (CV) algorithm for facilitating an automated classification of corrosion severity in RC bridge piers, to use for a fast assessment of bridge pier typologies. The goal is to enable a simplified assessment of the seismic vulnerability of RC bridges, accounting for observed defects and uncertainties in material properties (knowledge-based uncertainty), to improve reliability in risk prioritization of bridges [12].

By incorporating advanced image processing techniques, this methodology classifies corrosion severity into three distinct levels, each one associated with stochastic mass loss values. Based on the proposed classifications, automated pushover analyses are performed, accounting for uncertainties in the mechanical properties of the materials.

The proposed approach aims to improve the current risk assessment methods by leveraging on the synergy between CV techniques and simplified structural modeling and analysis, helping to identify which bridges require further investigation.

2 CNN-BASED CORROSION CLASSIFICATION FRAMEWORK

The quantification of the corrosion degree consists of extracting information from images showing exposed steel reinforcement, retrieved by onsite inspections. For the case at hand, three distinct levels of corrosion intensity were considered, i.e., Low, Medium, and High, according to the classification proposed by the Italian guidelines [3]. According to the obtained value of corrosion intensity, a range value of mass loss can be assigned, and then implemented in the simplified modelling-analysis duo.

Focusing on the CV part of the proposed framework, an automated system for classifying corrosion severity in steel reinforcement images was elaborated by using Convolutional Neural Networks (CNNs). In particular, the method was set to process small image patches and to determine the corrosion level in each region.

This approach aims to create a labelled datasets for training models, simplifying the process and increasing the data volume. The overview of the proposed CV-based architecture is shown in Figure 1, while the next subsections provide a definition of each step.

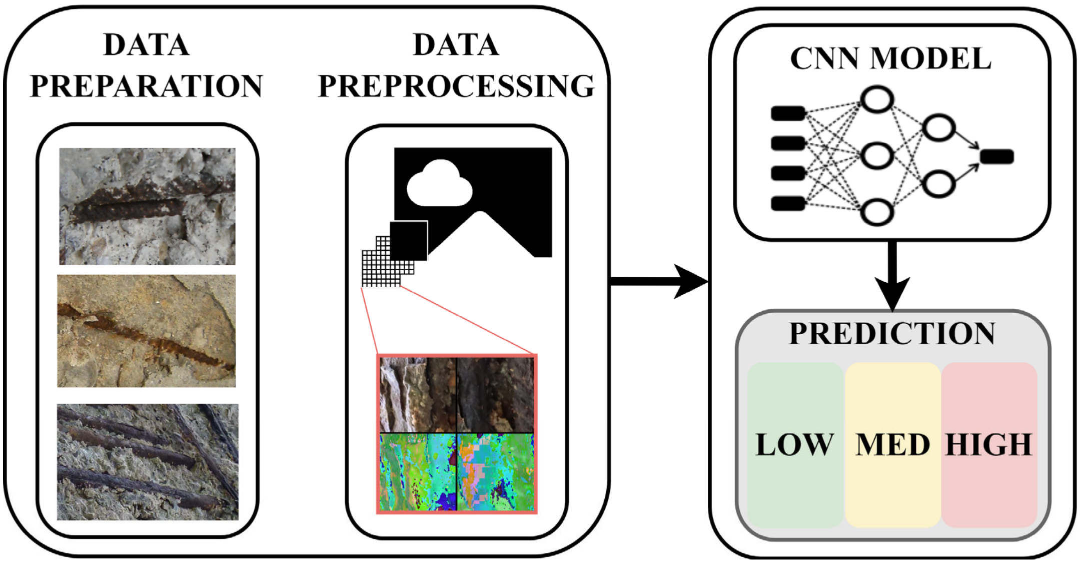

Figure 1: Computer Vision Framework for Corrosion Intensity Classification.

2.1 Dataset Preparation

The first step is preparing a dataset of classified images for training the algorithm. This process includes image selection and domain expert classification, in the following order:

1. *Image Selection:* High-resolution images of corrosion-damaged steel reinforcement are selected. Additional images can be gathered from open datasets, i.e., dacl10k [13], to ensure diversity and data balancing [14].
2. *Manual Classification:* Domain experts categorize each image into three corrosion intensity levels: high, medium, and low, based on structural engineers' knowledge and experience. For the case at hand, the classification was guided by the definitions provided in the Italian guidelines [3], which describe low intensity as surface oxidation without significant material loss, medium intensity as initial section reduction due to corrosion, and high intensity as severe degradation with substantial cross-section loss.

2.2 Dataset Preprocessing

The preprocessing phase optimizes the image representation and prepares the data for training:

1. *Multi-Color Space Fusion:* Each image is converted into multiple color spaces (e.g., HSV and Lab), and features are combined to improve the visibility of corrosion patterns.
2. *Patch Extraction:* The images are divided into small patches of size 224x224, using a sliding window approach, each classified according to its associated corrosion intensity class. To address class imbalances, an equal number of patches are extracted for each corrosion class, and data augmentation techniques like rotation and flipping are applied [15].

2.3 CNN Model Architecture

The proposed CV algorithm is structured for feature extraction and classification tasks. It employs a combination of CNNs layers to automatically learn spatial hierarchies of corrosion patterns, improved by attention mechanisms enabling the model to focus on the most relevant aspects of the images. This attention-based architecture allows the model to prioritize critical features associated to corrosion, such as texture and color changes, while minimizing the impact of irrelevant background noise. The model includes multiple convolutional and fully connected layers, with attention mechanisms integrated via Squeeze-and-Excitation blocks. Major details are omitted for the sake of synthesis [16].

2.4 Preliminary Results

Preliminary evaluations suggest that the proposed CNN model performs adequately in classifying corrosion severity levels, achieving a classification accuracy of approximately 90%. The integration of attention mechanisms enhances feature extraction, improving robustness across diverse datasets. The model exhibits strong generalization capabilities, effectively distinguishing corrosion patterns while minimizing misclassifications. Figure 2 provides an illustrative example of the entire framework, showcasing a case study where the model correctly predicts the 'high corrosion' severity class.

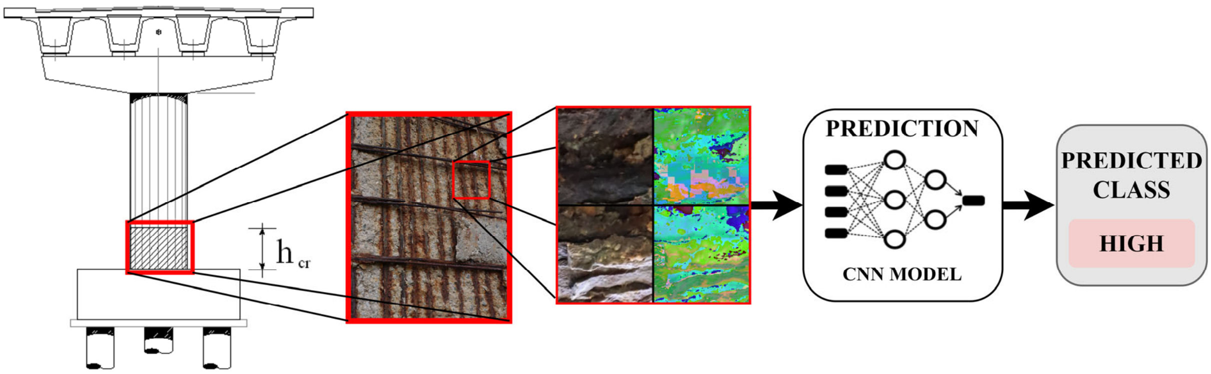

Figure 2: Illustration of the framework's prediction: a case study correctly classified as 'high' severity.

3 SEISMIC PERFORMANCE OF CORRODED RC BRIDGE PIERS

3.1 Material Properties Deterioration

The degradation of reinforcing steel due to corrosion is commonly quantified by mass (or weight) loss, indicated as Q_{corr}, as result of the reaction between steel and corrosive agents. This process reduces the cross-sectional area and affects key mechanical properties, such as yield strength, elastic modulus (even though slightly), and ultimate strain. Several state-of-the-art studies, such as Du et al. [17], Vu et al. [18,19], proposed regression models to estimate the residual cross-sectional area and mechanical properties of corroded steel reinforcement. The above models, calibrated for mass losses up to 25%, remain applicable until a value of mass loss of about 50%, as shown by Opabola [20]. Regarding the elastic modulus , a reduction can be estimated through the formulation proposed by Lee and Cho [21], while the variation of the ultimate strain can vary across studies [22]. For this study, the assumptions proposed by Opabola were accounted for, considering the possibility to predict seismic behavior also for higher corrosion levels (e.g., 50%).

Corrosion also impacts transverse reinforcement, reducing confinement effectiveness and degrading the compressive strength and strain capacity of the core. To account for these effects, this study employes a modified version of Mander stress-strain relationship [23], incorporating corrosion-induced reductions in transverse reinforcement properties.

The constitutive laws used in this study for steel and confined concrete are shown in Figure 3, reporting the variation of trends when mass loss increases.

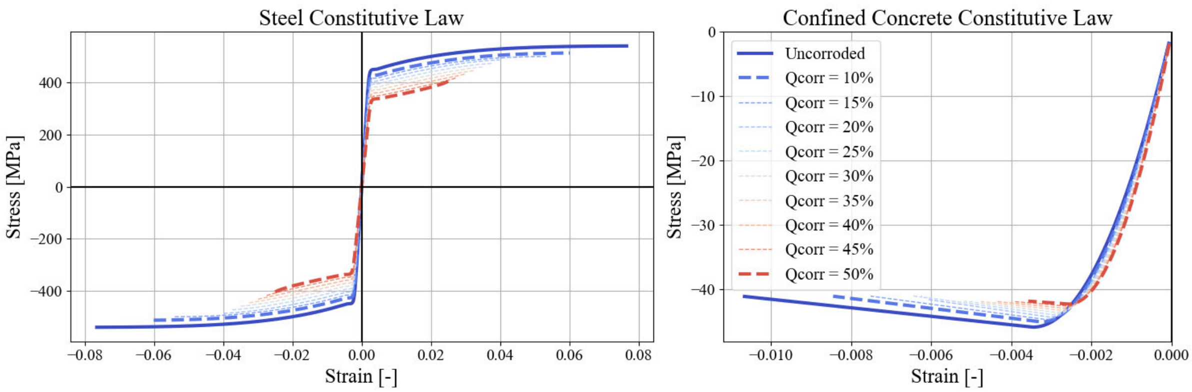

Figure 3: Constitutive law for steel (left) and concrete core (right) as a function of mass loss.

3.2 Numerical Modelling approach

A two-dimensional nonlinear fiber-based FE model was developed to simulate the structural behavior of RC bridge piers. The flexural response was modelled by using the force-based nonlinear *BeamColumn* element in OpenSees [24], adopting a "Fixed Location Integration" scheme. Two section types were defined: (a) uncorroded, by considering geometrical and mechanical parameters as in a new pier; (b) corroded, characterized by the concrete core without cover and complete corrosion of all reinforcing rebars and stirrups, according to the selected Q_{corr} value.

The materials were modeled by using *Concrete01* material for both cover and confined concrete, employing confinement effects through the abovementioned Mander approach. The *ReinforcingSteel* material was used to simulate the steel for longitudinal bars.

To account for the corrosion effects, the properties of the core were reduced to account for confinement degradation. This schematization was simulated in the lower part of the pier, in order to simulate the worst-case scenario under seismic actions. In fact, to detail the model, the *BeamColumn* element was discretized into two parts: (i) the lower segment, with a length equal to 0.1 times the total height, which was assigned to the corroded sections and solved by using three integration points; (ii) the upper segment, with the remaining part of the pier and representing the uncorroded sections, solved by using five integration points. For fiber section discretization, each section was discretized into 30 fibers in both the circumferential and radial directions, both for the concrete core and cover.

4 CASE-STUDY APPLICATION

In this section, a case-study test is performed to illustrate how the output of the CV-based corrosion detection and classification can be used to estimate the corrosion-induced behavior of RC piers. The case study was simulated by investigating a single-column pier with circular section. To simulate the uncertainty related to modelling and analysis, the geometrical parameters were simulated as deterministic, while the mechanical parameters, i.e., compressive strength, f_c, yield strength of steel reinforcement, f_y, and elastic modulus, E_s, were simulated as random variables. The geometry parameters are assumed as deterministic since, commonly, those are characterized by low uncertainty if original design documents are available and on-site metric survey are carried out. Regarding the location of defects, of interest for the scopes of this paper is the presence or absence of corrosion in the lower part of the pier, which can provide critical data on the position and extent of defects [25], and then can allow the schematization proposed in Section 3.2.

Regarding the index bridge pier, a circular cross-section with a 2 meters diameter and a total heigh of 8 meters was simulated. The reinforcement layout consists of 55 ϕ 20 mm longitudinal bars and ϕ 16 mm transversal stirrups with a 100 mm-spacing. The seismic mass of the pier (representing the tributary mass of the superstructure and the pier cap) was located at the pier top. Also this parameter was considered as deterministic and was assumed equal to 500 tons. Note that this parameter does not affect the results of the pushover analysis, but it is of significant importance for the definition of the axial load at the pier cross-sections. Figure 4 reports the schematization of the index pier according to the considered modelling approach, both for the corroded and uncorroded sections.

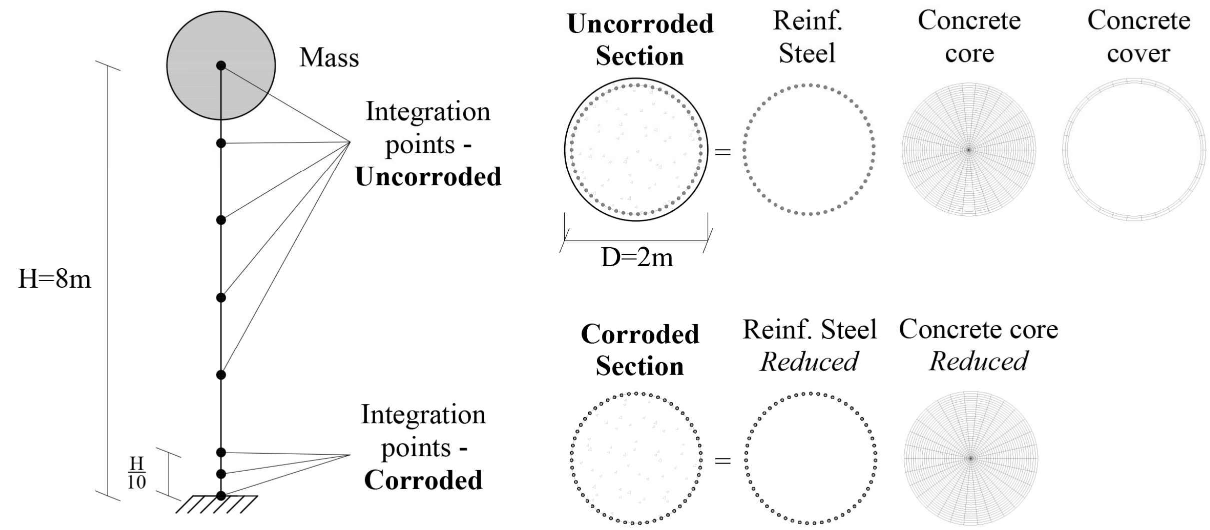

Figure 4: Fiber-modelling strategy employed on the index pier.

4.1 Sampling of Materials Properties and Mass Loss

The main source of uncertainty considered in this study was assigned to the mechanical properties of materials, and to the mass loss of steel reinforcements and stirrups due to corrosion. While the first class of uncertainty was simulated through a classical sampling approach, the second class of uncertainty was predicted by using the proposed CV-based algorithm. To model material uncertainties, the Gaussian Sampling method was employed to generate a representative dataset of bridge piers. This dataset was based on the statistical distribution of material properties (f_c, f_y, and E_s) provided by Zelaschi et al. [26], which defined the continuous distribution of the considered variables for a stock of existing Italian bridges. Table 1 reports the statistical distribution of the three considered parameters.

Parameter	Distribution	Mean	Standard deviation
f_c	Normal	40 MPa	7.440
f_y	Normal	504.40 MPa	157.840
E_s	Normal	203.82 GPa	19.426

Table 1: Summary of the statistical distribution of material properties.

Applying the sampling approach, a total of 300 samples were extracted and simulated in this study. To relate the prediction given by the proposed CV-based approach to the modelling-analysis process, the automated identification and localization of corrosion defects in the pier must be defined, and the related corrosion severity should be derived. Once the corrosion class is determined, the corresponding Q_{corr} value should be defined, and for the case at hand ranges of values were considered. in particular, the mass loss ranges associated to each corrosion intensity class (Low, Medium, and High) were defined according to CONTECVET guidelines [27], and are reported in Table 2.

This information represented the input of the modelling. In fact, the generated 300 samples were investigated with different levels of Q_{corr}. For this case study, 300 uncorroded and 300 corroded models were created, by adopting High Corrosion Intensity class, and then by varying the value of Q_{corr} between 10% and 50%, according to Table 2. The exact value of Q_{corr} in each numerical realization was defined by sampling it from an uniform distribution in the above range. In addition, it is worth observing that the Q_{corr} value was attributed to both longitudinal and transverse reinforcements, by assuming similar degradation of the pier.

Parameter	Low	Medium	High
Q_{corr}	1%-5 %	5%-10 %	10%-50 %

Table 2: Values of Corrosion Steel Mass Loss (Q_{corr}) at different corrosion intensity levels.

4.2 Pushover Analysis

Considering the stock of realization in both corroded and uncorroded states, a total of 600 nonlinear static analyses were performed, in order to assess the impact of corrosion on the structural performance of RC piers through capacity curves.

Figure 5 presents the results of the 600 nonlinear static analyses in terms of base shear and top displacement, showing at left the 300 capacity curves in the uncorroded condition and at right the 300 capacity curves in the corroded conditions. In addition, the median curves were derived, to show the effect of a high corrosion intensity level on the structural performance.

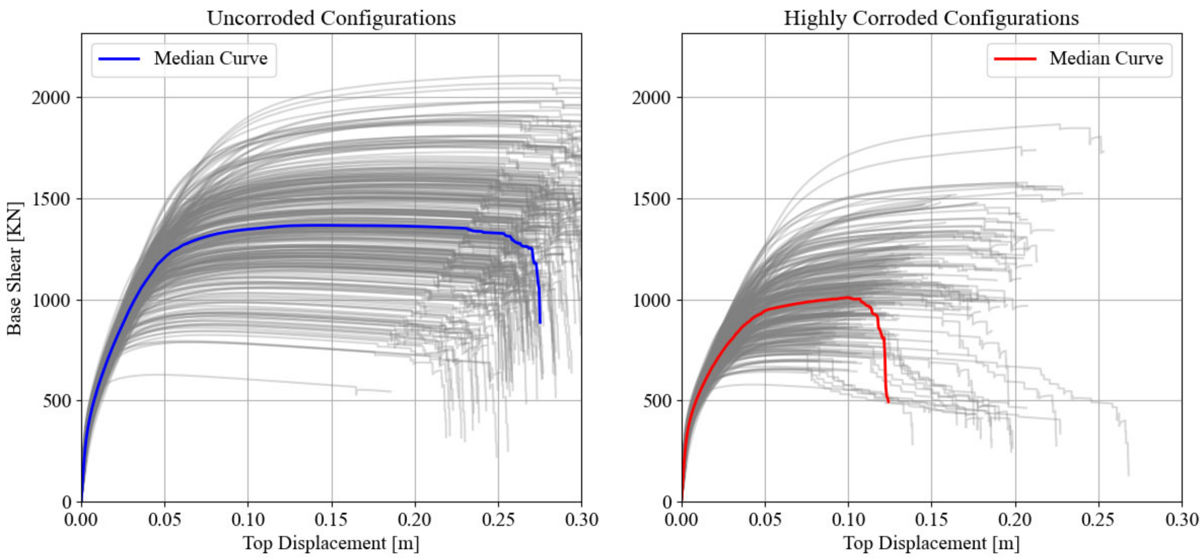

Figure 5: Pushover analyses results for Uncorroded (left) and Corroded (right) scenarios.

The obtained results can be evaluated by observing the variations of the median capacity curves in terms of yield displacement, ultimate displacement, and ultimate base shear between the uncorroded and corroded conditions. To derive those parameters, equivalent bilinearization of the curves is carried out. Figure 6 highlights a notable reduction in both ultimate displacement and maximum base shear, quantified as 54% and 25%, respectively. A key observation is that the most significant reduction in performance parameters of corroded bridge piers pertains to the ultimate displacement, which leads to a substantial decrease in ductility. In this context, the comparison of ductility between the uncorroded and corroded cases indicates a 30% decrease in ductility ratios.

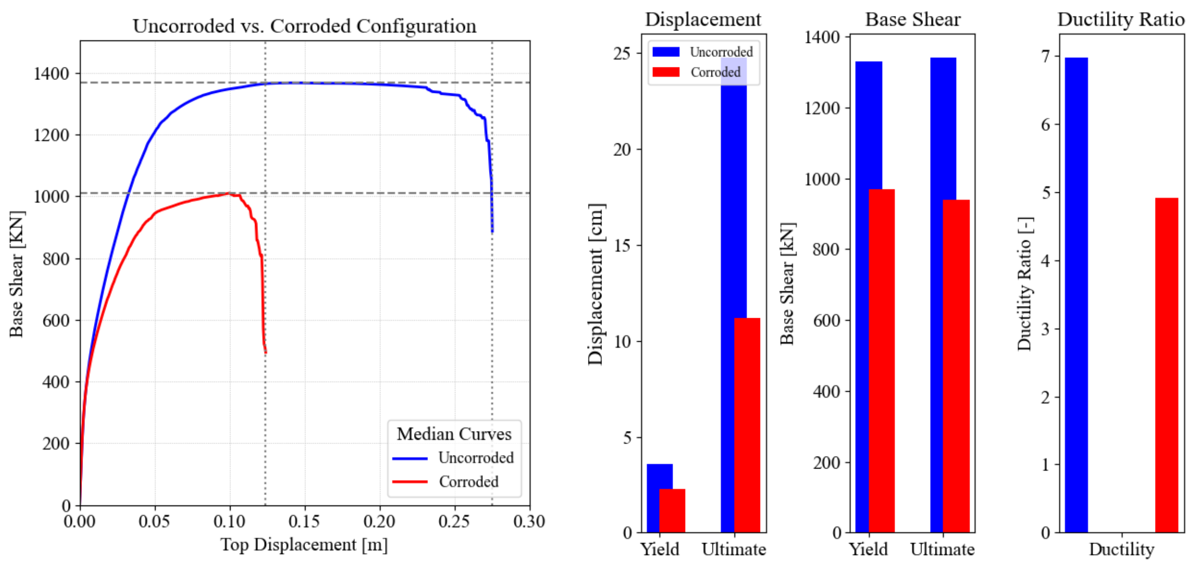

Figure 6: Pushover analyses results for Uncorroded (left) and Corroded (right) scenarios.

5 CONCLUSIONS

This study introduces a methodology to assess the seismic vulnerability of corroded RC bridge piers, addressing the challenge of quantifying corrosion severity through a CV-based algorithm, while considering material property uncertainties through classical seismic modelling and analysis approaches. The aim of the paper is to support bridge portfolio risk prioritization by leveraging data-driven tools.

The methodology is based on a CNN-based CV algorithm able to classify corrosion severity from images into three corrosion classes. These classes are then used to sample the mass loss within predefined ranges associated with the predicted corrosion class, to account for in numerical modelling. This latter can also account for the simulation of uncertainty, such as the material properties variation. The case study section illustrates how the output of the automatic corrosion classification can be used to estimate the seismic performance of an ideal pier. Pushover analyses on the index pier revealed substantial performance degradation due to corrosion:

- 25% reduction in maximum base shear.
- 30% loss in ductility.

A key finding is that the ultimate displacement is the most affected parameter, leading to a severe reduction in ductility. While this study provides important insights into the effects of corrosion on structural performance, some limitations need to be addressed in future research. In particular, future studies should include real-case bridge piers, demonstrating the output of defect detection methods and their impact on structural analysis. Additionally, further advancements are needed to better differentiate the corrosion degree between longitudinal and transversal steel reinforcement, as well as to refine the definition of mass loss ranges. Moreover, more accurate analysis methods, such as nonlinear time history analyses, should be considered to improve the assessment of structural performance under different corrosion scenarios.

In the end, by combining CV, probabilistic modelling, and advanced structural analysis, an approach, like the one herein presented, can lead to a significant step toward more accurate and efficient bridge portfolio health management. The integration of AI-driven corrosion assessment into seismic evaluations can provide to infrastructure management companies powerful decision-making tools, allowing targeted maintenance and improved resilience of aging bridge networks.

ACNOWLEDGMENTS

Sergio Ruggieri thanks funding by Fabre Consortium, within the research grant “Sviluppo e implementazione di strategie basate sulla Intelligenza Artificiale per l’analisi e il monitoraggio del rischio strutturale di ponti e viadotti esistenti”. Andrea Nettis and Giuseppina Uva thank funding by Centro Nazionale Sustainable Mobility Center, within the framework of “MOST” project, CUP code: D93C22000410001.

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