Evaluating 3D Reconstruction: A Side-by-Side Comparison of NeRF and Gaussian Splatting in Indoor and Outdoor Environments

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ABSTRACT

This study presents a comparative evaluation of Neural Radiance Fields (NeRF) and 3D Gaussian Splatting (3DGS) for 3D reconstruction in indoor and outdoor environments. High-quality 3D models are significant in a range of applications, from forensic investigations to cultural heritage preservation, architecture, and robotics, where detail accuracy and minimal noise are crucial. Leveraging continuous video footage captured with a stabilized full-frame camera setup, this research examines both algorithms across indoor and outdoor environments using consistent datasets. Key assessment criteria include reconstruction noise, detail preservation, and processing time. The results reveal that while both approaches generate high fidelity reconstructions, 3DGS outperforms NeRF in computational efficiency and noise reduction. These insights provide valuable guidance for selecting suitable reconstruction techniques across different professional domains. Due to the controlled scope and limited number of test scenes, the findings should be interpreted as indicative rather than statistically generalizable, serving primarily as a practical, application-oriented comparison.

Keywords-3D reconstruction; Neural Radiance Fields (NeRF); 3D Gaussian Splatting (3DGS); forensic imaging; radiance fields

I. INTRODUCTION

The role of three-Dimensional (3D) reconstruction in capturing and interpreting real-world environments in widespread applications is becoming increasingly significant. From criminal scene documentation and investigative procedures to architectural conservation, virtual reality, and robotics, generating a precise, spatially correct virtual representation of captured imagery or video has never been more useful. Such reconstructions enable professionals to examine and measure environments after the fact, assist in decision making, facilitate collaboration, and ensure long-term data preservation.

Traditional 3D reconstruction algorithms use photogrammetry [1, 2] or structured light scanning [3, 4], which may be slow, computationally intensive, or hardware dependent. Alternatively, new advances in radiance field-based methods have revolutionized the field, allowing for photorealistic reconstruction from comparatively simple video recordings or image sets. Two of the most prominent and promising approaches among these are NeRF and 3DGS.

A. Neural Radiance Fields

NeRF [5], introduced in 2020, is a paradigm-changing approach in 3D reconstruction. Rather than explicitly constructing 3D geometry, NeRF learns an underlying volumetric scene function defined by a neural network. Such a function provides an estimate of colour and density at an arbitrary point in space, given a viewpoint. In training, a Multi-Layer Perceptron (MLP) is optimized by NeRF to mimic the look of a scene in various views from an input set of imagery. NeRF generates highly accurate renderings with rich detail and view-dependent effects like specular reflections. However, it comes with certain limitations. Training an NeRF model is slow and computationally costly, usually taking hours for each scene. Moreover, its view synthesis performance depends heavily on accurate camera poses and extensive training data.

Despite these challenges, NeRF has found extensive use in research and industry, across applications in visual effects, digitization of cultural heritage, and forensic visualization experiments, because of its realism and capacity to deal with complicated light. Since its introduction, NeRF has inspired a range of subsequent methods aimed at addressing specific limitations related to computational efficiency, robustness, and practical deployment.

B. 3D Gaussian Splatting

3DGS [6] tries to overcome some of the limitations of NeRF. It represents scene points in terms of an ensemble of 3D Gaussians rather than in terms of a dense neural network. Each of them possesses values for position, orientation, size, colour, and opacity, and they get rendered directly through rasterization. This results in significantly faster training and rendering, while maintaining impressive visual quality.

In contrast to NeRF, 3DGS can generate usable reconstructions within minutes rather than hours, so it is suitable for applications that incur time pressures or have limited resources. It also introduces fewer visual artifacts in some filming scenarios. These benefits have contributed to the rapid adoption of 3DGS in environments where speedy feedback and visual clarity are desirable, such as robotic navigation, augmented reality, and forensic documentation processes.

Although advances in algorithms are necessary, input data quality remains an important consideration in any 3D reconstruction. Properties of cameras, such as sensor size, resolution, lens quality, and image stabilization, impact the capacity of the model to reconstruct geometries and texturing. As demonstrated in [7, 8], full-frame sensors generally outperform crop sensors due to their higher sensitivity and broader dynamic range. Filming techniques, such as maintaining stable movement, capturing from multiple heights, or covering the full object/environment, also play a major role. Such parameters impact the algorithm's ability to reconstruct low-level details, eliminate occlusions, and manage lighting fluctuations.

The present study conducts a comparative analysis of NeRF and 3DGS under identical conditions using identical video datasets, recorded utilizing a professional-quality camera equipped with a full-frame sensor and wide-angle lens. The experiments are conducted in both indoor and outdoor settings, representative of real-world environments relevant to forensic and general reconstruction tasks. The study evaluates these algorithms using three key criteria: reconstruction noise, detail preservation, and efficiency of computation. The findings of the study are expected to guide professionals and researchers in selecting appropriate tools and capture strategies tailored to their domain-specific requirements.

C. Practical Contribution

This study provides clear, evidence-based advice for professionals who want to use 3D reconstruction technologies in practical applications. By evaluating NeRF and 3DGS using identical datasets and controlled filming techniques, the paper identifies which method is better suited for high-fidelity reconstructions in indoor and outdoor environments. These recommendations are beneficial for real-world applications in forensic examination, cultural heritage, and computer vision scene reconstruction, in which time and visual fidelity are critical. The insights also include useful advice for choosing cameras, movement strategy, and capturing data to ensure optimal reconstruction outcomes.

D. Theoretical Contribution

Theoretically, this paper advances existing comparative research in neural radiance field algorithms by formally detailing the advantages and drawbacks of NeRF and Gaussian Splatting in terms of reconstruction noise, detail precision, and computing time. A structured evaluation framework is introduced, which can be used to assess radiance field algorithms from a practical quality standpoint, rather than solely based on visual outputs, by combining controlled environments and algorithmic benchmarking. This research bridges the gap between technical development and applied 3D reconstruction practices.

II. METHODOLOGY

This study builds upon research focused on optimizing 3D reconstruction techniques for use in crime scene investigation and other professional fields. Previous work in this research stream has examined the impact of camera parameters, scene conditions, and data capture strategy on resulting reconstruction quality. The present study builds upon those findings by comparing two dominant radiance field algorithms, NeRF and 3DGS, against identical and validated filming conditions.

The methodology involves a comprehensive camera setup and data capture strategy, supplemented by an organized experimental design for indoor and outdoor environments. Care has been taken to standardize input conditions since data quality variations can have significant consequences for reconstruction and introduce bias in comparisons.

A. Camera Setup

The primary equipment was a SONY a7c [9] camera with a 24.2 MP full-frame Exmor R CMOS BS sensor. This camera was chosen for its full-frame sensor, which results in higher image quality. The lens combined with the camera is a Sigma 14 mm f/1.4 DG DN Art lens [10], with a wide-angle lens. This lens can capture more data in one pass, improving the quality of the 3D reconstructions. A DJI RS 4 gimbal was added to the camera setup to create an even more constant capturing method. The gimbal enables a smoother capture of the environment, with minimum vibrations and thus reduced blurry frames. Constant lighting conditions were maintained across all captures. To compare different 3D reconstruction algorithms, particularly in noise reduction, speed of reconstruction, and detail accuracy, Postshot version 0.4.1 [11] and an end-to-end software for Radiance Fields were used to generate the 3DGS and NeRFs. The goal was to determine which radiance field algorithm works best for inside and outside environments.

Two comparison experiments were conducted, and for both comparisons, an optimal dataset was created following the optimal capture methods and camera settings [7, 8]. The datasets were processed with the radiance field algorithms. The generated 3D reconstructions were evaluated based on noise, detail accuracy, and processing time. These criteria were chosen for their importance in forensic applications where both clarity and realism are important for analyzing evidence. This approach enabled the identification of the optimal algorithm for high-quality 3D reconstructions in indoor and outdoor crime scene scenarios, providing valuable insights for future forensic investigations.

B. Data Capture Process

The data capture process utilized in the current research was developed in adherence to best practice guidelines developed in [7], which tested different filming styles and camera movement tactics for effects upon 3D reconstruction quality. Based upon those recommendations, continuous video capture was performed while navigating predefined paths that guaranteed even scene capture, reduced occlusions, and facilitated correct camera pose determination.

Two different environments were utilized for capturing data: an indoor home setting (living room, kitchen, and hallway) and an outdoor city setting (a parking area containing different objects and textures). In each instance, the scenes were captured along a path of loops performed at three vertical heights, low, mid, and high, encircling the objects or environments of interest. This three-height capture approach has previously been demonstrated to optimize reconstruction fidelity, in particular for vertical structures and complex geometries [8]. The capturing was performed using a gimbal for stabilization. The movement was kept as smooth and continuous as possible to reduce motion blur and ensure consistency in camera trajectory. Care was taken to maintain a consistent walking speed and to avoid sudden camera rotations or changes in lighting, as these are known to introduce artifacts and disrupt parts of the reconstruction pipeline.

Environmental factors were also taken into consideration. The indoor data were collected in a residential interior that was brightly illuminated by both natural and artificial light sources, ensuring clear visibility of all objects and surfaces. The space featured a variety of furniture and textures to facilitate the capture of fine-grained details. Outdoor data were recorded during a sunny afternoon, resulting in high-contrast conditions in terms of shadows, which pose challenges for both algorithms in adapting to lighting. The captured video sequences were used as input to both 3DGS and NeRF to ensure that algorithms were tested in identical capture environments for an accurate comparison. This process simulates real-world capture cases in forensic or field-based use, where time, location, and illumination can never be fully controlled, but consistency is still crucial for scientific analysis.

C. Environmental Setup

To evaluate the performance of 3DGS and NeRF in real-world scenarios, two test scenarios were created: one indoors and one outdoors. Each setup was selected to include diverse elements with varying geometry, texture, and lighting, reflecting challenges commonly encountered in forensic and spatial reconstruction contexts.

1) Indoor Environment

The indoor experiment was performed in a complex multi-room setup comprising a living room, kitchen, and hallway. This room contained an assortment of items such as chairs, tables, tableware, closets, ceiling, and various light sources. These were chosen to offer variety both in terms of geometric complexity and surface detail, providing a robust test case for NeRF as well as 3DGS algorithms. A predefined scan path, illustrated in Figure 1, was used in data acquisition. For extensive coverage and vertical scene understanding, three loops were taken along this path at various heights. This multi-height methodology has been demonstrated to greatly enhance the fidelity in 3D reconstructions for indoor environments. Wide-angle coverage, combined with vertical diversity, was necessary to provide the maximum input for algorithms. The three heights were recorded in a single video clip, resulting in a video length of approximately 3:25 (min:sec) and a total of 5,375 frames. From these, 432 frames were selected for use in this study. Figure 2 shows six representative frames from the selected set.

Fig. 1. Top view of indoor environment with red scan path.

Fig. 2. Six representative frames from the indoor environment dataset.

D. Outdoor Environment

The outdoor experiments were conducted in an open parking area in natural daylight. The scene featured two lines of parking spots, one street lamp, three trees, grassy spots, and one white car. It was selected to offer an array of different materials and light dynamics, such as shaded and illuminated areas, hard ground, and leaves.

Data capture was performed in the afternoon of a summer's day in bright sunlight for consistent lighting. Its scan path, as depicted in Figure 3, had the operator follow four loops in the scene at varying elevations, similar to what was done for the indoor setup. This allowed the algorithms to leverage multi-angle viewpoints and improve spatial completeness, especially around objects such as the vehicle and vertical structures. The four heights were recorded in a single video clip, resulting in a video length of approximately 2:39 (min:sec), and a total of 3996 frames. From these, 320 frames were selected for use in this study. Figure 4 displays six representative frames from the selected set. Both datasets were captured with identical hardware and capture conditions using the same stabilizer and camera setup. This consistent approach facilitated direct comparison of the two algorithms in different environments.

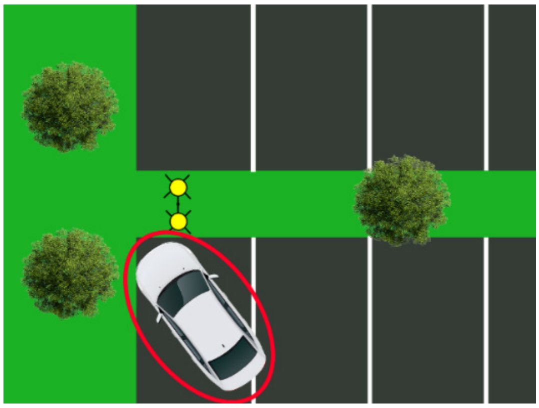

Fig. 3. Top view of outdoor environment with scan path marked in red.

E. Experimental Design

1) Algorithm Comparison

To determine which radiance field algorithm is more suitable for 3D reconstruction in different environmental contexts, two controlled comparisons were conducted—one in an outdoor environment and the other in an indoor environment. Both experiments used identical hardware and capture methodology to ensure consistency and to isolate the effect of the reconstruction algorithm.

Fig. 4. Six representative frames from the outdoor environment dataset.

a) Comparison I: Outdoor Environment

The first experiment focused on reconstructing an outdoor environment captured in a parking lot, featuring a mix of natural and artificial elements such as trees, grass, asphalt, a streetlamp, and a white car. The camera setup described earlier was used to capture a continuous video sequence following the predefined scan path, as illustrated in Figure 2. This dataset was then processed using both NeRF and 3DGS algorithms. The resulting 3D reconstructions were evaluated based on visual fidelity, processing efficiency, and artifact presence.

b) Comparison 2: Indoor Environment

The second experiment targeted a multi-room indoor environment, including a kitchen, living room, and hallway, as portrayed in Figure 1. The same camera configuration and multi-loop scan path strategy were applied to maintain data quality. The dataset captured in this space was also processed by both algorithms using identical software parameters. In both cases, the same datasets were provided to each algorithm to ensure a fair and unbiased comparison.

2) Evaluation Criteria

The evaluation strategy follows a viewpoint-based assessment model. After generating the 3D reconstructions, specific zones were selected within each scene that represent high forensic relevance and technical challenge. This targeted analysis approach allows for focused evaluation on areas where accuracy, noise suppression, and detail fidelity are significant.

a) Indoor Analysis Scene

For the indoor scene, the analysis centered on a coffee table area located in the living room. This zone presents complex surface textures, varying illumination, and multiple occlusions, making it an ideal location to test the reconstruction performance of each algorithm.

b) Outdoor Analysis Scene

In the outdoor scene, the primary analysis focused on the white car, specifically the region around the “Le Mans” text inscription on the upper left section of the vehicle. This detail presents subtle textural elements and curved surfaces, posing a challenge for radiance field rendering techniques.

c) Assessment Metrics

The comparison of NeRF and 3DGS was based on three core metrics:

- Model Noise (3D reconstruction noise): Evaluated by the presence of visual artifacts or distortions in the final reconstruction. Visual artifacts are any visible anomalies (e.g., flickering, floaters, or misplaced geometry) that detract from the realism or accuracy of the output. Distortion refers to systematic geometric inaccuracies in the reconstructed scene, such as straight walls appearing warped, round objects rendered as ovals, or surfaces unnaturally stretched or compressed. Figure 5 shows artifacts and distortion in the reconstruction along with the ground truth.
- Detail Precision: Assessed by visually comparing the reconstruction to the ground truth and judging how well fine textures and small features, such as sharp edges, text, or intricate patterns, are preserved and rendered in the model.
- Computational Efficiency: Defined by the total time required for processing each dataset using the respective algorithm.

(a)

(b)

Fig. 5. Artifacts and distortion: (a) 3D reconstruction, with visual artifacts and distortions marked with red and blue, respectively; (b) ground truth.

As presented in Table I, each algorithm's performance in these categories was rated on a 1–5 scale, facilitating a structured comparison and visualization of the results in tabular form. This scoring system allowed for both qualitative and semiquantitative evaluation, aligning with the study's forensic and applied orientation.

The entire experimental design was structured to reflect real-world constraints and priorities found in forensic and field-based 3D documentation tasks. The evaluation combines qualitative, viewpoint-based assessment with complementary quantitative image similarity metrics. Visual criteria, noise, detail preservation, and overall clarity were assessed using a structured ordinal scale, reflecting practical forensic and applied use cases where interpretability and visual reliability are significant. In addition, Learned Perceptual Image Patch Similarity (LPIPS), Peak Signal-to-Noise Ratio (PSNR), and

Structural Similarity Index Measure (SSIM) were computed for representative viewpoints to provide supporting numerical context. These metrics are not used as absolute performance indicators but rather as complementary measures that help contextualize observed visual differences. Given the limited number of scenes and controlled experimental scope, the evaluation emphasizes consistency and interpretability over statistical generalization.

TABLE I. CRITERIA FOR COMPARATIVE ANALYSIS

Criteria	1	2	3	4	5
Noise	Excessive noise is present, and nothing can be seen	Excessive noise is present, but the environment is visible	Some noise is present; however, the outline of the environment is still visible	Almost no noise is present, and the environment is quite clean in terms of visibility	No noise is present
Details	The reconstruction appears pixelated, yet it is discernible that an object should be present in that location	The reconstruction is pixelated, but it is still possible to identify the object type (e.g., table, chair, paper)	Object types can be easily identified	Object can be accurately identified along with the brand information	Extremely detailed; there is no visible difference between the model and the video
Processing time	The processing takes longer than 24 h	The processing takes longer than 12 h	The processing takes longer than 4 h	The processing takes longer than 2 h	The processing takes less than 2 h

III. RESULTS

The results include the outcomes of the two experimental comparisons: one conducted in an outdoor environment and the other in an indoor environment. For both scenarios, identical video datasets were used to process 3D reconstructions with the NeRF and 3DGS algorithms. The performance was assessed using three criteria: model noise, detail precision, and computational efficiency. Ratings were assigned using a 1–5 scale, with 5 representing the best performance. Ten testers participated in the sensory evaluation of the 3D reconstruction results to provide an unbiased assessment of visual quality and realism. Including multiple testers helps ensure the reliability and generalizability of the evaluation, as it reduces the influence of individual subjectivity.

A. Comparison I: Outdoor Environment

The first experiment focused on an outdoor scene consisting of a parking lot with varied elements such as asphalt, a streetlamp, three trees, patches of grass, and a white car—the central subject of the reconstruction. This environment presented challenges such as high-contrast lighting, reflective surfaces, and a mix of natural and artificial objects. Both NeRF and 3DGS successfully reconstructed the overall layout of the scene. The white car appeared well defined in both reconstructions, with clear outlines and recognizable surface features. However, differences became apparent upon closer inspection.

The NeRF-based reconstruction demonstrated strong object continuity and colour realism, but several small visual artifacts were noticeable around the edges of the car and in lower-textured background areas, particularly where occlusions occurred. These artifacts slightly degraded the perceived smoothness and clarity of the model. In contrast, the 3DGS reconstruction preserved a similar level of detail while introducing fewer visual distortions. Edges were cleaner, and transitions between different materials, such as the car's surface and the surrounding asphalt, were more stable. Additionally, 3DGS completed the reconstruction approximately 10 min faster than NeRF, making it more efficient from a computational perspective.

These observations are illustrated in Figure 6, which presents side-by-side visual comparisons of the outdoor scene reconstructions. Both the first and second rows display pictures of the entire car. In the upper right corner of each image, an enlarged section is shown: the first row provides a detailed view of the text on the car, while the second row focuses on the bottom side of the front bumper. These detailed views emphasize the differences in reconstruction quality between the two regions. The quantitative results for processing time, noise level, and detail precision are summarized in Table II.

Fig. 6. Outdoor environment comparison 3DGS (left) versus NeRF (middle), ground truth (right).

TABLE II. RESULTS OF COMPARISON I

Environment	Algorithm	Processing time (hr:min:s)	Noise	Details
Outdoor	NeRF	01:03:09	2.86	3
Outdoor	3DGS	00:52:24	3.8	4.5

In addition to the qualitative assessment, a set of standard image-based similarity metrics was computed for the outdoor reconstruction to provide complementary quantitative insights. As presented in Table III, the average LPIPS values were comparable for both methods, with NeRF and 3DGS achieving LPIPS values of 0.717 and 0.713, respectively. This indicates a similar level of perceptual similarity to the reference imagery. PSNR values were also close, measuring 10.91 for NeRF and

10.79 for 3DGS, suggesting no substantial difference in overall reconstruction fidelity as captured by pixel-wise error. SSIM showed a slight advantage for 3DGS (0.303) compared to NeRF (0.288), indicating marginally better preservation of structural information in the outdoor scene. Given the limited dataset and the challenging outdoor lighting conditions, these metrics are interpreted as supportive rather than definitive and are used to complement the qualitative visual analysis.

TABLE III. COMPARISON OF OUTDOOR LPIPS, PSNR, AND SSIM

Average	NERF	3DGS
LPIPS	0.716904819	0.713489532
PSNR	10.90859095	10.79039288
SSIM	0.287504232	0.302857503

B. *Comparison II: Indoor Environment*

The second experiment was conducted in a confined indoor space composed of a living room, kitchen, and hallway. The scene included diverse furniture items such as tables, chairs, closets, and various smaller objects like tableware. This environment introduced different challenges, including complex textures, variable lighting conditions, reflective surfaces, and tighter geometry with multiple occlusions. In this case, the NeRF algorithm delivered a superior performance across both criteria. The reconstructed indoor scene using NeRF exhibited smoother surfaces, better noise handling, and a higher level of visual sharpness. Details such as chair legs, lamp structures, and the texture of the floor were preserved more accurately. The overall appearance of the NeRF model was more cohesive and realistic, making it suitable for close inspection and forensic evaluation.

3DGS also generated a usable 3D model, but it suffered from increased noise levels and some visual artifacts, particularly in areas with occlusion, low texture contrast, or reflective surfaces. These imperfections affected the clarity of furniture outlines and caused minor inconsistencies in the scene geometry. In terms of processing time, 3DGS completed the reconstruction in just over 42 min, while NeRF required more than 74 min, reflecting a significant computational advantage for 3DGS in indoor scenarios. The visual comparison between the two models is shown in Figure 7, and detailed performance metrics are listed in Table IV.

TABLE IV. RESULTS OF COMPARISON II

Environment	Algorithm	Processing time (hr:min:s)	Noise	Details
Indoor	NeRF	01:14:07	3.5	3.85
Indoor	3DGS	00:42:23	3.35	3.65

These findings demonstrate that both NeRF and 3DGS are capable of producing realistic and structurally accurate reconstructions under optimal capture conditions. However, 3DGS consistently delivers equal or superior visual quality with reduced noise and significantly faster processing time, particularly in the complex and texture-rich outdoor environment.

Fig. 7. Indoor environment comparison 3DGS (left) versus NeRF (middle), ground truth (right).

For the indoor environment, quantitative image similarity metrics were computed to complement the qualitative visual assessment, with the results presented in Table V. The average LPIPS scores were 0.725 for NeRF and 0.731 for 3DGS, indicating comparable perceptual similarity between the reconstructed views and the reference imagery. PSNR values were similarly close, with NeRF achieving 11.08 and 3DGS 11.11, suggesting nearly equivalent pixel-level reconstruction fidelity. SSIM results showed a marginal advantage for NeRF (0.390) compared to 3DGS (0.388), indicating slightly better preservation of structural information in the indoor scene. As with the outdoor case, these quantitative metrics are interpreted with caution due to the limited number of test scenes and are intended to support, rather than replace, the qualitative and viewpoint-based evaluation.

TABLE V. COMPARISON OF INDOOR LPIPS, PSNR, AND SSIM

Average	NERF	3DGS
LPIPS	0.725389898	0.730744243
PSNR	11.08042717	11.10641893
SSIM	0.390289023	0.388407474

IV. DISCUSSION

A. *Interpretation of Results*

The results of this study demonstrate distinct performance patterns between NeRF and 3DGS, shaped by the characteristics of the environments and the inherent strengths and limitations of each algorithm. The experimental design allowed for a consistent and controlled evaluation of both methods, leading to a series of insights into how each performs under varying real-world conditions.

1) *Outdoor Environment*

In the outdoor scene, both algorithms succeeded in generating highly detailed 3D reconstructions of the environment, particularly the focal object, a white car. The reconstructions displayed accurate geometry, strong contour alignment, and clear surface features. However, a subtle but meaningful distinction emerged in the stability and artifact levels of the models. NeRF produced a visually realistic reconstruction with smooth transitions and nuanced colour rendering, due to its volumetric rendering framework.

However, this came at the cost of localized noise, particularly along edges and in less-textured areas such as the sky, tree foliage, and asphalt surface. These visual artifacts, while not catastrophic, reduce the clarity and uniformity of the model and may complicate post-processing or analysis tasks, especially in forensic contexts where interpretability is critical. 3DGS, in contrast, matched NeRF in structural fidelity but surpassed it in visual stability. The reconstructed car, tree trunks, and streetlight edges were significantly cleaner, with fewer distortions or noisy splats. This improved consistency can be attributed to the explicit spatial representation of Gaussians and the more deterministic rendering process in 3DGS. Furthermore, the algorithm completed the reconstruction in approximately 10 min, less than NeRF, providing a computational efficiency advantage without sacrificing model quality.

The results suggest that for open scenes illuminated by ample natural daylight, supplemented with artificial lighting, 3DGS achieves performance comparable to NeRF while offering advantages in processing speed and visual robustness.

2) Indoor Environment

The performance difference between the two algorithms was more evident in the indoor scenario. Indoor environments inherently introduce additional challenges for 3D reconstruction, including complex geometry, confined spaces, varied lighting conditions, and frequent occlusions. These factors significantly impact how reconstruction algorithms perform and often reveal weaknesses not visible in simpler settings. In the indoor environment, NeRF outperformed 3DGS on two evaluation criteria. The resulting NeRF model exhibited lower noise, higher detail preservation, and shorter processing time. Fine structures, such as chair legs, table edges, and decorative items on surfaces, were rendered with clarity and cohesion. Textural information, such as patterns on floors or furniture finishes, was maintained with minimal blurring or smoothing. Moreover, surfaces appeared smooth and well-connected, creating a more cohesive and interpretable spatial model.

3DGS, while still able to produce an accurate scene, introduced more visible artifacts, particularly in shadowed areas and regions with reflective surfaces such as countertops or metallic fixtures (any object or piece of hardware made from a metal material). These issues likely stem from NeRF's sensitivity to lighting inconsistencies and its reliance on implicit volumetric encoding, which struggles in low-contrast or high-occlusion regions. The training time for the NeRF model also significantly exceeded that of 3DGS by more than 30 min, further emphasizing its operational limitations in time-sensitive applications.

These observations underline that while NeRF remains a powerful tool for rendering photorealistic outputs, its practical usability in forensic or real-time scenarios may be limited by processing demands and stability under variable capture conditions. In contrast, 3DGS appears more robust to environmental complexity and provides a more predictable and efficient pipeline for indoor 3D reconstruction.

B. Comparison with Existing Literature

The findings of this study comply with research in the field of neural and point-based 3D reconstruction. It has been noted that NeRF excels in generating highly realistic renderings under ideal conditions but struggles with noisy or limited input data. Authors in [5], who introduced NeRF, focused primarily on small, controlled indoor scenes with static lighting and extensive input imagery. Subsequent research has explored specific limitations of NeRF, particularly related to computational efficiency and robustness. For example, FastNeRF focuses on accelerating rendering performance through factorized representations [12], while NoPe-NeRF addresses sensitivity to inaccurate camera pose estimation by reducing reliance on pose priors [13]. Despite these targeted improvements, the core NeRF framework remains computationally demanding and sensitive to inconsistencies in image quality and capture conditions, especially in real-world scenarios.

In contrast, Gaussian splatting has rapidly gained traction for its balance between speed and quality. According to [6], 3DGS can produce photorealistic results with significantly faster training and inference times than NeRF, especially in scenarios requiring fast deployment or live feedback. This observation is reinforced by the findings of the present study, particularly in the indoor environment, where 3DGS processed the scene 30 min faster while delivering smoother surfaces and less noise. Beyond radiance field methods, applied forensic research has explored alternative reconstruction paradigms that emphasize capture strategy and viewpoint coverage in constrained indoor environments. Authors in [14] demonstrated that micro-UAV–based photogrammetry can be effectively used for indoor crime scene reconstruction, achieving comprehensive spatial coverage while minimizing operator intrusion into the scene. They highlighted the importance of viewpoint diversity and controlled acquisition paths in achieving reliable reconstructions, reinforcing the present study's emphasis on structured capture strategies and viewpoint-aware evaluation.

Additionally, the use of viewpoint-specific evaluation in the present study is informed by prior forensic reconstruction studies that emphasize practical scene interpretability and analytical reliability over purely synthetic metrics, as in [15, 16]. This perspective reflects a broader shift toward evaluation frameworks that prioritize accuracy, clarity, and operational usefulness in real-world investigative contexts. However, many prior studies have not examined the combined impact of indoor and outdoor environments using the same capture setup and evaluation strategy. In this context, the present study provides a significant contribution by directly comparing NeRF and 3DGS under field-relevant conditions, using consistent hardware, capture methodology, and assessment criteria.

C. Practical Implications

The findings of this research provide significant implications for scientists and academics who use 3D reconstruction in practical applications, especially those dealing with time-sensitive or precision-based applications. In forensic inquiries, precision and interpretability are crucial, and 3DGS's capability to generate clean, artifact-free reconstructions in less computing time is extremely beneficial. Spatial detail, clarity, and minimized visual noise improve the reliability of 3D evidence for documentation, analysis, and even presentation in court.

Outside of forensics, implications reach areas of cultural heritage conservation, architectural surveys, and robotics. For instance, in the digitization of historical locations, especially interior environments, 3DGS presents a solution for rendering high-fidelity environments without extensive data processing, which typically constrains field operations. Correspondingly, robotic applications demanding real-time or near-real-time understanding of space would benefit from increased rendering speed of 3DGS for faster navigating, localizing, or interpreting a scene. In contrast, NeRF's robust performance in rendering smooth surfaces and photorealism might still be useful in cinematic visual effects, educational simulation, or other use cases for which aesthetic fidelity takes precedence over computing constraints.

Finally, this comparative assessment enables practitioners to choose the best instrument for the particular needs of their field, whether for speed and strength or for realism and visual richness. Placing the assessment under real-world conditions of filming and considering indoor and outdoor environments, the research offers practical and transferable knowledge for the broader community of 3D reconstruction.

D. Limitations

Although this research provides an organized and practical comparison of 3DGS to NeRF, some limitations need to be addressed to offer a suitable context for its implications. Specifically, experiments were performed using one particular camera rig, a SONY α7C, alongside the gimbal and the wide-angle Sigma lens, used in previous research within this ongoing research. Despite this being an optimized and reusable setup, its generality for other hardware configurations is yet to be tested. Various sensor types, lens focal lengths, or stabilization devices might possibly affect data quality and, in turn, the reconstruction algorithms' performance.

Furthermore, the research used proposed or default parameters for each of NeRF and 3DGS as used in Postshot's software setup. Although this facilitates fairness and ease of reproduction, it does imply that additional gains in performance can be achieved using advanced tuning and tailored pipeline adjustments, something that remains unexplored during this study. A further consideration is the limited scene diversity. One scene indoors and one outdoors were analyzed, each designed to represent common forensic or practical reconstruction environments. However, this scope excludes more dynamic or adverse conditions, such as nighttime scenes, rapidly changing lighting, or environments with moving objects. A diverse set of test environments would be necessary to adequately test algorithmic robustness and flexibility.

Finally, while the assessment process utilized a scaled 1–5 rating system for critical criteria, an element of subjective interpretation was still used in the qualitative determination of noise and detail retention. While efforts were made to standardize scoring and focus on relevant viewpoints, more objective, ground truth-based metrics could enhance future evaluations by providing quantifiable and reproducible benchmarks.

E. Future Work

Building upon the results and constraints of this research, several promising directions for future work become apparent. A natural next step is to increase the diversity of environments within the experimental setup, both in terms of size and complexity. Adding environments with low light, specular surfaces, dynamic objects, or repetitive geometries would challenge the algorithms further and expose further challenges in performance in ways not yet tested. It would also be useful to investigate how domain-specific operators, such as forensic investigators, cultural heritage conservators, or drone pilots, use and make sense of each reconstruction. Conducting user studies focused on practical usability, clarity, and decision-making support could reveal which algorithmic characteristics matter the most in real-world deployments.

Finally, further investigation into hybrid workflows or optimization strategies could prove useful. For example, developing preprocessing methods that improve input quality for NeRF or integrating semantic segmentation into the 3DGS pipeline could enhance reconstruction accuracy and context awareness. Such developments would support the growing need for fast, robust, and interpretable 3D models across a wide range of disciplines.

V. CONCLUSION

This study presented a systematic and methodologically grounded comparison between Neural Radiance Fields (NeRF) and 3D Gaussian Splatting (3DGS), two cutting-edge approaches for generating photorealistic 3D reconstructions from captured imagery. By evaluating both algorithms under identical conditions, using the same full-frame camera setup, consistent filming techniques, and controlled indoor and outdoor environments, this study provides a balanced, application-oriented perspective on the strengths and limitations of each method.

The findings demonstrate that while NeRF remains a powerful tool for producing high-quality reconstructions, it is limited by its computational demands and its sensitivity to challenging lighting and occlusion conditions, particularly indoors. In contrast, 3DGS offers a more efficient alternative, delivering reconstructions of comparable or superior visual quality with significantly reduced processing times and fewer visual artifacts. These advantages are especially relevant for time-critical and precision-driven domains such as forensic investigation, security documentation, and indoor spatial analysis.

This study contributes to a growing body of applied 3D reconstruction research by not only benchmarking performance but by doing so within a realistic data capture framework grounded in prior experimental validation. It bridges the gap between technical algorithm development and real-world operational deployment, offering guidance for practitioners seeking effective, scalable solutions. Nonetheless, the study also highlights the importance of context: no single algorithm universally outperforms the other across all scenarios. The decision to use NeRF or 3DGS should be informed by the specific needs of the application, whether it is reconstruction speed, visual interpretability, model sharpness, or computational constraints.

This paper sets the stage for future exploration into more complex environments, automated evaluation metrics, and user-centered design studies. By expanding the scope of tested scenarios and integrating feedback from domain experts, future work will further raise the understanding of how 3D reconstruction technologies can best serve practical, high-impact use cases.

In conclusion, 3DGS emerges as a promising method for efficient and reliable 3D reconstruction in indoor and outdoor environments, offering strong potential for adoption in applied fields where performance, speed, and accuracy must coexist.

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