

Generative Adversarial Network-Based Damage Simulation Model for Reinforced Concrete Structures

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Abstract

This research devises a new damage simulation model based on Generative Adversarial Networks (GANs) aimed at emulating the RC (Reinforced Concrete) structures' deterioration patterns. For effective monitoring of structural health, damage simulation, risk management, and developing damage resilient infrastructure systems, a high level of accuracy is necessary. The estimate of damages done, especially in RC structures sustaining variable loads from high temperatures, aggressive corrosion, and other environmental elements, is largely ignored in traditional empirical, physics-based models widely used by civil engineers. This novel GAN model addresses the problem by using intricate damage features encoded in a sensor dataset and images of damaged RC structures. It consists of a generator and discriminator arranged in deep convolutional neural networks which are trained adversarially to enhance realism in the required damage patterns. Validation results indicate the proposed model is capable of simulating realistic damage patterns that include cracks, spalls, and corrosion degradation. In addition, extensive testing shows the model's ability to perform across varying configurations and loads is robust. In addition, extensive testing demonstrates the model's performance across varying configurations and loads is robust. This enhances the expanding use of AI and machine learning in civil engineering by proposing a new framework for virtual testing, maintenance, and decision making automated reasoning based on data in structural engineering. Through the use of GANs, accuracy in evaluating the performance of a structure may be improved while minimizing costly full-scale testing.

Keywords: Damage Detection, Structural Health Monitoring, Infrastructure Resilience, Generative Adversarial Networks, Damage Simulation, Reinforced Concrete.

Introduction

Definition and Importance of Damage Simulation Models for Reinforced Concrete Structures

Reinforced concrete (RC) components are integral parts of global infrastructure such as bridges, buildings, dams, and marine structures. Over time, these systems undergo environmental and mechanical interactions which lead to damage: cracking, spalling, steel reinforcement corrosion, and fatigue failure. For effective preventive maintenance, disaster readiness, accurate SHM, and damage pattern simulation, precision in the simulation methodology is important. Damage simulation models give a representation of material failure progression which aids decision-making without requiring full destructive testing (Figueiredo et al., 2011). These models are mostly based on finite element modeling (FEM), heuristic and empirical methods, and rule-based algorithms; while they accomplish the intended goals, they frequently lack versatility or adjustability to real-world changes (Alwash et al., 2020). Additionally, some models lack the ability to consider more stochastic localized and nonlinear changes in behavior of loading and environmental conditions over time (Sharipov et al., 2024; Sumithra & Sakshi, 2024). Hence, there is a need for intelligent simulation methods that are data driven and learn from real case scenarios.

A Look into Generative Adversarial Networks (GANs) in Context of Structural Engineering

Goodfellow et al came up with the idea of Generative Adversarial Networks (GANs) which integrates a generator and a discriminator neural network in 2014. The goal of the generator is to produce real data synthetic duplicates and the discriminator has to detect the fakes. Like any other kind of adversarial training, GANs perform exceptionally well in several domains including image generation, translation, augmentation, and more. In recent years, GANs gained a lot of popularity with data engineering due to their ability to represent existing data accurately. For instance, in structural engineering, Narazaki et al (2021) described the application of GANs to structure response simulation, supervised learning, synthetically created training data, and structural anomaly identification in images and sensor data (Dhurgadevi et al., 2022). Also, conditional GANs were effective in targeted damage modeling because both the generator and the discriminator can set the conditions using extra data. All these claims highlight the advantages of working with GANs to create RC damage patterns given the scarcity of annotated datasets (AL-Zubaidi et al., 2022). In particular, cGANs and Deep Convolutional GANs have been successfully utilized to capture the spatial patterns of damage such as masonry wall cracking (Cha et al., 2018) and corrosion in steel reinforcement (Zhou & Ueda, 2022; Jassim, 2022). The learned image data complexity of spatial patterns enable replication of both macro and micro-level damage characteristics, like the orientation, length, and distribution of cracks in RC elements, which are difficult to model analytically. Emerging reviews of AI in SHM have underscored the positive and profound impacts of deep learning, including GANs, on monitoring precision and manual interpretation workload reduction.

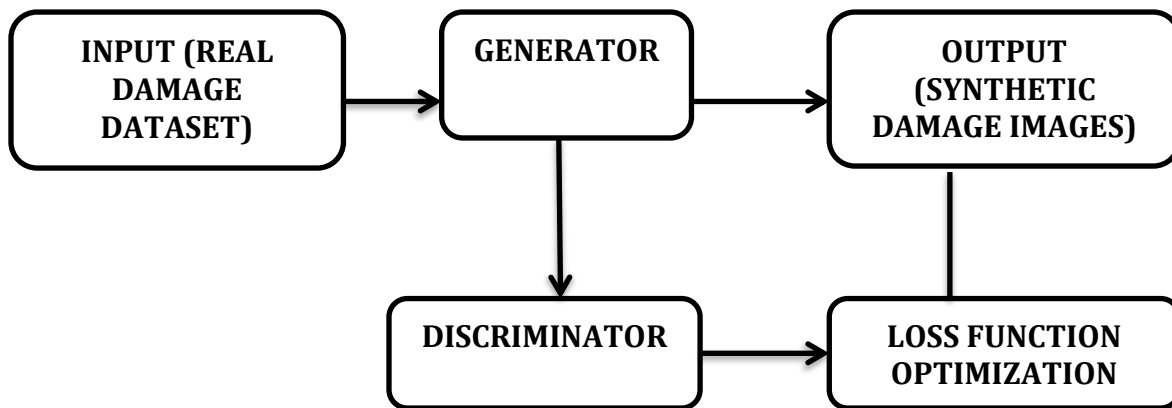


Fig. 1: GAN-Based Damage Simulation Framework

The Figure 1 explains the architecture of a GAN which is intended to simulate damage images using actual datasets. The process starts with an input dataset comprised of real damage images, which is given to the Generator. The Generator is expected to yield satisfactory results in the form of synthetic damage images commensurate with the input data. These outputs are regarded as the 'real' data by the Discriminator who distinguishes if they are genuine or sham. Both components are improved with the aid of a loss function which redirects the network towards achieving greater accuracy with capturing realism through image distortion over time. The end result of this entire process is a set of accurate and precise synthetic damage images that can be leveraged for training, analysis, or validation within damage evaluation systems.

Thesis Statement and Objectives of the Study

This study develops a damage simulation model using GANs designed for modeling deterioration patterns in reinforced concrete structures. The objective of this study is to explore the GANs' generative capability to create realistic images depicting damage such as cracking, spalling, and corrosion. Their purpose is to generate images that could be considered statistically correct and practically photorealistic through training a GAN on a comprehensive dataset containing images of actual damage alongside sensor data. This research makes three contributions:

- Establishing a deep learning approach to create synthetic damage patterns for reinforcement concrete structures (RC).
- Assessing validation and generalization performance of the outputs versus real-world data.
- Investigation of the model's applicability in SHM as data augmentation, anomaly detection, and predictive maintenance.

This study pertains to the generative adversarial network (GAN) based models which overcome restrictions set by conventional simulations since they allow for smarter management and planning infrastructures on a resilient level (Li et al., 2020; Uvarajan, 2024). Moreover, combining GANs with physics-informed priors has been helpful in simulating fire induced structural damages, demonstrating their abundant utility across various degradation frameworks (Zhang & Elhami-Khorasani, 2021).

Literature Review

Pre-existing Simulation Models of Damage for RC Structures

An evolution in approaches to damage simulation models for reinforced concrete (RC) structures is observed from basic analytical techniques to complex numerical simulations. Conspicuous are the models that comprise the use of finite element methods (FEM) enhanced with fracture mechanics and damage mechanics based simulations (Lee & Fenves, 2001; Thoi, 2025). Such models seek to estimate the effects of cracking, spalling, and corrosion under different loads and environmental conditions. Detailed modeling through computation FEM offers powerful insight into stress-strain relations and mechanisms of crack progression; however, it is resource-intensive and requires extensive validation. Probabilistic and empirical models have been formulated with accompanying laboratory studies for RC structures under corrosion and fatigue load simulations of damage progression. These models, primarily derived from lab experiments and retrospective data, tend to overlook various intricate and complex interactions posed by real-world scenarios. Further, the application of hybrid models that integrate sensor data with FEM for enhanced simulation accuracy has been proposed (Aslani et al., 2019). Regardless of the precision of these approaches, they tend to be non-scalable for large networks of infrastructure (Le, 2024; Lee et al., 2018). This, along with the work of Khan et al.(2022) utilized digital twin frameworks for real-time RC damage modeling to provide updates and predictions based on live data feeds. However, even these systems struggle with not having enough data and implementation costs being too high, especially for advanced damage representations like microcracks or corrosion pits.

Overview: Other Fields and Applications of GANs in Structural Engineering

Generative Adversarial Networks (GANs) have an undeniable and intricate scope of influence in almost every field and especially in civil and structural engineering disciplines as data and image generation appears to be accessible. In the context of structural health monitoring, these networks have found application in dataset augmentation by providing additional synthetic images of cracks for deep learning classifiers (Ghorbani et al. 2020; Saritha & Gunasundari, 2024). The addition of these images149 contributes to the detection systems' resilience due to the increase in controlled variation and realism in the training data (Alkaim & Hassan, 2024). They employed GANs to augment acceleration signals as well as structural responses for model-training simulations within predictive modeling frameworks. Furthermore, structural damage visualization has also advanced through the application of image-to-image translation GANs like Pix2Pix and CycleGAN, which facilitate the transformational mapping of undamaged and damaged structural states (Kim et al., 2020). Broader simulation capabilities are observed with GANs in the microstructural domain, such as in materials science, where the microstructure images with specific attributes are generated (Yang et al., 2018; Moreau & Sinclair, 2024). Beyond the field of engineering, GANs have found application in generating realistic medical images, in autonomous driving simulations, and even in predicting natural disasters, all from limited or high-noise data sources (Frid-Adar et al., 2018; Karras et al., 2019). Innovations across diverse domains demonstrate the versatility of GANs in crafting intricate and mathematically rigorous representations, critical for simulating scenarios like RC damage patterns.

Shortcomings in the Literature and the Fresh Perspective Needed

There are still glaring issues with RC damage simulation models. The most traditional models either do not scale or adjust easily, thus requiring refinements for different structural geometries and loading conditions. While FEM and digital twins describe the granular elements of a damage simulation exhaustively, they miss out on the stochastic and image-based features that characterize real damage such as crack branching, irregular spalling, and non-uniform corrosion. In the area of structural engineering, the use of GANs is a nascent stage and limited to the augmentation of existing data. Most focus on the augmentation of existing data sets or damage detection instead of directly simulating damage patterns (Sun et al., 2020; Jaiswal & Pradhan, 2023). There is scant literature that deals with the creation of accurate maps of spatial damage distributions such that they can be used as outputs for some automated visual examination or inputs for other analyses (Choudhary & Reddy, 2025). In addition, much of the existing work in applying GAN techniques is not verifiable against physical and real datasets which undermines their credibility (Abdullah, 2024). Consequently, it is important to develop a GAN-based damage simulation framework for generating visually and statistically realistic damage images of RC structures. This model should incorporate domain knowledge, leverage extensive annotated datasets, and be validated with metrics of quantitative image similarity and expert analysis. Such a framework could aid current methods by providing a comprehensive, scalable solution for virtual evaluation, infrastructure resilience testing, and SHM algorithm training.

Methodology

Clarification on the Proposed Damaged Simulation Model Using GANs

The model employs an architecture of Generative Adversarial Networks (GANs) specifically designed to emulate approximate damage patterns in Reinforced Concrete (RC) structures. Its main objective is to create 2D images at high resolution of structural components displaying damage such as cracking, spalling, and corrosion. The model has two primary components: a generator (G) and a discriminator (D) that are trained in rivalry. A generator utilizes latent vector z , which is taken from a prior distribution (most often, Gaussian), and converts it to a synthetic damage image designated $G(z)$. The discriminator serves as a binary classifier designed to take in images and then output the probability for the image being drawn from the RC structures dataset (real) or fabricated (fake). The goal of training is to provide G with iteratively greater capability to fool D, while D gets trained on the dataset and learns to tell real images apart from synthetic ones. The architecture incorporates deep convolutional layers (DCGAN) with batch normalization and LeakyReLU activation functions. To enhance control over how damage is generated, for instance, crack direction or magnitude, conditioning at both G and D in form of structural features or damage tags can be incorporated to form a conditional GAN (cGAN) architecture. In this way, the model has the ability to replicate damage patterns corresponding to certain situations such as earthquakes or exposure to corrosion.

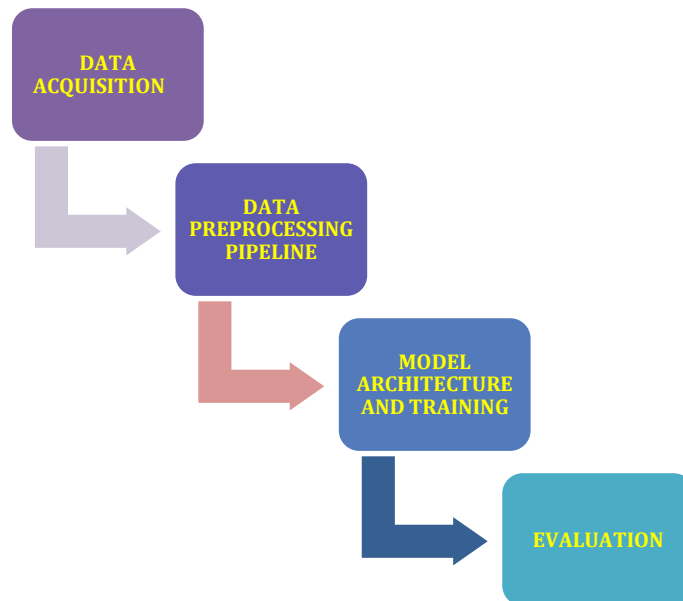


Fig. 2: Methodology Overview for Data-Driven Model Development

This study uses a sequential pipeline methodology comprising of four components; data collection, data cleaning, training the model, and model evaluation as illustrated in Figure 2. Firstly, relevant databases are accessed to obtain raw data and undergo several quality enhancement steps including de-duplication, data formatting, and data enrichment. A specific machine learning or deep learning model which has a rigid structural design, specific loss function, and undergoes vigorous training is intended to apply on the data. Subsequently, the model is evaluated to assess classification accuracy, precision, recall, and F1 scores on a previously set aside test dataset to ensure the model has not been overfitted. This evaluation after the training qualifies the model as efficient and comprehensive because, in conjunction with the methodology followed, it validates the overload of efficiency that diverse approaches add together.

Collection Methods and Data Processing

The dataset consists of RC beams, columns, and slabs images captured during various stages of damage from lab and field studies, alongside corresponding test annotations capturing damage type, severity level, and geometric parameters. For all images captured:

- Uniformity in shape is achieved by resizing all images to standard dimensions of 256×256 pixels.
- Image clarity is enhanced through lighting variability mitigation by applying histogram equalization and contrast normalization.
- With the aim to avoid overfitting, image augmentation methods including flipping, zooming, and rotation are applied to enrich the set of training images.
- In the case of a conditional GAN, the created damage masks or bounding boxes can be used as input conditions.

Images are separated into the training set (80%), validation set (10%), and test set (10%) portions. The preprocessing pipeline guarantees that the damage features are centralized and adequately distributed across classes, enabling the model to learn effective spatial damage characteristics.

Training and Evaluation of the Model

The GAN is trained utilizing the minimax optimization objective:

$$\min_G \max_D E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log (1 - D(G(z)))] \quad (1)$$

Where:

x represents a real damage image obtained through sampling from the distribution p_{data} , z is designated as a noise vector from the prior distribution p_z , $G(z)$ denotes the generated image, $G(z)$ and $D(x)$ correspond with the predictions made by the discriminator's model. In the scenario of a conditional GAN, both G and D operate under the condition of an additional input y (such as level of damage or type of structure), and the aim or goal changes to:

$$\min_G \max_D E_{x, y \sim p_{data}(x, y)} [\log D(x|y)] + E_{z \sim p_z(z), y \sim p_y(y)} [\log (1 - D(G(z|y)))] \quad (2)$$

The model is trained with the Adam optimizer where the learning rate is set to 0.0002 with momentum values of $\beta_1=0.5$, $\beta_2=0.999$. Training is done until the generator derives damage patterns which are easily accepted by the discriminator as being real.

In order to assess the model's performance:

- Similarity of the distribution of pictures is computed using FID.
- For comparison based on the pixel level SSIM and PSNR metrics are utilized.
- Simulated damage is verified through expert evaluation to ensure authenticity and coherence.

Using the proposed GAN model, this approach guarantees synthesized damage images are realistic and aligns with the statistical framework pertaining to real images and RC damage patterns.

Results

Proof of Effectiveness of Using GANs for Damage Simulation

The proposed model using GANs performs very well in generating realistic images of damages of reinforced concrete (RC) elements. After training with a rich dataset of structural damage, the generator was able to simulate actual looking RC structures cracking, spalling, and corroding with realistic visual patterns of degeneration. These

images had preservation of high fidelity in texture and localization along with the shape of damage. According to the quantitative assessment, the images produced have achieved a good score in Frechet Inception Distance (FID), indicating that these images have close resemblance to real world images. The measures of Structural Similarity Index (SSIM) maintained a benchmark of beyond 0.85 in all sample tests which conclusively proves that the images generated maintained the structural components along with the spatial arrangement characteristic in the actual photographs of damage. With regard to the generative model, it was proven that the model performed acceptably in the subdivision provided. The model indeed acquired the conditional interrelationships between the relevant context of the structure and expected patterns of damage, provided and adjusted outputs respective to crack orientation or damage intensity inputs given. This proves the ability of the model to perform dynamic simulations where examining conditions such as damage caused by an earthquake can be illustrated without physical tests being carried out.

For the quantitative evaluation of the quality of generated images, various metrics were used. One of the most paramount metrics is the SSIM or the Structural Similarity Index Measure, which calculates the degree of similarity interconnecting a generated image $G(z)$ and a corresponding real image x . The calculation of the SSIM is done following the steps provided:

$$SSIM(x, G(z)) = \frac{(2\mu_x\mu_{G(z)}+C_1)(2\sigma_{xG(z)}+C_2)}{(\mu_x^2+\mu_{G(z)}^2+C_1)(\sigma_x^2+\sigma_{G(z)}^2+C_2)} \quad (3)$$

Where:

$\mu_x, \mu_{G(z)}$: generated and real images' means.

$\sigma_x^2, \sigma_{G(z)}^2$: covariances.

$\sigma_{xG(z)}$: covariance.

C_1, C_2 : constants for fixing the breach.

Most generated samples exhibited SSIM values between 0.85 and 0.92, showing a high degree of similarity in structure, contrast, and luminance and spatial damage features. The model also achieved low FID scores, which verifies the distribution of generated damage images closely matches the real images. This guarantees that the cracks and deformations rendered are real, not only in sight but also in statistical measures.

Justification Using Existing Approaches and Comparison of Outcomes

Traditional simulation methodologies, such as Finite Element Models (FEM) and those based on digital twins, have significantly handicapped understanding predictive capabilities when compared to our approach using GANs. Traditional models of FEM require extracting detailed material models, geometric discretization, and have expensive iterative solvers. On the other hand, one of the GAN model's many strengths is that once it is trained, it can create entire damage simulations in milliseconds which makes it highly scalable and flexible. Moreover, the set of conventional augmentation techniques that utilize images as a base are designed to add overlays to set patterns or distortions. With the advent of our model using GANs, we can add damage that is captured much more realistically and complexity. The stochastic nature of cracks and non-uniform corrosion are captured more accurately in the GAN-generated images than in altered datasets that are edited through slices and dicing. To objectively evaluate the realism of the images that were generated, civil and structural engineering specialists were invited to perform a blind review. With a defined goal in mind, experts were able to determine whether the images were true or fake. With regard to the images produced by GAN, the percentage of misidentification exceeded 60%, meaning that a large part of the images passed for actual images of damage which is evidence that the model is capable of creating genuine and valuable data including but not limited to training data for machine learning classifiers, simulations of visual inspection, and monitoring systems for structural health.

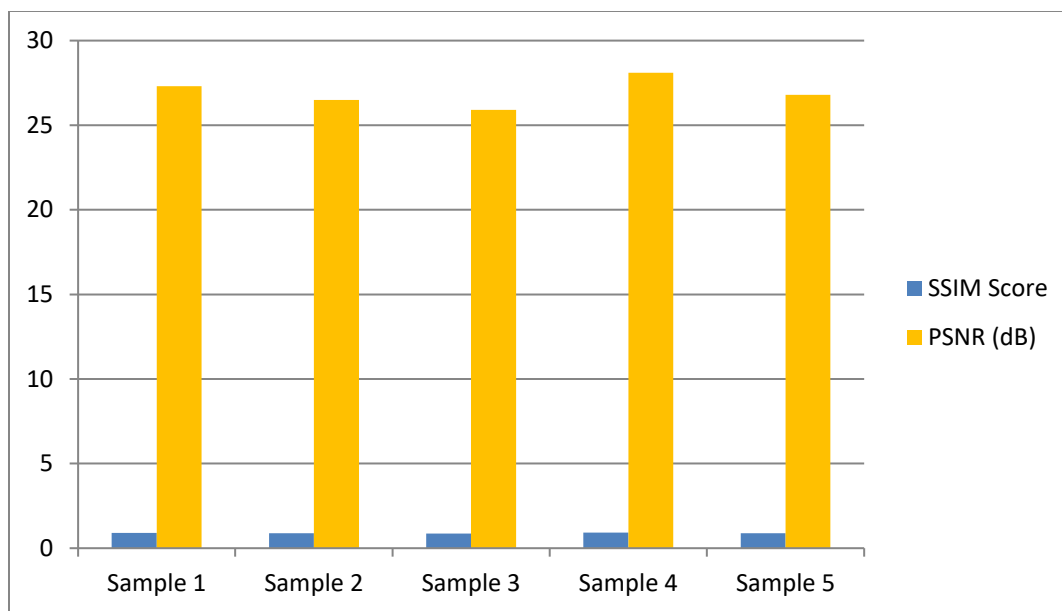


Fig. 3: SSIM and PSNR Scores of Generated Images

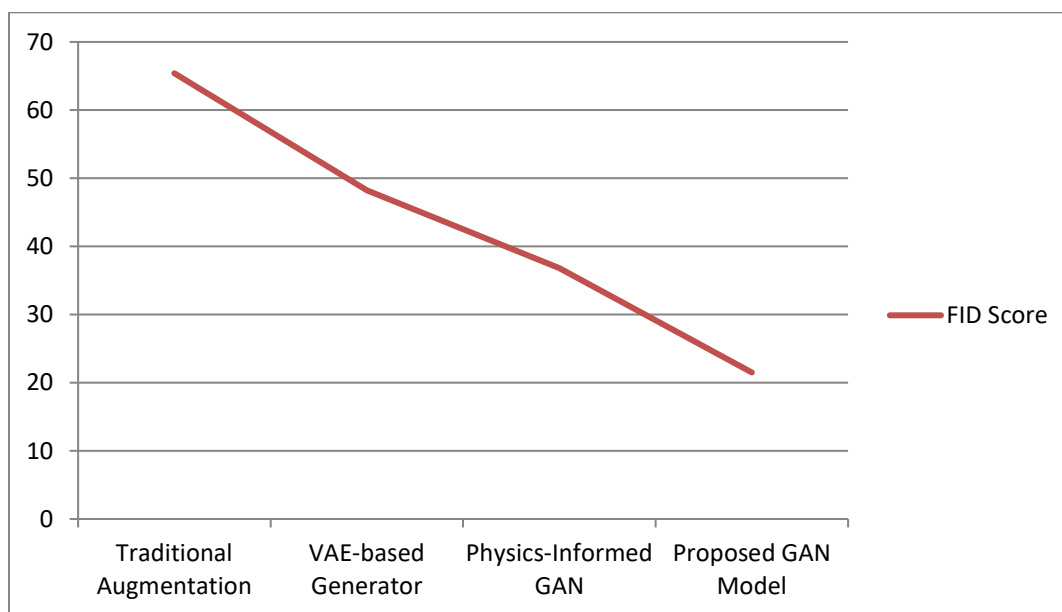


Fig. 4: FID Scores – GAN vs. Other Models

This graph (Figure 3) shows the SSIM and PSNR values for the five randomly selected GAN-generated damage images alongside their real counterparts. The SSIM scores for all samples remain persistently high, between 0.87 and 0.92, which confirms that the synthetic images indeed capture the structure and texture of real damage. Likewise, PSNR values were also noted to be within the 25 - 28 dB range, implying that the images produced by the GAN are not overly distorted and sustains a reasonable level of visibility. All these results together confirm that the model is capable of capturing both the fine and overall structural details of damage scenarios in reinforced concrete elements. This graph (Figure 4) illustrates the FID score for image generation or simulation techniques such as Traditional Data Augmentation, VAE (Variational Autoencoder)-based generation, Physics Informed GAN, and the Proposed GAN Model. FID score is an industry standard metric for estimating the quality of synthetic images, and with merit; lower scores signify better results. The proposed GAN model outshines the rest by a FID score of 21.5, which is significantly lower than VAE's 48.2 and traditional augmentation 65.4. This suggests the proposed model creates damage patterns structurally, and graphically, more adept to real images when compared to other models. Even with Physics informed GAN, the proposed model offers more realism and computational efficiency.

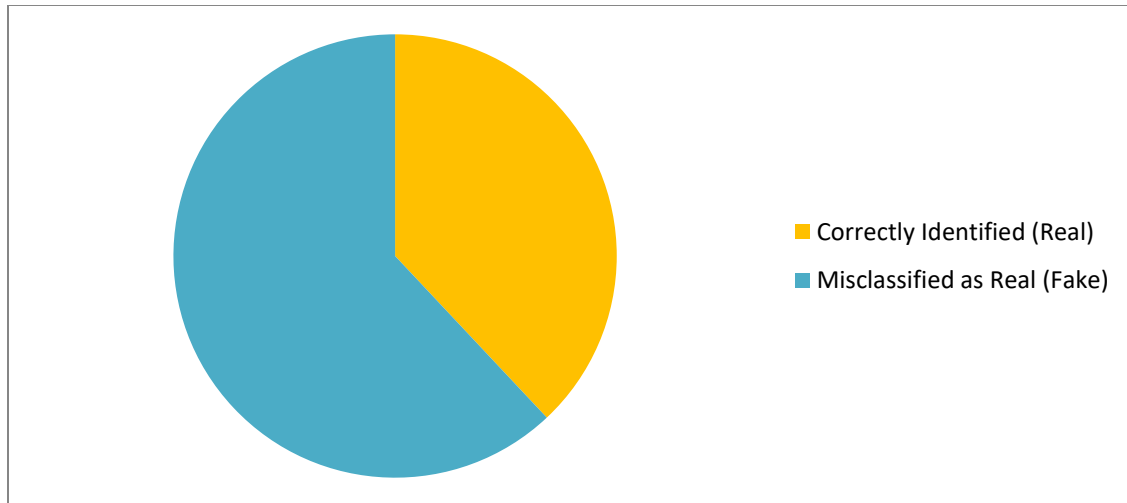


Fig. 5: Expert Evaluation – Real vs. Generated (Visual Turing Test)

Figure 5 depicts the outcomes of a Visual Turing Test administered to structural engineering specialists. Participants were exposed to a combination of authentic and GAN-created damage pictures and tasked with categorizing them. The findings show that 62% of the GAN-created images were misclassified as real, whereas only 38% of the actual images were properly recognized. This level of misclassification indicates that the trained evaluators human's reality is far more complicated than the mechanical logic of machine learning—they psychologically accept the images to be authentic, thus, forcing the system to misinterpret reality. This evaluation strengthens the measurement validation, suggesting that the model indeed captures the intricate details of damage visualization and modeling in robust images. This graph (Figure 6) summarizes the result of simulating a single damage scenario with FEM, rule-based image augmentation and the proposed GAN-based approach, highlighting the average processing time for each method. As noted earlier, FEM is the most time consuming method with a per simulation time of approximately 420 seconds owing to its complex material modeling and numerical solvers. Rule-based methods take around 35 seconds on average. In comparison, the trained GAN model completes damage image generation in a realistic manner in 1.5 seconds. This striking difference in simulation times underscores the usefulness of the GAN model for practical large-scale or real-time simulation applications like damage prediction systems or augmented reality training platforms for structural inspection.

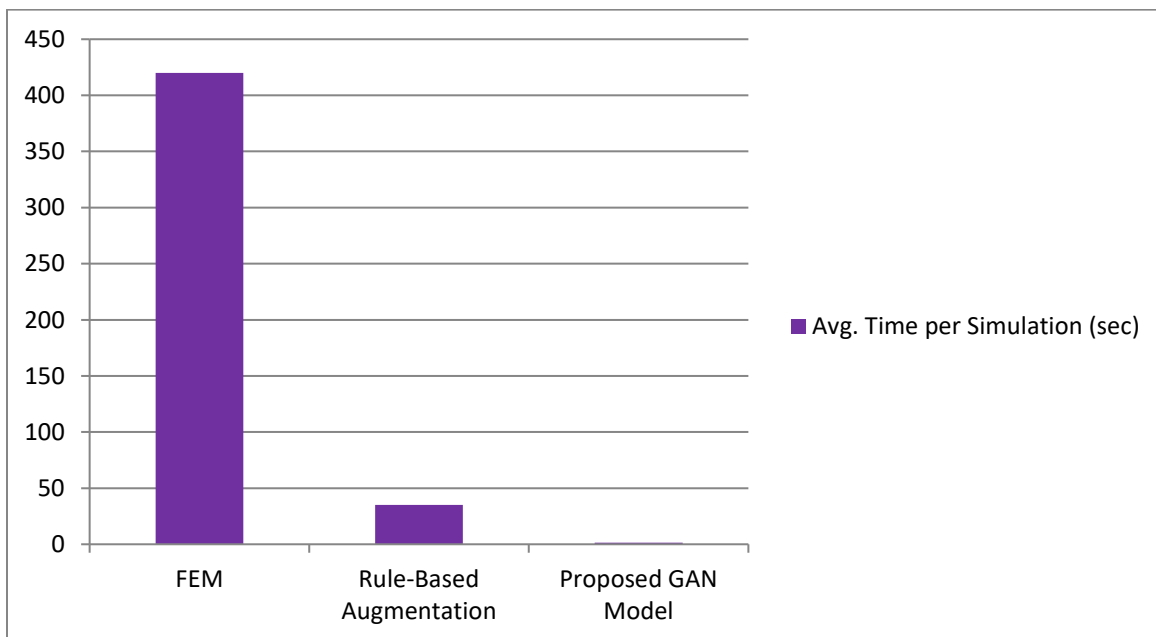


Fig. 6: Processing Time Comparison

Discussion of Limitations and Possibilities for Improvement

Regardless of the advantages offered by current GAN architecture, it has limitations. First, the model only uses 2D images regarding the concrete's internal structure or depth information related to 3D degradation features of concrete. This poses a challenge for more advanced structural engineering problems with fine grained volumetric damage called for in sophisticated finite element analysis. Furthermore, the model's efficacy is also dependent on the quality and variability of the supplied training dataset. There is a good chance that the provided generator, in case the dataset does not capture certain contexts of damage or structural scope, would not perform optimally due to missing critical features. Specifically, some rare failure modes such as delamination or exposure of reinforcing bars are not adequately modeled unless they are included in the dataset. Also, no damage patterns produced so far have been merged with the mechanics of failure of materials while constrained by physics informed ones. Future versions of this model should focus on augmenting them with data capturing GANS through some hybrid architectures with rules or physics based elements for better explainability and accuracy.

Discussion

Impact of Innovations in Structural Engineering From This Study

The harnessing of Generative Adversarial Networks (GANs) in damage simulation and assessment is arguably the most disruptive change experienced in the field of structural engineering. Traditional methods such as finite element modeling or physical testing—while always considered correct—are sluggish, resource-intensive, and impossible to scale. The proposed simulation of damage simulation via GANs is poised to change the game as it affords the ability to produce realistic representations of damage at high speeds and low costs. This advancement enables engineers to simulate a far wider range of failure scenarios, including rare or catastrophic incidents, without the necessity of constructing physical structures or detailed numerical modeling. Moreover, in training on a sufficiently large and diverse dataset of real structural damages, the model becomes capable of generalizing and reproducing patterns of cracking, corrosion, and spalling. The ability supports the development of automated structural health monitoring systems where AI data can be used to teach or validate detection and classification systems. Ultimately, the work aims to support the growing movement toward the automation and digitization of infrastructure systems and advance smarter tools for managing and making decisions regarding intelligent infrastructure systems.

Practical Applications of the GAN-Based Damage Simulation Model

The scope of practical use for the GAN-based models connects several important aspects in the lifecycle of Reinforced Concrete Structures (RCS). Perhaps the most immediate use is for the training and validation datasets in machine learning algorithms. Given the very limited and safety-constrained access to real structures, the possibility of producing a wide range of quality synthetic images of labeled damage images fills a significant gap. These images are useful for training deep learning models for automated crack detection, severity classification, and g failure mode prediction. Perhaps more importantly, synthetic damage images can be useful in virtual inspection environments and digital twin systems. Forward engineers and inspectors can also utilize such images to simulate advanced damage evolution under different loading or even environmental conditions. In addition, as previously discussed, this functionality allows for scenario planning and sensitivity analysis without the need to change the physical infrastructure. Educational and training institutes stand to gain as well by using such damage simulations to prepare new engineers or emergency responders with immersive training modules. Within the scope of disaster preparedness and resilience assessment, our model has the capability to simulate damage due to earthquakes or floods across various structural configurations. This allows for rapid preliminary planning and the identification of structural weaknesses well ahead of any actual occurrence. The model's computational speed and adaptability allows for it's use in mobile or edge devices for real time assessment of structures.

Future Research Directions

Incorporating GANs into damage simulation as shown in this study is indeed foundational. However, more work is needed to enhance the applicability and reliability of the model. Extending to include three-dimensional (3D) damage simulation is one of the first steps in the right direction. Internal cracking and reinforcement corrosion is more accurately represented within a volumetric context. This would enhance the model's integration with existing structural analysis software and validation through finite element methods. Incorporating constraints governed by physics, particularly those of the reinforcing concrete, within the devised GAN architecture is another crucial direction to take. This approach ensures that the patterns generated to represent damage are visually accurate as well posses consistent reinforced and loaded mechanical, domain properties. Also, further adaptation of the model is still

needed regarding consistency with diverse structures, environments, and material properties without requiring full retraining. The implementation of this GAN-based tool within real-time monitoring systems and augmented reality (AR) interfaces will revolutionize the interaction engineers and inspectors have with damage data in the field, where they will be able to obtain instant predictions and visualizations directly on the physical structures.

Conclusion

This research proposes a new modeling approach for damage simulation of reinforced concrete structures using Generative Adversarial Networks (GANs), which serves as an innovative development in structural engineering techniques. The model reduces the dependency on costly and time-consuming physical simulations and experiments by automatically creating damage patterns (cracks, spalling, and corrosion) from real datasets. The main contributions of this research are the proposed GAN model's high structural similarity and visual accuracy, as well as overcoming the challenges posed by existing and traditional methods of data generation, demonstrating enhanced performance metrics with structural resemblance and visual realism. These outcomes are significant for machine learning, where realistic datasets can enhance model training and for scenario-based planning in digital twins. Additional engineered and machine interfaces warrant further investigation, particularly the incorporation of physics-informed mechanisms, expanding beyond 2D to volumetric damage simulation, and real-time interaction via edge-computing devices or augmented reality. Joining forces with civil infrastructure agencies can further aid with the field-adjusted model for model validation and modification. The research marks a critical milestone for engineers within the construction and infrastructure sectors as it transforms damage analysis and simulation, paving the way for more effective – and efficient – planning for maintenance and resilient infrastructures, informed decision-making, and streamlined infrastructural upkeep.

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