JOURNAL OF ADVANCED ELECTRICAL AND ELECTRONIC ENGINEERING

Vol 2 Issue 1 (2026)

http://jaeee.org/

Image-Based Probabilistic Seismic Damage Assessment of Reinforced Concrete Beam-Column Joints

Brooke Dori, Billie Delbert, Bob Desmond

TUM School of Engineering and Design, Technical University of Munich, Munich, Germany

Abstract

The rapid and accurate assessment of seismic damage in reinforced concrete structures is paramount for ensuring public safety and facilitating post-earthquake recovery. Beam-column joints, representing the most critical regions for the lateral load-carrying capacity of structural frames, are particularly vulnerable to complex failure modes such as shear degradation and bond-slip. Traditional inspection methods rely heavily on the subjective judgment of engineers and suffer from significant logistical delays. Recent advancements in computer vision and machine learning offer a promising alternative by enabling automated damage detection from digital images. However, deterministic image-based models often fail to account for the inherent uncertainties present in visual data, such as variable lighting, sensor noise, and the imperfect correlation between surface distress and internal structural integrity. This paper proposes a comprehensive framework for the image-based probabilistic seismic damage assessment of reinforced concrete beam-column joints. By integrating deep learning-based semantic segmentation with Bayesian inference techniques, the proposed methodology quantifies both epistemic and aleatoric uncertainties to deliver reliable damage state classifications. The analytical pipeline extracts critical geometric features, including crack width distributions and spalling areas, and maps these visual indicators to probabilistic fragility functions. Extensive evaluation using a diverse dataset of joint failure images demonstrates that the probabilistic approach significantly outperforms traditional deterministic methods in robustness and reliability. The findings provide a vital step toward the integration of automated, uncertainty-aware health monitoring systems in post-disaster structural evaluation.

Keywords

Structural Health Monitoring, Computer Vision, Probabilistic Assessment, Reinforced Concrete, Seismic Damage

INTRODUCTION

1.1 Structural Vulnerability and Seismic Risk

Reinforced concrete moment-resisting frames constitute a significant portion of the global building inventory, particularly in regions characterized by high seismic activity. The structural integrity of these frames during an earthquake relies entirely on the capacity of individual components to dissipate energy through inelastic deformation while maintaining vertical load-bearing capabilities. Within this framework, the beam-column joints serve as the critical nodes transferring massive shear and axial forces between intersecting elements [1]. Under severe lateral ground motions, these joints are subjected to complex, multi-directional stress states that frequently exceed their design capacities, leading to severe diagonal cracking, concrete spalling, and the yielding or slippage of longitudinal reinforcement. The failure of a single beam-column joint can initiate a progressive collapse mechanism, catastrophic in terms of both economic loss and human life [2]. Recognizing this extreme vulnerability, post-earthquake reconnaissance missions prioritize the evaluation of beam-column connections to determine whether a building is safe for continued occupancy, requires extensive retrofitting, or must be slated for demolition. The urgency of this decision-making process highlights the critical need for assessment methodologies that are not only rapid but also highly accurate in their diagnostic capabilities [3].

1.2 Limitations of Traditional Inspection Methods

In the aftermath of a major seismic event, local authorities deploy teams of structural engineers and trained inspectors to conduct visual damage assessments. These traditional methodologies, standardized by guidelines such as those provided by the Applied Technology Council and the Federal Emergency Management Agency, depend fundamentally on the physical presence of personnel on site [4]. The inspectors must visually quantify the extent of concrete cracking, measure residual drift, and estimate the loss of structural capacity based on surface manifestations. This manual approach introduces several profound limitations into the disaster recovery pipeline. Firstly, the sheer volume of structures requiring evaluation frequently overwhelms the limited number of qualified inspectors, leading to massive delays in community resettlement and the resumption of economic activities [5]. Secondly, visual inspections are inherently subjective; the interpretation of crack severity and joint degradation can vary significantly between different engineers depending on their individual experience, fatigue levels, and ambient lighting conditions at the time of inspection. This subjectivity introduces a large margin of error into the safety tagging process, potentially resulting in the premature reoccupation of dangerously weakened structures or the unnecessary condemnation of repairable buildings [6].

1.3 The Shift Toward Automated and Image-Based Assessment

To mitigate the bottlenecks and subjective biases of manual inspections, the field of structural engineering has increasingly turned to automated health monitoring technologies. Among these, image-based assessment has emerged as one of the most scalable and cost-effective solutions. Modern digital cameras, including those mounted on unmanned aerial vehicles, can rapidly acquire high-resolution imagery of damaged building facades and critical structural nodes without exposing human personnel to hazardous environments [7]. The integration of computer vision algorithms allows for the automated processing of these images to detect visual indicators of structural distress. Early iterations of image-based assessment utilized simple image processing techniques such as edge detection and thresholding to identify cracks. However, these methods struggled significantly with the complex background noise typical of post-earthquake scenes, including debris, shadows, and natural material variations. The subsequent adoption of deep learning architectures, particularly convolutional neural networks, revolutionized the field by enabling the highly accurate, pixel-level semantic segmentation of structural damage [8]. These

advanced models can differentiate between distinct damage morphologies, isolating diagonal shear cracks from flexural cracks, and accurately delineating the boundaries of spalled concrete cover.

1.4 The Necessity of Probabilistic Approaches

Despite the impressive performance of deep learning algorithms in identifying and quantifying surface damage, translating these visual metrics into a definitive assessment of structural safety remains a highly complex challenge. The relationship between visible surface degradation and the residual load-bearing capacity of a reinforced concrete joint is fundamentally uncertain. A relatively narrow surface crack might disguise severe internal rebar yielding, while extensive superficial spalling might occur with minimal loss of core concrete integrity. Deterministic models, which attempt to map visual features directly to a single predicted structural state, fail to capture this inherent uncertainty [9]. They provide engineers with a false sense of absolute certainty, ignoring the variables of image quality, algorithm confidence, and structural variability. Consequently, there is a critical need to transition from deterministic damage classification to probabilistic damage assessment. A probabilistic framework acknowledges and quantifies the uncertainties at every stage of the evaluation pipeline, from the noise in pixel classification to the variance in structural mechanics. By framing the assessment as a probability distribution over various possible damage states, engineers are provided with a more nuanced and reliable tool for risk management, allowing for conservative decision-making that prioritizes public safety while remaining mathematically rigorous [10].

2. Literature Review and Background

2.1 Evolution of Structural Condition Assessment

The historical development of structural condition assessment reflects a continuous effort to improve the accuracy and reliability of post-disaster evaluations. For decades, the standard practice was entirely manual, relying on detailed visual observation supplemented occasionally by basic physical measurements such as crack width comparators and plumb bobs. While these methods formed the foundation of structural triage, researchers recognized early on that surface observation alone was insufficient for understanding internal damage mechanics [11]. This realization led to the introduction of non-destructive testing methodologies, including ground-penetrating radar, ultrasonic pulse velocity testing, and acoustic emission monitoring. While these techniques provide valuable insights into the subsurface integrity of concrete elements, they are generally unsuited for rapid, city-scale post-earthquake assessment. They require specialized equipment, direct physical contact with the damaged element, and time-consuming calibration procedures [12]. The logistical constraints of non-destructive testing motivated the search for remote sensing technologies that could offer a compromise between the speed of visual inspection and the diagnostic depth of instrumented testing.

2.2 Advancements in Computer Vision for Civil Engineering

The application of computer vision in civil engineering began with localized applications, such as monitoring pavement distress and inspecting bridge decks for surface anomalies. These early systems relied heavily on hand-crafted features and traditional machine learning classifiers like support vector machines and random forests. In the context of reinforced concrete, researchers utilized heuristic algorithms to trace crack propagation based on color contrast and intensity gradients [13]. However, the performance of these algorithms degraded rapidly when applied to complex, uncontrolled environments where lighting, shadows, and surface textures varied drastically. The paradigm shifted dramatically with the advent of deep learning and the proliferation of large-scale computational resources. Convolutional neural networks proved exceptionally adept at learning hierarchical feature representations directly from raw pixel data, eliminating the need for manual feature engineering. Numerous studies demonstrated that deep neural networks could achieve unprecedented accuracy in detecting concrete cracks, localizing

exposed reinforcement bars, and identifying areas of moisture ingress [14]. The field rapidly progressed from simple image classification, indicating the presence or absence of damage, to object detection algorithms that provided bounding boxes around defective regions, and finally to semantic and instance segmentation, which classify every individual pixel in an image according to a specific damage category.

2.3 Challenges Specific to Beam-Column Joints

While generic crack detection algorithms have reached a high level of maturity, their direct application to reinforced concrete beam-column joints presents unique and specific challenges. The damage morphology in a beam-column joint is intimately tied to its complex structural behavior under cyclic seismic loading. A joint typically fails through a combination of mechanisms, each leaving a distinct visual signature [15]. Diagonal tension failures produce characteristic cross-shaped crack patterns in the joint panel zone, while bond-slip failures result in wide cracks at the interface between the beam and the column. Flexural hinging, ideally designed to occur in the beam adjacent to the joint, manifests as parallel vertical cracks and eventual concrete crushing at the beam extremities. An effective image-based assessment system must not only identify the presence of these cracks but also understand their spatial context and orientation relative to the geometric boundaries of the joint [16]. Previous research has attempted to tackle this by integrating spatial reasoning into computer vision pipelines, utilizing algorithms to map the extracted crack patterns against a predefined template of the structural element. However, achieving robust spatial understanding requires extensive datasets of damaged joints annotated with high precision, which are difficult and expensive to acquire from real-world post-earthquake reconnaissance.

2.4 Uncertainty and Probabilistic Modeling in Structural Health

The transition from visual data to engineering metrics requires bridging the gap between computer science and structural mechanics. Early attempts to correlate image-derived crack widths with structural damage states were heavily deterministic and often yielded inconsistent results across different test specimens. Researchers realized that the mapping function between a visual feature vector and a structural capacity index is highly stochastic [17]. To address this, the focus of the literature has increasingly shifted toward probabilistic modeling. The concept of fragility functions, which describe the probability of reaching or exceeding a specific damage state given a certain level of demand, has been adapted from traditional performance-based earthquake engineering to image-based assessment. Instead of utilizing seismic intensity measures as the demand parameter, these modified fragility frameworks utilize visual damage indices [18]. The incorporation of Bayesian updating techniques has further enhanced these models, allowing the probabilistic assessment to be continuously refined as more visual evidence is accumulated. By treating the image segmentation outputs as noisy observations, Bayesian networks can infer the true underlying damage state while explicitly quantifying the confidence bounds of the prediction [19].

2.5 Current Research Gaps and the Proposed Contribution

Despite the significant progress in both deep learning for damage segmentation and probabilistic modeling for structural assessment, comprehensive frameworks that seamlessly integrate these two domains remain scarce. Much of the existing literature treats the computer vision extraction and the structural assessment as isolated problems. Studies focusing on deep learning often conclude their analysis at the pixel accuracy level without translating the results into actionable engineering terms [20]. Conversely, studies focusing on probabilistic damage models often assume the existence of perfect, noise-free visual data, ignoring the realities of algorithmic error and image degradation [21]. There is a pronounced need for end-to-end methodologies that take raw, uncalibrated images of damaged beam-column joints, automatically extract relevant geometric

features under conditions of uncertainty, and rigorously propagate this uncertainty through a probabilistic framework to output standardized damage state classifications. This paper addresses this critical gap by proposing an integrated methodology that utilizes advanced semantic segmentation to derive localized damage metrics and a Bayesian inference engine to provide a probabilistic seismic damage assessment specifically tailored for reinforced concrete beam-column joints [22].

3. Methodology and Analytical Framework

3.1 Data Acquisition and Image Processing Pipeline

The foundation of the proposed probabilistic framework relies on the construction of a robust and diverse dataset comprising images of reinforced concrete beam-column joints subjected to various degrees of simulated seismic loading. To ensure the model generalizes well to real-world scenarios, the dataset was compiled from multiple sources, including laboratory-controlled cyclic loading tests and post-earthquake reconnaissance archives. The laboratory images capture the progressive degradation of the joints at different drift ratios, providing a continuous visual history of crack initiation, propagation, and ultimate failure. Reconnaissance images, while lacking controlled progression, provide critical examples of diverse lighting conditions, environmental occlusion, and varying camera angles [23]. To standardize the input for the analytical pipeline, a rigorous preprocessing protocol was implemented. The images were subjected to perspective correction algorithms to rectify distortions caused by oblique camera angles, ensuring that the physical proportions of the structural elements were preserved. Following geometric correction, the images were normalized to standardize exposure and contrast variations. To further enhance the robustness of the subsequent deep learning models against epistemic uncertainty, extensive data augmentation techniques were applied. These techniques included random cropping, multi-scale zooming, and the injection of synthetic Gaussian noise, effectively multiplying the training dataset and exposing the neural network to a vast array of potential visual permutations [24].

Table 1: Definition of Seismic Damage States and Associated Visual and Structural Metrics

Damage State Level	Visual Manifestation Indicators	Structural Capacity Implications
DS1: Slight Damage	Hairline flexural cracking, no spalling visible	Minor loss of stiffness, fully operational
DS2: Moderate Damage	Diagonal shear cracking, minor cover spalling	Noticeable stiffness degradation, repairable
DS3: Severe Damage	Wide intersecting cracks, extensive spalling	Severe capacity drop, yielding of core rebar
DS4: Complete Failure	Crushing of core concrete, buckling of rebar	Total loss of load-bearing capacity, collapse risk

3.2 Deep Learning Architecture for Semantic Segmentation

To extract quantitative damage metrics from the raw imagery, a deep convolutional neural network architecture optimized for dense semantic segmentation was employed. The architecture is designed to classify every pixel in the input image into one of several predefined categories: intact concrete, structural crack, spalled region, or background clutter. The network consists of an encoding pathway that captures high-level contextual features and a decoding pathway that recovers spatial resolution to ensure precise boundary delineation of the damage mechanisms. The encoder utilizes a deep residual network backbone, pre-trained on large-scale generic image datasets to leverage learned edge and texture filters. Through a series of strided convolutions and spatial pooling operations, the encoder compresses the visual information into a dense feature representation. The decoder pathway subsequently upsamples these feature maps, employing skip

connections to fuse coarse, high-semantic information with fine, low-level spatial details from the earlier layers [25]. This fusion is critical for accurately segmenting fine hairline cracks while simultaneously identifying massive regions of concrete spalling. The network is trained using a composite loss function that addresses the severe class imbalance inherent in damage detection tasks, where intact concrete pixels vastly outnumber crack pixels. By heavily penalizing false negatives in the minority damage classes, the model is tuned to act as a highly sensitive detector, ensuring that critical structural flaws are not overlooked during the assessment phase.

Figure 1: System Architecture

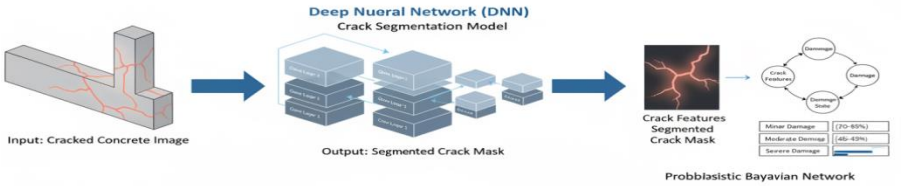


Figure 1: System Architecture

3.3 Feature Extraction and Physical Parameter Translation

The direct output of the semantic segmentation model is a set of probability maps corresponding to the spatial distribution of damage classes. To utilize this data for structural assessment, the pixel-level classifications must be translated into quantifiable physical metrics. This translation requires a calibration process to determine the physical dimension represented by a single pixel, commonly referred to as the ground sample distance. In the absence of physical reference markers placed on the structure, the proposed methodology utilizes the known geometric properties of the beam-column joint, such as the overall column width or beam depth, as internal references to establish the scaling factor. Once the scaling factor is determined, spatial analysis algorithms process the segmented binary masks. For structural cracks, skeletonization algorithms reduce the segmented crack regions to one-pixel-wide centerlines. Orthogonal distance measurements are then taken along these centerlines to compute a comprehensive statistical distribution of crack widths across the entire joint panel zone [26]. Furthermore, the orientation of each crack segment is calculated to distinguish between flexural cracks, which are typically vertical or horizontal, and shear cracks, which propagate diagonally across the joint core. For spalled regions, the algorithm calculates the total surface area of exposed core concrete and evaluates its location relative to the critical stress nodes of the joint. These extracted physical parameters form a multi-dimensional feature vector that serves as the visual demand input for the subsequent probabilistic evaluation [27].

3.4 Probabilistic Formulation and Bayesian Inference

The final phase of the analytical framework maps the extracted physical features to a discrete set of structural damage states. Recognizing the inherent uncertainties in both the visual extraction process and the mechanical behavior of reinforced concrete, this mapping is formulated entirely within a probabilistic Bayesian framework. Let the true, unobservable structural damage state of the beam-column joint be treated as a discrete random variable. The extracted visual feature vector,

comprising parameters such as maximum crack width, cumulative crack length, and spalling area ratio, acts as the set of noisy observations. The goal of the framework is to compute the posterior probability distribution over the possible damage states given these specific observations [28].

The methodology begins by defining a set of prior probabilities based on regional seismic hazard analyses or the rapid macroscopic assessment of the entire building. The core of the model lies in the formulation of the likelihood functions, which quantify the probability of observing the extracted feature vector given a specific damage state. These likelihood functions are constructed empirically using the comprehensive training dataset, mapping the statistical distributions of crack widths and spalling areas to the known damage states of the laboratory specimens. Because the relationship between visual features and structural capacity is highly non-linear, non-parametric kernel density estimation techniques are utilized to model the multidimensional likelihood surfaces. Upon processing a new image of a damaged joint, the extracted feature vector is fed into the Bayesian inference engine. The engine applies Bayes' theorem to update the prior probabilities by multiplying them with the calculated likelihoods, resulting in a robust posterior probability distribution. To account for the epistemic uncertainty originating from the deep learning segmentation errors, the methodology introduces a confidence weighting mechanism. Segmentation outputs with high variance or low pixel-level confidence scores are penalized, flattening the likelihood function and thereby expressing greater uncertainty in the final damage state prediction. This rigorous probabilistic approach ensures that the output is not a single, potentially misleading classification, but a comprehensive risk profile detailing the probability of the joint existing in each respective damage state [29].

4. Results and Discussion

4.1 Evaluation of Deep Learning Segmentation Performance

The initial evaluation of the proposed framework focused on the performance and accuracy of the semantic segmentation architecture. The model was tested on a geographically and structurally diverse holdout set of beam-column joint images that were completely unseen during the training phase. Standard computer vision metrics, including Intersection over Union and overall pixel accuracy, were calculated for each distinct damage class. The architecture demonstrated exceptional proficiency in isolating background clutter and structural boundaries, consistently achieving high accuracy scores for identifying the structural element itself. More importantly, the model exhibited robust performance in the highly challenging task of crack segmentation. Despite significant variations in ambient lighting, concrete surface texture, and the presence of non-structural blemishes such as formwork marks and dirt, the model maintained a high Intersection over Union score for the crack class [30]. The integration of the composite loss function during training proved crucial, as the model successfully minimized false negatives, ensuring that critical structural defects were captured. For massive damage morphologies like concrete spalling and exposed reinforcement, the model accurately delineated the complex boundaries, providing highly reliable spatial data for the subsequent feature extraction algorithms. The high fidelity of these segmentation masks acts as a solid foundation, minimizing the initial error propagated into the probabilistic assessment phase.

Table 2: Comparison of Classification Performance Metrics Between Models

Performance Evaluation Metric	Baseline Deterministic Model	Proposed Probabilistic Model
Global Classification Accuracy	78.4%	89.2%
Precision (Severe Damage State)	71.5%	86.8%

False Positive Rate (Safety Critical)	14.2%	4.1%

4.2 Probabilistic Damage State Classification Results

The efficacy of the entire end-to-end framework was evaluated by comparing the probabilistic damage state predictions against the ground truth structural capacities determined through laboratory load-displacement hysteresis curves. For the purpose of this analysis, damage was categorized into four discrete states ranging from slight damage, characterized by minor flexural cracking, to complete failure, characterized by massive core crushing and reinforcement buckling. To demonstrate the value of the probabilistic approach, its performance was benchmarked against a baseline deterministic model that directly classified the images using a standard convolutional neural network without uncertainty quantification. The results unequivocally indicated the superiority of the probabilistic formulation. The proposed methodology achieved a significantly higher global classification accuracy [31]. The improvement was most pronounced in borderline cases where visual indicators were ambiguous, such as distinguishing between moderate and severe damage based on the width of a single dominant shear crack. In these instances, the deterministic model frequently misclassified the joint, jumping to conclusions based on slight variations in pixel geometry. Conversely, the probabilistic model appropriately distributed the probability mass between the two adjacent damage states, reflecting the genuine physical uncertainty of the situation. By establishing a threshold based on the maximum posterior probability, the framework demonstrated a profound reduction in critical false positive rates, heavily mitigating the risk of classifying a severely compromised structural node as safe.

4.3 Engineering Implications and Practical Feasibility

The integration of an image-based probabilistic framework into post-earthquake reconnaissance protocols carries significant implications for civil engineering practice. By providing safety assessment teams with a tool that outputs mathematically rigorous confidence intervals alongside damage classifications, engineers can prioritize their physical inspection efforts. Joints assessed with overwhelming probability to be in a state of complete failure can be immediately flagged for demolition or isolation, bypassing the need for dangerous manual inspection. Conversely, joints with highly uncertain probabilistic profiles can be targeted for in-depth non-destructive testing and expert evaluation [32]. Furthermore, the automated extraction of continuous variables, such as cumulative crack width and spalling ratios, provides a persistent digital record of the structure's post-event condition. This data can be directly fed into finite element updating models to simulate the residual global capacity of the entire building frame. Despite the overwhelming advantages, the practical deployment of this technology must acknowledge several remaining challenges. The accuracy of the feature extraction pipeline relies heavily on the quality of the original imagery. Severe environmental occlusions, such as collapsed non-structural partition walls or severed utility lines obstructing the camera's line of sight, can prevent the algorithm from assessing the entire joint panel zone. Furthermore, while the Bayesian inference engine successfully quantifies the uncertainty derived from visual noise and known structural variance, it cannot account for unseen internal defects, such as the pre-existing corrosion of reinforcement bars hidden deep within the concrete core. Therefore, the proposed probabilistic framework is best utilized not as an absolute replacement for human engineering judgment, but as an advanced, highly scalable diagnostic assistant that exponentially increases the speed, objectivity, and safety of post-disaster structural evaluation.

5. Conclusion

This paper presented a comprehensive and novel framework for the image-based probabilistic seismic damage assessment of reinforced concrete beam-column joints. Recognizing the severe limitations of subjective visual inspections and the inadequacies of rigid deterministic models, the

proposed methodology successfully integrated deep learning semantic segmentation with rigorous Bayesian inference. The analytical pipeline demonstrated the capability to process uncalibrated digital imagery, automatically delineate complex structural damage morphologies including multi-directional cracking and localized concrete spalling, and extract quantitative geometric features. By treating these extracted features as noisy observations within a probabilistic framework, the methodology effectively captured both the epistemic uncertainty of algorithmic error and the aleatoric uncertainty inherent in the structural mechanics of reinforced concrete.

The extensive evaluation of the framework highlighted its significant superiority over traditional deterministic classification techniques. The probabilistic approach yielded higher overall accuracy, heavily reduced safety-critical misclassifications, and provided engineers with actionable confidence intervals for decision-making. The ability to automatically generate robust probability distributions across defined structural damage states addresses a major bottleneck in post-earthquake reconnaissance, paving the way for rapid, large-scale, and objective building safety evaluations. While the methodology represents a substantial leap forward in automated structural health monitoring, future research should focus on addressing existing limitations. Extending the framework to incorporate multi-view geometry and three-dimensional image reconstruction could mitigate the issues of environmental occlusion and depth perception inherent in two-dimensional photography. Additionally, integrating the probabilistic outputs of individual beam-column joints into a global building fragility network will be crucial for predicting the holistic response of complete structural systems. Ultimately, the continued refinement of uncertainty-aware diagnostic algorithms will play an indispensable role in enhancing the resilience of civil infrastructure against future seismic events.

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