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ABSTRACT

Building façade inspections are of paramount importance for public safety, as defect-related falls have led to severe accidents over the years. Traditional, expertise-reliant manual methods are laborious, time-consuming, and unsafe due to height-related risks. Consequently, there has been a growing interest in employing computer vision, especially deep learning (DL), techniques for automated defect detection. However, the effectiveness of DL models is significantly hampered by a shortage of extensive, annotated defect datasets. While collecting and annotating façade defect images contributes to data scarcity and varying frequency of occurrence of defects creates an imbalance in datasets. This is concerning because such infrequent defects still pose significant safety risks. This study tackles these data imbalance and scarcity issues by deploying Generative Adversarial Network (GAN) algorithms to create synthetic images of façades with defects. Multiple GAN algorithms have been evaluated using Fréchet Inception Distance -FID and visual evaluations. Outperforming GAN algorithm is suggested to furnish a balanced training dataset for façade defect identification models.

INTRODUCTION

The necessity of the Façade Inspection and Safety Program (FISP) in New York City is clear, as it mandates regular and thorough inspections of New York City buildings over six stories to prevent potential safety hazards. Despite stringent FISP protocols, which include detailed scrutiny by licensed professionals and the comparison of façade conditions across inspection cycles, the city continues to witness alarming accidents (Bookman, 2015; Otterman and Haag, 2019). These accidents, coupled with statistics on complaints about façade falls, indicate that defects are overlooked, and the current practice requires methods for comprehensive inspections. The prevalent methods of façade inspection, which rely heavily on manual and visual inspections and the use of scaffoldings or dropdowns, have been shown to carry inherent risks while attempting to prevent them. Such methods sometimes lead to catastrophic events such as the scaffold collapse in Manhattan in July 2020, which resulted in one fatality and three injuries (Villeda, 2020). Furthermore, the task of comparing façade conditions between the current and previous inspection cycles is ineffective and not thorough (Shi and Ergan, 2020). These methods, with their susceptibility to human error and the physical dangers they pose, underscore the urgent need for automated inspection techniques. Transitioning to such systems offers enhancements in reliability and safety of façade inspections for the densely populated urban environments.

In the context of façade safety, the emergence of computer vision and deep learning (DL) represents a significant advancement, offering accuracy that sharply contrasts with the hazards inherent in traditional inspections. This innovation could revolutionize the process of façade inspection, contingent upon the availability of comprehensive and balanced datasets to power these algorithms. The crux of the challenge lies in the data scarcity and lack of balanced datasets – a consequence of the unpredictable and irregular occurrence of façade defects. Rare samples (e.g., efflorescence, rolling blocks) on varied materials (e.g., brick, concrete) do not regularly present themselves for analysis, leading to a scarcity of examples and an imbalance in the data necessary to effectively train deep learning models. The rarity of these occurrences can render their collection impractical or even unfeasible, and accumulating a sufficient volume of data can be exceedingly time intensive. Hence, we should look beyond traditional data collection methods and adopt innovative approaches that ensure diverse and high-quality data.

Utilizing data augmentation strategies emerges as a viable approach. Generative Adversarial Networks (GANs), which are sophisticated deep learning models composed of two neural networks—the generator and the discriminator—work in tandem in an adversarial setting to create new, realistic data samples (Goodfellow et al., 2014). Despite the promising utility of GANs in broadening the diversity and volume of training data, their application in façade defect identification faces unique limitations. In standard GAN applications, easily visible and distinct pixels are replicated to create clear features, but for façade defects, the challenges are unique; the defects range from small-scale issues like erosion to larger ones like efflorescence, as illustrated in Figure 1b, and are often overshadowed by the prominent patterns of the materials in the background, leading GANs to replicate these material patterns instead of the defects. Given the distinctive challenges in using GANs for façade defect identification, it becomes imperative to assess and compare GAN models specifically for their ability to discern and replicate these nuanced irregularities.

This study evaluates the state-of-the-art GAN architectures for their ability to generate building façade images with a diverse set of defects, while addressing their unique representational challenges (e.g., modifying defect characteristics as compared to the façade component itself). We have selected three advanced GAN algorithms for evaluation and trained each model from scratch without transfer learning. DCGAN (Radford et al., 2015) is chosen for its foundational architecture that sets a baseline; Lightweight GAN (Liu et al., 2020) is selected due to its ability to learn from a limited number of samples, an essential feature for modeling rare defects without demanding extensive computational resources; BigGAN (Brock et al., 2018) has the ability to produce high-resolution, class-specific images, crucial for capturing the intricate details of defects, ranging from subtle erosion to pronounced instances of spalling. The best-performing GAN will be used to expand our dataset, which is crucial for the development of segmentation models, thereby enabling automated defect detection.

BACKGROUND

Studies on addressing data scarcity. To mitigate the challenge of limited data availability, research studies either focused on enhancing existing datasets with DL approaches or innovating alternative model training techniques. Dataset enhancement related studies include methods such as data resampling (Mohammed et al., 2020), data augmentation (Shorten and Khoshgoftaar, 2019), and generating synthetic data by GANs (Kiper et al., 2023), and simulation tools (Kiper et al., 2022). Data resampling techniques such as oversampling or undersampling tackle the distribution of overrepresented or underrepresented classes to achieve a more balanced dataset. Yet, these methods are often limited by merely replicating existing samples or removing valuable data, potentially leading to overfitting or underfitting in models. Meanwhile, augmentation further enriches the dataset, with methods ranging from simple geometric transformations widely used in the machine learning (ML) domain—like flipping, cropping, and color adjustments—to more complex schemes such as MixUp and CutMix (Kiper and Ergan, 2023). Additionally, synthetic data generation has been segmented into distinct approaches to enhance datasets. GAN algorithms (i.e., DCGAN) have been leveraged to produce realistic 2D images from images to reflect a variety of façade defects (Kiper et al., 2023). In parallel, software simulations have been used to create a variety of defect scenarios; physics-based graphics models were utilized to project detailed 2D images from 3D models to evaluate post-earthquake structural damages (i.e., cracks, spalling, and exposed reinforcement bars) (Hoskere et al., 2022) while software tools (i.e., Blender) were utilized for rendering 3D point cloud of defects (i.e., bulging) (Kiper et al., 2022).

Innovative training techniques are also being employed to optimize DL performance in the face of limited data. Approaches, such as the few-shot classification (Cui et al., 2022), enable models to interpret new defect types from minimal examples, and meta-learning streamlines the learning mechanism, facilitating quick adaptation to new tasks. Semi-supervised learning leverages a combination of a small amount of labeled data and a larger pool of unlabeled data to improve learning efficacy. Transfer learning enables the transfer of knowledge from one domain to another, which is particularly valuable for underrepresented classes (Kiper and Ergan, 2023). These strategies improve the model's precision and flexibility. However, they inherently face the limitation of inadequate generalization from constrained training data to the unpredictable variety found in real-world settings, underscoring the necessity for a well-curated and balanced dataset.

GAN algorithms and GAN-based data augmentation. GANs are an innovative concept in machine learning involving two neural networks—the generator and the discriminator—that work against each other to produce highly realistic data. The generator network's role is to produce data from a random noise input aiming to mimic real data. It learns to generate new data points (e.g., images) that are realistic enough to pass as real. Discriminator's task is to differentiate between real data and the fakes produced by the generator. As depicted in Figure 1a, this interaction is guided by loss functions for both networks, with the Generator's loss aimed at crafting increasingly convincing data, while the Discriminator's loss focuses on correctly identifying real and synthetic data. This process continues until the generator produces data so convincing that the discriminator can no longer easily tell it apart from real data (Goodfellow et al., 2014).

The generative modeling field has grown rich with a wide variety of GAN architectures, each engineered for specialized tasks: from image generation where models (e.g., DCGAN, BiGAN) are used to create new images that resemble a given dataset of images, to super resolution enhancing image clarity from low to high resolution. Additionally, GANs are instrumental in Style Transfer – adapting the aesthetic of one image to another (CycleGAN), and in text-to-image synthesis – converting descriptive text into corresponding visuals (StackGAN). Recognizing the extensive array of GAN architectures there arises a research gap in identifying the GAN architectures that suit façade defect identification. To address this gap, our study extends the foundation laid by prior research (Kiper et al., 2023) that employed DCGAN to generate images with façade defects for data augmentation. We aim to evaluate the performance of three GAN models – DCGAN, Lightweight GAN, and BigGAN – aiming to provide insights into their applicability in façade defect detection. These models were selected based on their capabilities to generate defects that show significant differences in size (e.g., erosion defects observed as small cavities dispersed over a brick, or efflorescence covering a sizable area of multiple brick surfaces) and characteristics (e.g., cracks signified with their lengths and depths vs. spalling signified with areas) as shown in Figure 1b. Particularly smaller defects often are overshadowed by the prominent patterns of the materials and textures of components in the background, leading GANs to replicate these material patterns instead of the defects. With the comparison of these preselected GAN architectures, we investigate their adaptability and performance in providing high quality and diverse datasets for training of defect detection models to be deployed in façade inspection domain.

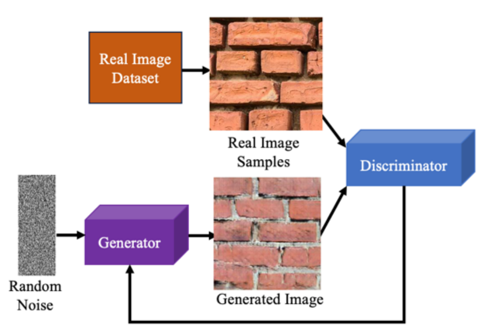

Figure 1a. General GAN Architecture.

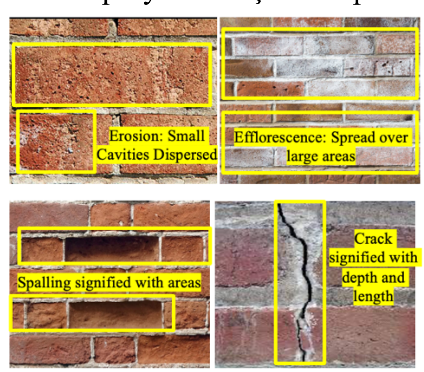

Figure 1b. Façade defects characteristics.

GAN Architectures. In this study, we utilized three distinct GAN models—DCGAN, BigGAN, and Lightweight GAN—each built upon deep neural network frameworks, yet they diverge in their specialized approaches and optimizations, summarized in Table 1. DCGAN streamlines its architecture by leveraging convolutional networks and removing fully connected layers, incorporating batch normalization to stabilize learning. Batch normalization is a technique used to improve performance and stability in neural networks by normalizing each layer's inputs so that they have a mean of zero and a standard deviation of one. BigGAN extends the concept by scaling up the network and batch size for greater detail and complexity in image generation, incorporating Orthogonal Regularization, which encourages the weights of each layer in the network to remain independent from each other to maintain training stability. Self-Attention enables the model to consider the entire image when making decisions to capture long-range dependencies within images by assigning weights to spatial locations based on their relevance to each other. Lastly, BigGAN uses a Truncation Trick method, which fine-tunes the variety and realism of the generated images by adjusting the input noise. In contrast, Lightweight GAN prioritizes computational efficiency by integrating a self-supervised discriminator that refines its understanding of data without external labels. It also incorporates Skip-Layer Excitation (SLE), a technique that connects different network layers directly, allowing fine details to be preserved and emphasized throughout the network to enhance the flow of information and maintain high resolution in the generated images, even when working with limited resources. Computational efficiency in this context refers to how effectively a model uses computational resources (e.g., processing power and memory). DCGAN exhibits moderate computational efficiency, balancing resource usage with performance capabilities. In contrast, BigGAN's approach is resource-intensive, necessitating significant computational resources, whereas Lightweight GAN achieves high efficiency, generating detailed images with minimal resource use.

Table 1. Differences in selected GAN algorithms.

Feature	**DCGAN**	**BigGAN**	**Lightweight GAN**
Architecture	Deep Convolutional Neural Network	Deep Convolutional Neural Network	Deep Convolutional Neural Network
Model and Batch Size	Standard	Significantly Scaled Up	Optimized for Efficiency
Special Mechanisms	Batch Normalization	Orthogonal Regularization, Self-Attention, Truncation Trick	Skip-Layer Excitation (SLE), Self-Supervised Discriminator
Primary Focus	Stability in Training	High-Quality, Large Scale Image Generation	Efficiency
Computational Efficiency	Moderate	Resource Intensive	High

RESEARCH METHOD

This study aims to compare the performance of three distinct Generative Adversarial Networks (GANs) - DCGAN, Lightweight GAN, and BigGAN - in producing high-fidelity synthetic images of façade defects for improving the robustness of new defect detection systems. The goal is to identify the GAN architecture that demonstrates high performance in evaluation metrics and generated image quality/usability, which will be essential in defect segmentation using the generated images. The workflow of this study is presented in a four-step process in Figure 2. In a nutshell, it begins with the collection of a robust dataset through strategic data scraping using keywords (i.e., spalling brick, efflorescence, etc.,) pertinent to façade defects. The scope of this work is targeted on four specific defects, i.e., spalling, efflorescence, erosion, and missing mortar, Spalling, being the most abundant in previous studies, serves as a representative class, while the inclusion of efflorescence, erosion, and missing mortar aims to address the limited coverage and scarcity of samples in previous studies, as these defects are relatively rare. The dataset preparation also includes resizing images to a uniform resolution for computational efficiency. The next step entails the careful selection of GAN models based on a set of defined criteria aimed at optimizing performance for façade image synthesis. Subsequently, with the selected GAN architectures that fit to the problem domain, we trained the models using the captured dataset and tuned the hyperparameters (e.g., batch size and number of epochs). The final step involves a rigorous evaluation of the models, leveraging established GAN evaluation metrics (i.e., FID score and visual inspections) to validate the quality and diversity of the synthetic images for their suitability of use in defect detection applications. Details of the steps are as follows:

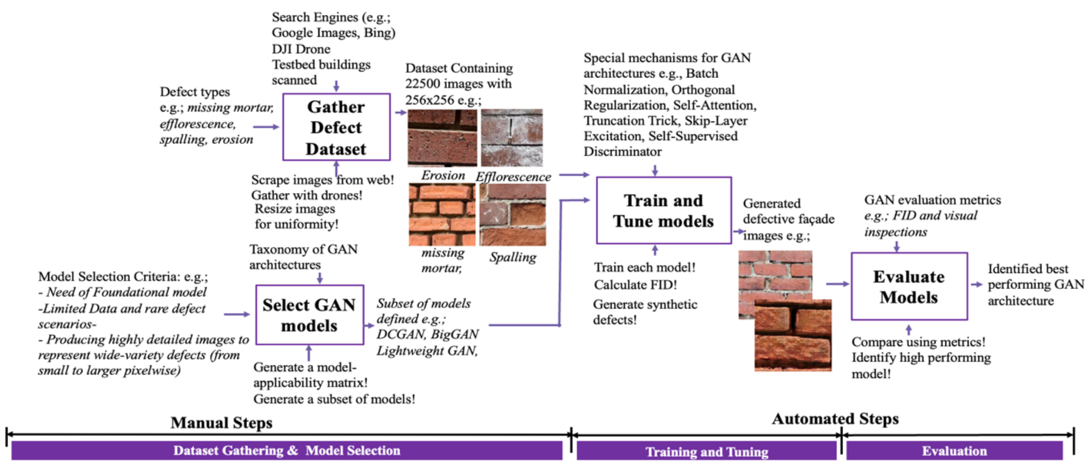

Figure 2. The workflow of this study.

Step 1: Dataset Gathering. In the initial phase, we assembled a dataset by scraping around 10,000 images with different resolutions using keywords indicative of façade defects, such as 'spalling', 'efflorescence', 'missing mortar', 'eroded brick', 'eroded wall', 'brick defects', 'brick spalling', and 'spalled brick'. To enhance relevance, we excluded irrelevant images, and refined the dataset by slicing images into uniform 256x256 pixels, maintaining detail without downsizing. A final review further eliminated non-defective and duplicate images, resulting in a dataset of 22,500 images.

Step 2: Model Selection. The selection of GAN models for this study was driven by a set of criteria specifically tailored to meet our objective of generating high-quality synthetic images of diverse ranging façade defects. Each model was specifically chosen for its capabilities that align with the critical needs of our dataset enhancement, addressing the challenges of scarcity and imbalance to improve overall generalizability. DCGAN was chosen for its stability and its status as a baseline model in the field of GANs, recognized for its straightforward architecture and ease of implementation, making it an excellent starting point for generating a diverse range of defect images. Lightweight GAN, adept at handling limited data and resources scenarios, was specifically chosen to address the challenge of rare defects, as it excels in generating images with minimal sample requirements and efficiently utilizes limited computational resources. BigGAN's inclusion was driven by its superior performance in producing highly detailed images, aligning with our goal of capturing even subtle defects (e.g., erosion) as well as prominent defects like efflorescence.

Step 3: Training and Hyperparameter Tuning. We trained and optimized each GAN on a GPU-based setup with Keras and TensorFlow. The aim was to fine-tune the generation of detailed façade defect images, measuring quality through the Fréchet Inception Distance (FID) score which compares the similarity of generated images to real ones; lower scores indicate better quality. Visual inspections validated generated images practical applicability for façade inspection tasks, the specifics of which are explained in the evaluation step. We initially set each GAN model using the suggested parameters from their respective publications. We then focused on adjusting the batch size and the number of epochs to optimize the image output. The batch size, which is the number of training samples (i.e., images) processed during the training phase in one iteration of updating weights in the model, and epoch, the number of times the entire dataset is passed forward and backward through the neural network for the training phase, were fine-tuned to balance between computational efficiency and image quality. For DCGAN, we adhered to standard practices with batch sizes of 8 to 16 and epoch counts up to 200. Lightweight GAN was configured for batch sizes of 4, 8, and 16, reflecting its design for limited-resource environments, and trained for 200 epochs. BigGAN's training, due to its larger scale and complexity, demanded larger batch sizes of 128 and 256 with 300 epochs. This extended training is necessary for BigGAN due to its sophisticated architecture, which is designed to generate images with exceptional detail. Other model-specific parameters were kept at their default settings as outlined in their original papers (Radford et al., 2015), (Liu et al., 2020), (Brock et al., 2018) to provide a baseline for performance comparison. Post-training, we computed the FID scores to assess the model's efficacy to select the best model for data augmentation and to assist in advancing towards semantic segmentation.

Step 4: Evaluation. Finally, we evaluated the synthetic images produced by the three implemented GANs. Evaluating GANs is particularly challenging due to the absence of a definitive objective function, hence we used FID as our quantitative metric, along with qualitative visual inspections. FID evaluates image quality by comparing the feature distributions from real and synthetic images extracted via the InceptionV3 model, measuring the distance between their means and variances (Heusel et al., 2017). A lower FID score indicates synthetic images closely resemble real ones in key features, indicating better quality. Thus, we supplemented the FID analysis with visual inspections to assess the generated images' realism and contextual accuracy for façade defect identification. Human evaluators assessed the practical utility of the generated images through manual visual inspections. Approximately 1000 images were generated for each GAN, and meticulously reviewed for usability based on specific criteria: the presence of defect features and the overall visual coherence with the real images. Images that lacked distinct defect outlining, exhibited unrealistic textures, or departed substantially from the dataset's context were considered unusable and eliminated. This process resulted in an average usable image rate per model, offering insight into each GAN's ability to generate practical synthetic images for façade defect analysis. This dual approach of quantitative FID scores and qualitative human review ensures our generated images are both statistically and practically useful for enhancing our dataset and task of semantic segmentation in façade inspection.

RESULTS AND DISCUSSION

The FID scores for each model with their respective best parameters are presented in Table 2, reflecting the synthetic image quality generated by each GAN model. DCGAN, trained with batch sizes of 16 and for 100 epochs, achieved an FID score of 92.17. With this, DCGAN establishes a solid baseline, confirming its reputation for stability and reliability in image generation tasks. BigGAN, despite its advanced capabilities for high-resolution image synthesis, faced challenges with larger batch sizes of 256 across 300 epochs, leading to the highest FID score of 141.97. The model's sophisticated architecture demands considerable computational power, which, when paired with our dataset's size and complexity, may have contributed to the several system crashes we observed during training. This prevented us from realizing the model's full potential and suggests that while BigGAN has the potential for exceptional detail in image generation, a careful balance must be maintained in managing its resource-intensive nature. Finally, Lightweight GAN achieved the most favorable FID score of 31.68, with a batch size of 8 and 300 epochs. Its good performance can be linked to its design, which is optimized for learning efficiently from fewer samples to produce highly realistic images. This characteristic proves advantageous in our dataset comprising various defect types, some of which are significantly underrepresented. Such efficiency is particularly beneficial given the diversity of our dataset and the presence of less commonly occurring defect types, making Lightweight GAN an advantageous choice for balancing computational demands with the need for high-quality image synthesis.

Table 2. FID Scores for selected GAN model performance.

Model	Batch Size	Epochs	FID Score
DCGAN	16	100	92.17
BigGAN	256	100	141.97
Lightweight GAN	8	300	**31.68**

Our study also included visual assessments to gauge the usability of the images generated by each GAN model. This evaluation revealed that 68% of BigGAN's images, 83% of DCGAN's, and 91% of Lightweight GAN's were deemed usable for our application. These findings are visually supported by Figure 3, where column (a) displays real images from our dataset, providing a benchmark for comparison. Columns (b), (c), and (d) present the synthetic images produced by BigGAN, DCGAN, and Lightweight GAN, respectively. Notably, Lightweight GAN's synthetic images demonstrate the closest resemblance to the real images with defects, aligning with its high usability score and its lower in the FID score. This visual confirmation strengthens the argument for Lightweight GAN's efficacy in generating training data that could significantly improve the defect detection process in façade inspections.

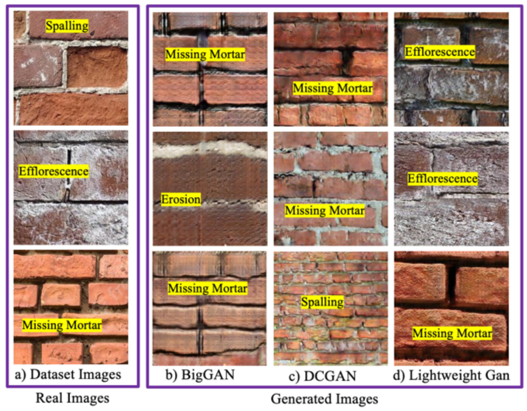

Figure 3. Visual Comparison of (a)Real Images and Synthetic Images by (b)BigGAN, (c)DCGAN, and (d)Lightweight GAN

CONCLUSION

In this study, we investigated the use of GANs to enhance façade inspection datasets, aiming to address challenges related to data scarcity and imbalance commonly encountered by deep learning models. Employing DCGAN, Lightweight GAN, and BigGAN, we generated synthetic images of façade defects to expand our training dataset, evaluating their performance through FID scores and expert visual inspections. While DCGAN provided a reliable baseline, Lightweight GAN produced the most realistic images, with the highest usability rate and the lowest FID scores. However, computational limitations were encountered with BigGAN, highlighting the necessity for more efficient GAN architectures for facade defect context. The limitation of our study was the lack of control over the randomly generated defects, which points to the necessity for a more targeted generation approach. Ongoing research, which will be published in a subsequent venue, focuses on integrating these synthetic images into deep learning models for defect detection specifically assessing whether these images can effectively enhance model performance and accuracy. This will constitute the validation of the results presented in this paper. This approach holds promise for improving inspection accuracy and contributing to safer building practices.

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